Feature Extraction Using Statistical Moments of Wavelet Transform for Iris Recognition

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***Abstract*—Iris is unique for each person, so that it can be used as one alternative solution for human identification. In this study, an iris recognition system is developed to automatically identify a person by using eye image data. Firstly, iris area of eye image is detected using Canny Edge Detection and Hough Transform methods. Secondly, texture feature of iris image is extracted using statistical moments of Wavelet Transform. Furthermore, the texture feature representation is recognized using Support Vector Machine classifier method. Experiment on CASIA eye image dataset gives good recognition rate, that is 93.5%.**

Keywords—wavelet transform; statistical moments; support vector machine; iris recognition.

I. INTRODUCTION

Iris is an annular part between the sclera (white area) and pupil (black area) of an eye image. Iris has unique pattern for each person, and the pattern is stable from infancy to adulthood. Capturing an iris data and converting it into an image can be simply done by using camera. Among various biometric techniques, such as face, palm vein, finger print, and signature, iris-based recognition is the most promising for high security environment. It is because of the unique, stable and non-invasive characteristics of iris.

Iris-based recognition has its growing use in large sectors such as transportation (iris as a living passport), healthcare (iris for tracing wanted persons), and physical access control in facilities (iris as a living password). In addition, the using of iris-based recognition can also be found at airports and border crossings, such as for immigration control without passport or gain access for airports crew to restricted areas [1]. Widely used electronic devices also utilize iris-based recognition because it is non-intrusive with a touch less sensor and has a higher recognition rate than fingerprint-based recognition [2]. Iris recognition involves challenges concerning quality of iris images such as pixel intensity, contrast, and symmetrical position in an image because they may produce texture deformations. Quality factors of iris images influence the success of processes within iris-based recognition problems.

In recent years, several feature extraction methods have been proposed for iris recognition. The iris recognition system was first developed by Daugman [3][4]. It extracts the iris oriented-based texture features using a complex valued 2D Gabor filters. Daugman chose the Gabor filters for iris recognition because the frequency, orientation and representation of Gabor filters are similar to that of the human visual system. Other feature extraction method was proposed by Bole and Boashash [5]. They used zero crossing representation of 1D wavelet transform to characterize the features of iris pattern that are represented by using a fine-to-coarse approximation. This method was applied on small samples and it is sensitive to the gray value changes. Ma et al [6] developed an iris recognition system by characterizing key local variations. The local sharp variation points of iris patterns are used as features. The normalized iris image is decomposed into a set of 1D intensity signals represented by using dyadic wavelet transform to obtain feature vector. Gray-scale morphological skeleton is proposed by Hayashi and Taguchi [7] to extract the features of an iris image. The morphological skeleton of an iris image is derived from the skeletons, which are extracted from binary pattern of images. Bharath et al [8] proposed radon tranform thresholding to extract prominent features of iris from the pre-processed image. The preprocessed image using gradient-based isolation obtains the salient iris textures. To find the optimal feature, a binary particle swarm optimization was applied as feature selection algorithm.

In this study, we develop an iris recognition system by using Canny Edge Detection and Hough Trasnform as the methods of iris area detection, statistical moments of Wavelet Transform as the method of feature extraction, and Support Vector Machine as the method of classification. Main focus of this study is to investigate performance of the texture feature representation based on statistical moments of Wavelet Tranform in iris recognition system. The rest of this paper presents detail explanation of the implemented iris recognition system, experiment, and conclusions in section 2, 3, and 4, respectively.

II. THE IRIS RECOGNITION SYSTEM

Processes schema of the implemented iris recognition system is shown in Fig. 1. There are two main phases, namely training and testing phase. Objective of the training phase is to develop a classifier model for iris recognition, while the testing phase is to evaluate recognition performance of the developed classifier model. In the training phase, a set of eye images is pre-processed to obtain a set of normalized iris data. Hereafter, texture feature of each iris data is extracted to get a set of feature vector by using first order statistical of wavelet transform. The set of texture feature vectors is used to train the iris recognition model by using Support Vector Machine method. In the testing phase, eye image which will be recognized, must go through the pre-processing and the feature extraction steps before entering the recognition step.

