Designing a New Adaptive Filter for Iris Feature Extraction

Hamed Ranjzad

hamedranjzad@gmail.com,

Department of electrical Engineering Sahand University of Technology,

Abstract- with a growing emphasis on human identification, iris recognition as a biometric identification has recently received increasing attention. In these systems, matching error is of utmost importance. In this paper for feature extraction of iris a new adaptive filter is designed. This filter represents the texture features of iris more accurately. The scope and directions of this filter changes depending on situation and texture variations around each pixel. Finally extracted feature by some methods of texture analysis are combined. In order to reduce the lengths of feature vectors, PCA is imposed locally on them. For matching operation a new approach is proposed as well. The simulation results represent the better performance of our new designed system with reduced matching error rate tending to zero.

Key words: ***Iris recognition system, matching error Adaptive filter, locally PCA***

1. INTRODUCTION

Biometric authentication has been receiving extensive attention over the past decade with increasing demands in automated personal identification [1, 2, 3]. Among many biometrics techniques, iris recognition has gained match attention due to its high reliability for personal identification. Iris segmentation is done in four steps: 1 segmentation2: normalization 3: feature extraction 4: matching [3, 4]. Consequently the success of matching step in iris recognition depends on exclusivity of feature vectors which has been extracted in step3. For the last decade, a number of researchers have worked on iris recognition with the ambition to improve the application's performance accuracy.

Recently, texture analysis is one of the important and efficient approaches which are used widely in computer vision. Naturally, random iris pattern can be seen as texture, so many well-developed texture analysis methods can be adapted to recognize the iris. In [5] multichannel Gabor filters are used to extract the iris features. Circular symmetric filters were used in [6, 7] for iris texture analysis. In [8, 9] four-level Laplacian pyramid has been used for iris texture analysis and the quality of matching was determined by the normalized correlation results between the acquired iris image and the stored template. In [10] a 2-D Haar wavelet transforms has been used four times to decompose the iris image and constructed a compact code from the high-frequency coefficients. Log Gabor filters has been used for iris texture analysis in [11]. The accuracy of matching processes depends on the uniqueness of the extracted feature vectors. In this paper a new adaptive filter is designed in order to provide a more accurate texture feature extractions. This new filter extracts the texture feature of iris more accurately in radial and angular directions. The scope and directions of this filter changes depending on situation and texture variations around each pixel. Therefore extracted features should be more accurate. Final features are specified by combining some conventional feature used in computer vision with our approaches in feature extraction .In order to reduce the length of feature vectors PCA is used locally on extracted features. Matching operation of features extracted by texture analysis is based on locally matching of them. For each method feature extraction one weight is considered. These weights are selected based on the accuracy of features of that particular method. Finally the class with the highest score would be considered as the selected class. The rest of this paper is divided to different sections as described below. In the 2th section some conventional methods for texture analysis as well as our new adaptive filter for texture analysis of iris are described. In the 3th sections principle component analysis and the proposed method for local matching are described. Section five includes the experimental results and finally in the 6th section we conclude this paper.

2. TEXTURE ANALYSIS

The most appropriate method for feature extraction is to use texture analysis. In this section, some practical methods for texture analysis are described.

2-1-Local Standard Deviation:

In this method, standard deviations for the pixels inside windows are calculated by considring one window adjusted to each pixel. Choosing window size is dependent to the texture feature under analysis. In case of rapid texture variations, small size for window should be selected otherwise a bigger size should be chosen.

2-2- Local Entropy

This method is based on information theory. The entropy for a two dimensional discrete set is defined as bellow:

$$D=\sum_{i}\sum_{j}-p_{i,j}\log p_{i,j} \tag{1}$$

$P_{i,j}$ is the possibility of pixel occurrence with similar intensity with the current pixel in the *i,j* coordinates. For a more accurate operation, this method should be done locally.

2-3- Local Gabor wavelet

These filters are directional filters that generally used in directional feature extraction, since these filters are imposed on normalized image of iris they should be used in polar coordinates. This filter in polar coordinates, functions on normalized image as in equation (2)

$$G=\mathrm{sgn}_{\{\mathrm{Re},\mathrm{Im}\}}\int_{r}\int_{\theta} I(r,\theta)e^{-j\omega(\theta-\theta_0)}e^{-(r-r_0)^2/\alpha^2}e^{-(\theta-\theta_0)^2/\beta^2}\,r\,dr\,d\theta \tag{2}$$

$I(r,\theta)$ is the normalized image, α,β are scale parameters for Gaussian function and r_0 ,θ_0 are respectively radial and angular block centers of normalized image. Since the phase with respect to amplitude is of greater importance in texture analysis, in the above relation phase information is used as features.

2-4-Texture features extraction using directional laplacian pyramids

Nowadays laplacian pyramids are used widely in texture synthesis and analysis. These pyramids decompose two dimensional signals into different spectrums. The pyramid base corresponds to image details and its apex represents low frequency information of image. Since texture variations mostly occur with high frequency, usually the components including details are chosen for feature extraction. For a more accurate operation of laplacian pyramids in feature vector extraction, sometimes these pyramids are combined with directional filters that each pyramid component would be decomposed into some directional filters. These filters in frequency domain are represented as arcs of circular bands. Figure (1) represents frequency spectrum of two dimensional directional laplacian pyramids.

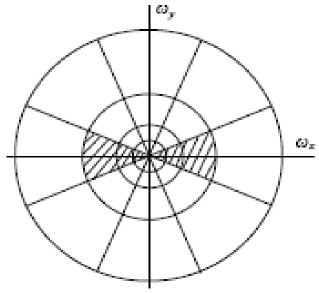


Figure (1) two dimensional directional laplacian pyramids in frequency domain

2-5-designing and implementation of a new adaptive filter

For a more accurate texture feature extraction, a new adaptive filter is designed. The idea is taken from Gabor filters. The new filter is represented as in bellow relation.

$$\begin{aligned}&Adaptive\_Gabor(x,y,x_i,y_i)=\exp\left(\frac{-x^2+y^2}{2\sigma^2}\right)\sin(x\cos(\theta)+jy\sin(\theta))\\&\theta=\arctan\left(\frac{x_i-x_0}{y_i-y_0}\right)\\&\sigma\propto Local\_entropy(xi,yi)\end{aligned} \tag{3}$$

In the above relation, x_0,y_0 are the iris center coordinates. x_i , y_i are the coordinates of a specified pixel in the iris image. θ is the direction of Gabor filter in the pixel. σ is the scale of Gaussian filter. Thus filter functions on the image as in the below relation.

$$\mathrm{Im}_{out}(m,n)=\sum_{y=-y_w}^{y_w}\sum_{x=-x_w}^{x_w}\left(\exp\left(\frac{x^2+y^2}{2\sigma^2}\right)\sin(x\cos(\theta)+jy\sin(\theta))\right)*\mathrm{Im}(n-x,n-y) \tag{4}$$

Operator window length equals $2X_w+1$ and its widths equal $2Y_w+1$. The prominent feature of the filter is that it is adaptive .Gabor filter represents texture feature only in one direction but in this new designed filter, as it was shown in relation (3) the direction and radius of filter in each part of image, depends on its positional coordinates. This filter is not only directional but also radial. Therefore, it can show texture features in the radial and angular direction at the same time. Since texture variations of iris occurs both in radial and angular directions, it is desired that this filter extracts texture features of iris more accurately. The scale of smoothing Gaussian function in each pixel is selected regarding to the texture variations around that pixel. Therefore, the scale of the smoothing function is chosen proportional to local entropy of that pixel. If texture variations around each pixel are intense, the rate of local entropy in that pixel would be high. So the radius of the smoothing filter in the frequency domain of that specific area is low. This is also through vice versa. Figure (3) represents the kernel frequency response of the designed adaptive filter in some specific points of the sample image of iris. White squares represents texture variations window around each pixel. These squares are numbered for the behavior analysis of function. Figure (3) shows the kernel of adaptive filter in the frequency domain for the specified pixels with the center of aforementioned square. As it can be noted here, the kernel function in the frequency domain is co-directional in each point with the angle of drawn lines from iris center toward that point. Furthermore, the radius of this filter in the frequency domain is proportional to the rate of texture variations around that pixel.

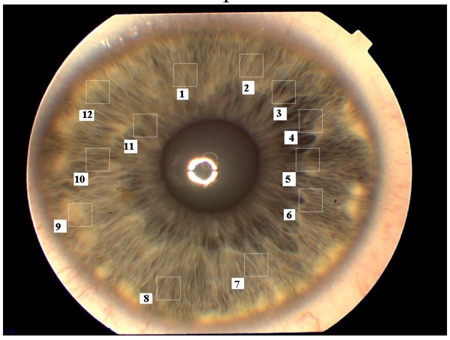


Figure (2) analysis of kernel function of adaptive filter in some points of the sample image