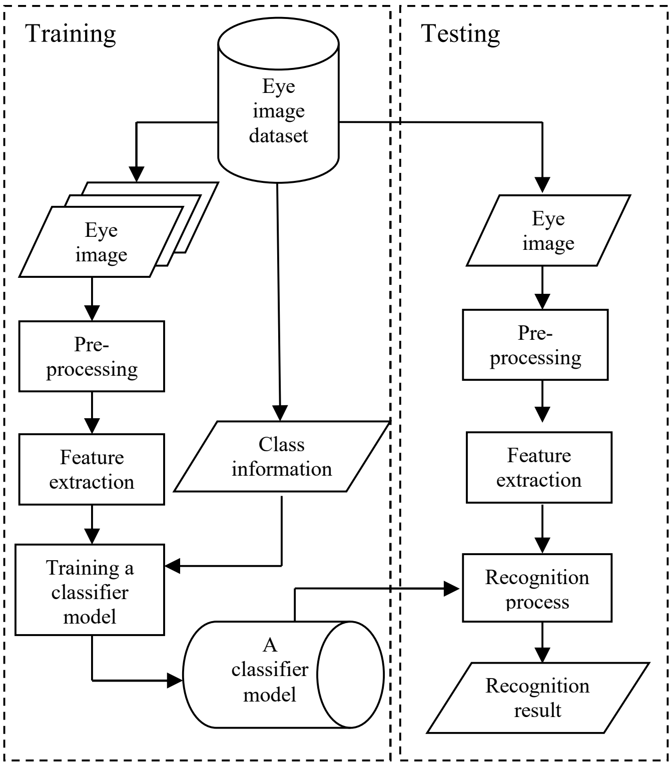


Fig. 1. Processes schema of iris recognition system

A. Pre-processing

The purpose of pre-processing step is to localize the iris region of an eye image. The pre-processing consists of four step, such as edge detection, inner and outer boundaries detection of iris region, and iris normalization.

1. Edge Detection

In this step, canny edge detector is applied to detect iris edges. The process of canny edge detection are smooth the image and eliminate noise, find the edge strength and define edge direction, do non-maximum suppression to make the edge become thinner, and then apply double thresholding and edge tracking the image using hysteresis [9][10]. The result of edge detection on eye image using canny operator is shown in Fig. 1(b).

2. Inner and outer boundaries detection of iris region

In order to detect both inner (pupil-iris) and outer (iris-sclera) boundaries of iris region, we apply circular Hough transform [11]. The circular Hough transform aims to find the circular formations, of a given radius *r*, within in an image. This detection is similar to a convolution process between an image and a circle operator. To apply the Hough transform, a circle is represented by (1).

$$(x_c - a)^2 + (y_c - b)^2 = r^2 \tag{1}$$

where (x_c, y_c) is the coordinate points of the circle, (a,b) is the center points of the circle, and r is the radius of the circle.

Next, eyelid and eyelashes are removed from the iris region. Fig. 1(c) shows the result of inner and outer boundaries of iris region. While Fig. 1(d) shows the result of eyelid and eyelashes removal.

3. Iris normalization

Daugman's Rubber sheet model [12] is applied on the selected iris region to normalize the image. The Rubber sheet model is described in (2).

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta) \tag{2}$$

where $x(r,\theta) = (1-r)\, \alpha_p(\theta) + r\, \alpha_i(\theta)$ and $y(r,\theta) = (1-r)\, \beta_p(\theta) + r\, \beta_i(\theta)$, $I(x,y)$ is the iris region image, (x,y) is the original Cartesian coordinates, (r,θ) is the corresponding normalized polar coordinates, and (α_p,β_p) and (α_i,β_i) are the coordinates of the centers of pupil. Fig.1(e) shows the result of iris normalization.