AS it shown in figure(3) the radius of kernel function in the frequency domain of the pixels which have more intense texture variations, is shorter and vice versa. Since generally iris texture has more intense variations around pupil, frequency response of the adaptive kernel filter has a longer radius around these points. In the areas near the sclera, texture variation is slow. As it can be realized here the radios of frequency response is shorter in these areas. The advantage of this new filter is its locality and adaptivity. This filter as extracting frequency features specifies positional features too. Therefore it could be called adaptive wavelet. This designed filter is adaptive booth in radial and angular direction. In order to extract features, new designed filter is imposed on annular image of iris. Then this filtered image should be normalized. Choosing different values for the length of kernel window, leads to different behavior of filter. This image can be decomposed to several images by choosing different values for the length of kernel window. If the length of window is short, the extracted features would be more local. By increasing the kernel window length, the extracted features would be more global. In order to have more accurate extracted features, the local and global features should be combined. Since the accuracy of local features is more than global features and global features have less sensitivity to noise, this would increase the accuracy of extracted features. Figure (4) shows output of new adaptive filter for various lengths of kernel window.

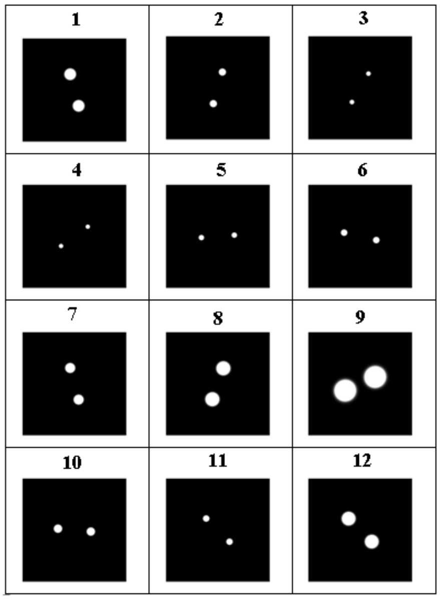


Figure (3) the frequency response of kernel adaptive filter in some specific points of image

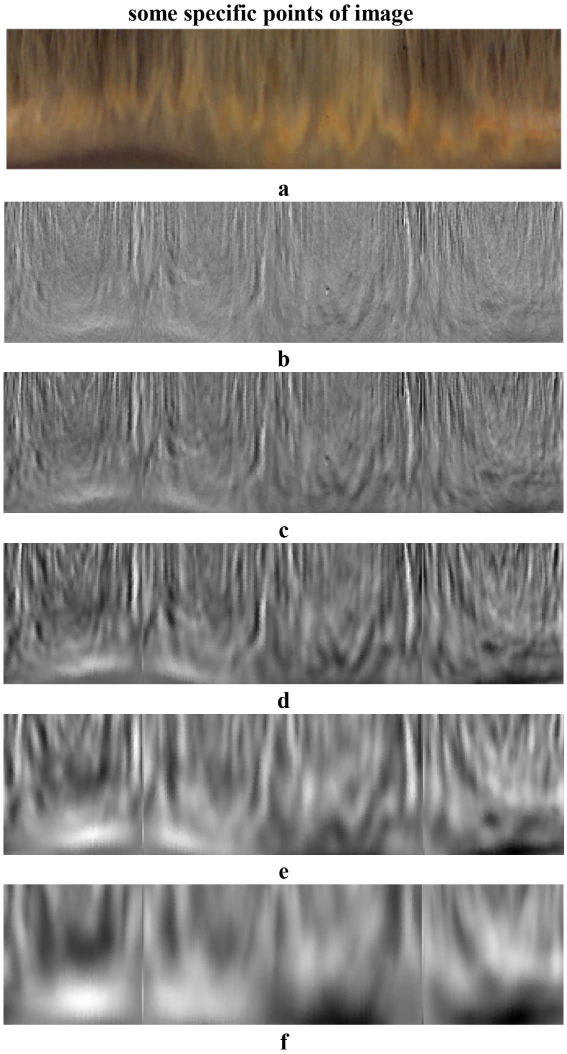


Figure (4) Extracted 2-d Feature signals by adaptive filter for various lengths of kernel window a: Normal Iris image b: w=5, c: w=9 d: w=17 e: w==33 f: w=65

3-Matching

The final step in iris recognition is to match experimental pattern with the patterns available in the database. Therefore test pattern is compared to all the patterns available in the database. If the test pattern matches with one pattern in the database, this pattern would be accepted. Otherwise it would be rejected. The performance of matching steps is evaluated by the rate of errors. In this section the analysis of principal component (PCA) is presented. Then the used approach for matching operation is described.