B. Feature extraction using Statistical Moments of Wavelet Transfrom

The Discrete Wavelet Transform (DWT) which is based on subband coding is among the most popularly wavelet transforms [13]. The DWT provides information useful for many image analysis tasks, such as de-noising, segmentation, and feature extraction. The DWT is also easy to implement, and requires less computation time. Image decomposition can be performed by applying the 1D wavelet transform along the rows of the image first, and then along the columns. This process results four decomposed sub-band images, i.e. low-low (LL), low-high (LH), high-low (HL), and high-high (HH), which correspond to approximation image, different information in horizontal, different information in vertical, and different information in diagonal, respectively. The wavelet decomposition process can be repeated on to the resulted approximation image to obtain another four sub-images in the next decomposition level. In this study, Daubechies wavelet is considered to compute wavelet decomposition of iris image because it has compact support characteristic and requires less computational complexity.

Fig. 3 shows illustration of wavelet decomposition of normalized iris image. After one level wavelet decomposition, the normalized iris image in (a) which has size 512 x 64 pixels is decomposed into four sub-images with size 256 x 32 pixels shown in (b). The four sub-images consists of appoximation image (top left), different image in horizontal (top right), different image in vertical (bottom left), and different image in diagonal (bottom right). Furthermore, two level of wavelet decomposition is performed to the approximation image resulted from the previous level of wavelet decomposition. Four sub-images computed from two level wavelet decomposition are shown in (c). All sub-images in (c) has size 128 x 16 pixels, and consists of appoximation image (top left), different image in horizontal (top right), different image in vertical (bottom left), and different image in diagonal (bottom right). Wavelet decomposition can be performed further, each time by using approximation image from the previous decomposition as the input.

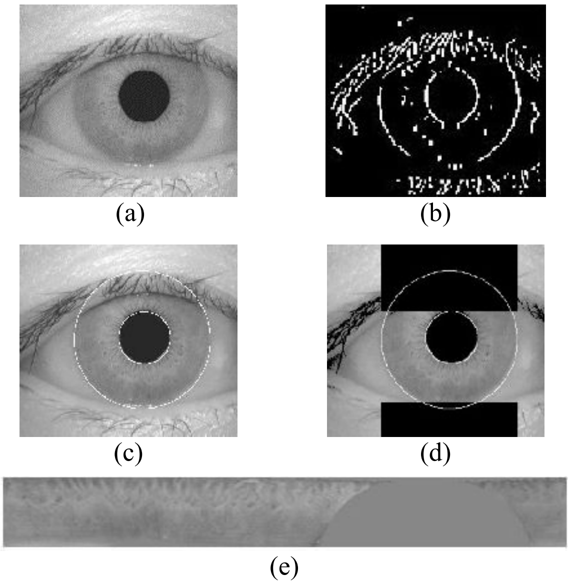


Fig. 2. The results of pre-processing on eye image. (a) Eye Image, (b) Edge Detection, (c) Inner and outer boundaries of iris region, (d) Eyelid and eyelashes removal, (e) Iris normalization.

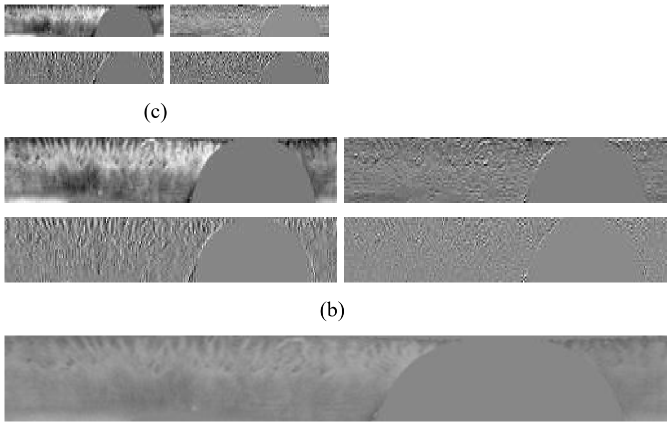
All value resulted from the wavelet decomposition is used for texture analysis, which provides measures of properties such as smoothness, coarseness, and regularity [14]. There are three approaches to describe the texture of a region in image, i.e. statistical, structural, and spectral. In statistical approach, the statistical moments of images, such as mean, 2nd moments, 3rd moment and 4th moment are computed to describe the texture features.