3-1 analysis of principle component

Analysis of principle components analysis generally in recognition systems is done for reducing dimensions and compacting. This method also is called mapping onto particular subspace. PCA maps the image onto the subspace that its first dimension has the greatest diffraction and its last dimension has the shortest diffraction. PCA algorithm for reducing the dimension of feature vector and their classification is described here:

- The average of vector is commuted and each vector is subtracted by it.
- Covariance matrix is commuted for these vectors.
- Particular vectors of covariance matrix should be computed and arranged in decreasing order. This matrix is called mapping matrix.
- *d* as the first dimension which has desired energy should be selected.
- The test vector should be transformed to new sub space using mapping matrix. The Euclidian distance is computed. The test vector is related to corresponding class with minimum distance which is shorter than threshold distance.

3-2-Matching operation for texture analysis

Using the combination of extracted feature vectors base on iris texture, would result in greater accuracy of classification in matching stage.

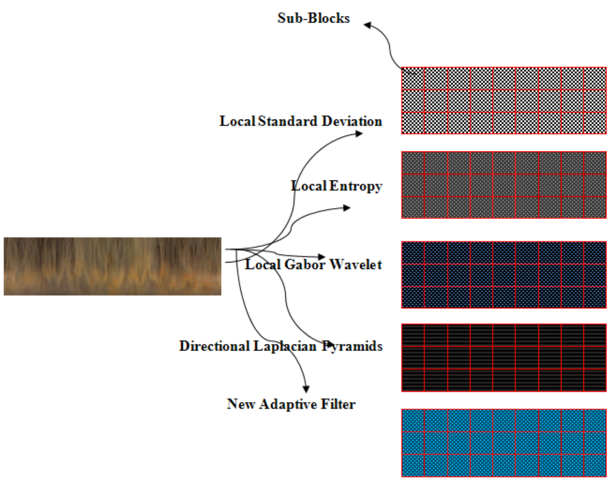


Figure (5) Extraction feature vectors based on texture analysis

Therefore, the combination of feature vectors depending on the texture is used in this paper. By imposing each of these methods on normalized image, a two dimensional feature signals would be obtained. Then the two dimensional feature signals are divided into blocks with fixed size. See figure (5). Two dimensional signals of each block are arranged in the corresponding feature vector of that block. So far each method and for each block, one feature vector is obtained. This operation is done on all images. In each method the feature vector of corresponding blocks for images are positioned in the column in the column of feature matrix. Then, PCA is imposed on this feature matrix. The dimension of feature vectors are reduced proportional to 90% of their energy. This operation is repeated for each feature extraction method. Finally for each block, we would have mapping matrix and feature vectors depending on the feature extraction method used.

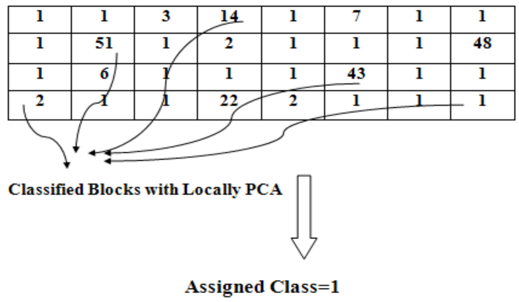


Figure (6) Classified blocks for the sample image

The test image is analyzed by different methods of feature extraction. Two dimensional signal of each method are divided into blocks with their former size. Classification operation for each block is performed by using the algorithm described in section 3-1. Therefore, various blocks of two dimensional signals in each method are assigned to one specific class. The class with the greatest iteration is considered as the final assigned class for the test image in the method used. Figure (6) shows an example which represents two dimensional feature signal blocks using classified local PCA method. Finally for each image relative to the number of feature extraction methods used, one class assigned. The class with the greatest iteration is the class selected in this method.

3-3 Final matching operation

For each image according to the number of feature extraction methods used, one class is assigned. The accuracy of the selected class depends on the efficiency and accuracy of the feature vectors of that method. The lesser the length of feature vectors using PCA, the greater the uniqueness and accuracy of feature vectors. For the selected class, one weight proportional to the accuracy of that class is chosen. For each specific selected class, using different methods, the sum of the weights assigned to it, is considered as the score of that class. The class with the highest score is the final specified class. Figure (7) represents the way, weights are assigned to each class by using different methods. It also shows the way the score is specified.

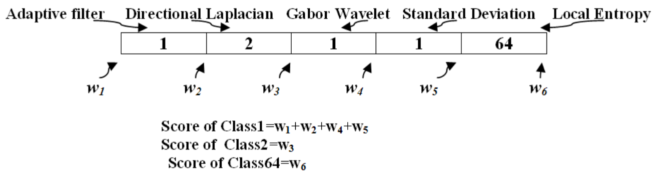


Figure (7) Scoring operation and final classification

Firstly, it is better to review the results of using geometrical methods.

5-Experemental Results

UOPL images are used as database. This data base is available in reference [16]. These images have resolution of 576×768. Some preprocessing operation is done on this image. So inappropriate edges, like the edges of specular regions in texture lines would not be shown. By using segmentation operation, the texture lines of image are separated from the rest of image.

In other methods, their weight is selected by reducing the length of feature vectors using PCA and 90% of its energy. After preprocessing and segmentation operations, the annular area of iris is formed into rectangular image of 100×360 dimensions. Texture analysis described in this paper is imposed on the images. Two dimensional signals are divided into blocks with 20×360 dimensions. Therefore, 50 blocks with the same size exist. The elements of these blocks are positioned on the vectors with the length of 720. Then PCA is imposed on each block. Considering 90% of signal energy, the length of feature vectors reduces greatly. This variation was not the same for different blocks and vectors. Averagely the length of feature vectors reduces to 1/3 of its initial size.

Figure (8) represents the reduction of feature vector length for 50 blocks of two dimensional feature signals. Since the length of extracted signals in various methods is different, in order to show the effect of PCA on reducing the length of extracted feature signals, the length of feature signals before imposing PCA is normalized to 1.

As iris shown in figure (8) dimension reduction in extracted features using the new adaptive filter is not very significant. That is due to the existence of more accurate extracted features by using this method. The average of normalized length of feature vectors in each method and for various blocks is selected as the weight for that method. Using this approach, wrong matching error would tend to zero. Table (1) shows comparison of FMR (False Match Rate) of iris recognition system designed with some different feature extraction methods.

Feature extraction method	FMR
Gabor wavelet	4.9
Laplacian filter bank	3.8
New Adaptive filter bank	1.6
Compound method	0

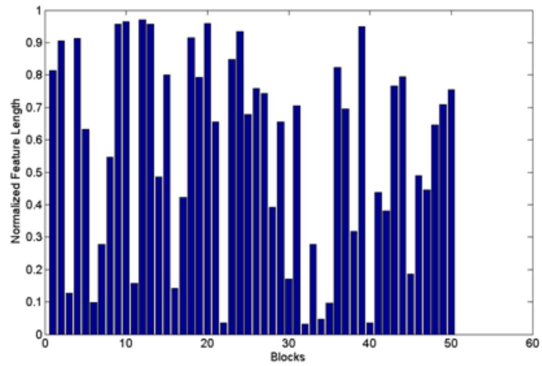
Table 1: comparison of FMR

6. Conclusion

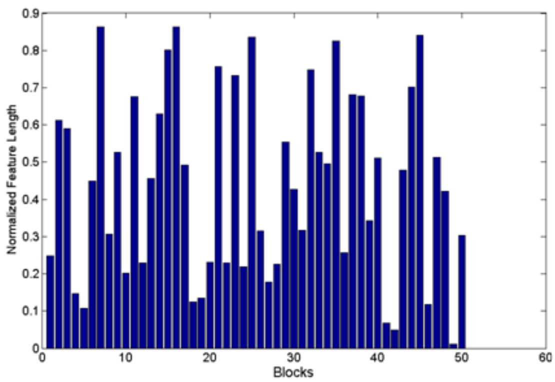
In this for more accurate extraction of texture features, a new adaptive filter has been designed. In order to reduce matching error to zero a combination of extracted feature with different methods and a new approach for matching operation is exploited.

ACKNOWLEDGMENT

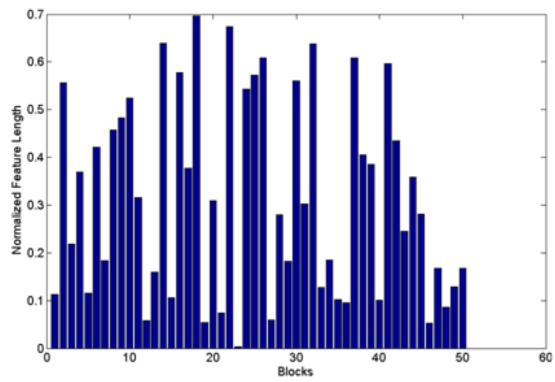
This research was supported by Iranian Telecommunication Center (ITRC)



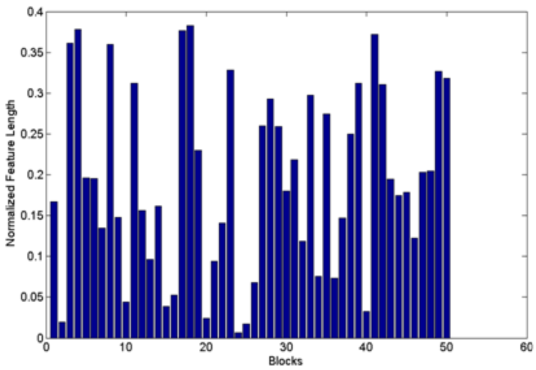
a



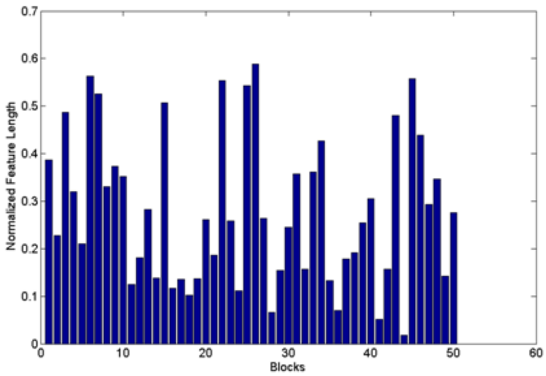
b



c



d



E

Figure (8) reducing feature vector by imposing locally PCA on 50 blocks of feature signals a:new adaptive filter b:Gabor wavelet c:Laplacian pyramid d:Entropy e:standard deviation

REFERENCES

[1] A. K. Jain, R. M. Bolle, and S. Pankanti, Eds., Biometrics: Personal Identification in Networked Society, Norwell, MA: Kluwer, Jan. 1999.

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

[3] Ehsan M. Arvacheh," A Study of Segmentation and Normalization for Iris Recognition Systems",Master apllied thesis, Waterloo, Ontario, Canada, 2006

[4] L. Ma, T. Tan, Y. Wang, D. Zhang. "Efficient Iris Recognition by Characterizing key local variations", IEEE Trans. Image Processing , vol. 13, pp. 739–750, Jun. 2004.

[5] J. Daugman, "How Iris Recognition Works," IEEE Trans. Circuits and Systems for Video Technology, vol. 14, no. 1, pp. 21-30, Jan. 2004.

[6] L. Ma, Y. Wang, and T. Tan, "Iris Recognition Using Circular Symmetric Filters," Proc. 16th Int'l Conf. Pattern Recognition, vol. II, pp. 414-417, 2002.

[7] L. Ma, T. Tan, Y.Wang and D. Zhang, " Personal identification based on iris texture analysis," IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 12, pp. 1519–1533, Dec. 2003.

[8] R. P. Wildes, J. C. Asmuth, G. L. Green, S. C. Hsu, R. J. Kolczynski, J. R. Matey, and S. E. McBride, "A machine-vision system for iris recognition," Mach. Vision Applicat., vol. 9, pp. 1–8, 1996.

[9] R. P. Wildes, "Iris recognition: An emerging biometric technology," Proc. IEEE, vol. 85, no. 9, pp. 1348–1363, Sep. 1997.

[10] 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. 61–70, 2001.

[11] J. Huang, L. Ma, Y. Wang, and T. Tan, "Iris recognition based on local orientation description," in Proc. 6th Asian Conf. Computer Vision, vol. II, 2004, pp. 954–959.

[12] Yambor W.S., "Analysis of PCA-Based and Fisher Discriminant-Based Image Recognition Algorithms", Technical Report CS-00-103, Computer Science Department, Colorado State University, July 2000.

[13] Martinez A.M. and Kak A.C., "PCA versus LDA", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 23, No.2, pp. 228-233, 2001.

[14] Hyvärinen, A., "Fast and Robust Fixed-Point Algorithms for Independent Component Analysis", IEEE Transactions on Neural Networks, Vol. 10, No. 3, pp. 626-634, 1999.

[15] Comon P., "Independent component analysis. a new concept", Signal Processing, Elsevier, vol. 36, pp. 287--314, Special issue on Higher-Order Statistics, April 1994.

[16] M. Dobes and L. Machala, "Iris Database," http:/www.inf.upol.cz./iris/2007