Let r denotes intensities of an image I, and $p(r)$ correspondes to image histogram, with L distinct intensity levels. Mean, which denotes average intensity of pixels in an image, is computed using (3). The nth moments of r, i.e. standard deviation (2nd moments) which refers to the measure of contrast in an image; skewness (3rd moment) which deals with the degree of histogram asymmetry around the mean, and kurtosis (4th moment) which represents a relative flatness, is computed using (4).

$$m = \sum_{i=0}^{L-1} r_i p(r_i) \qquad (3)$$

$$\mu_n(r) = \sum_{i=0}^{L-1} (r_i - m)^n p(r_i) \qquad (4)$$

By applying (3) and (4) to all four sub-images, there will be 16 descriptors in each decomposition level. The level number of decomposition process determines total number of descriptors.



(a)

Fig. 3. Illustration of wavelet decomposition: (a) An normalized iris image, (b) Four subimages after 1 level wavelet decomposition, (c) Four subimages after 2 level wavelet decomposition

C. Classification using Support Vector Machine

Support Vector Machine (SVM) is a method that can be used to obtain optimal hyperplane of two sets in a vector space, without depend to the probabilistic distributions of training vectors [15]. Its main idea is to locate the most distant hyperplane from the vectors nearest to the hyperplane in both of the sets. The optimal hyperplane should also classify unknown vectors, as well as the training vectors. Since the hyperplane is the most isolated one from both of the sets, then it is expected to produce optimal classification of the sets. Support vectors are defined as training vectors closest to the hyperplane. Fig. 4 illustrates the optimal hyperplane computed by SVM method.

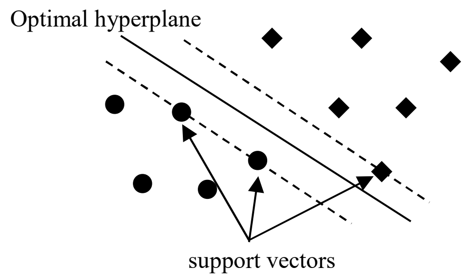


Fig. 4. Optimal Hyperplane of Support Vector Machine

The distance between the vectors nearest to the hyperplane in both classes is called margin. So, the hyperplane is obtained by weight coefficient vector w and bias term b values as shown in (5).

$$w.x + b = 0 \quad (5)$$

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} t_i \quad (6)$$

In (6), the parameter C is penalty value from missed classification. The optimal w and b values are obtained by using constraints and objective function as shown in (7).

$$y_i(wx_i + b) + t_i \geq 1 \quad (7)$$

In order to solve the optimization problem above, the Lagrange method is applied the transformation equation (8), with constraint determined in (9).

$$\max \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} y_i y_j \alpha_i \alpha_j x_i^T x_j \quad (8)$$

$$\alpha_i \geq 0, \sum_{i=1}^{l} \alpha_i y_i = 0 \quad (9)$$

In order to find the α_i value, the quadratic programming (QR) is applied. After calculating the α_i value, we obtain hyper plane function as shown in (10) and (11), where z is training data.

$$w = \sum_{i=1}^{s} \alpha_i y_i x_i^T \quad (10)$$

$$f = w^T z + b = \sum_{i=1}^{s} \alpha_i y_i x_i^T z + b \quad (11)$$

To solve the nonlinear problem, the SVM use kernel concept to transform the problem into the higher dimensional feature space. The kernel function is a function that corresponds to the inner product into some feature space [16]. The example of kernel functions, i.e. linear, polynomial, and radial basis function are shown in (12).

$$k(x, y) = \begin{cases} x.y \\ (\gamma\langle x^T\ y\rangle + C)^p \\ \exp(-\gamma|x\text{-}y|^2) \end{cases} \quad (12)$$

where p is polynomial order and γ is scaling factor. The radial basis function (RBF) usually achieves the best performance in classification [17].

In this study, we use SVM multiclass for iris recognition. Basically, the procedure of SVM binary class is similar with the SVM multiclass. The SVM binary class build only one mode classification according to the optimal hyperplane, while the SVM multiclass build n classification models, where n is number of classes. The illustration of SVM multiclass is shown in Fig. 4.

III. EXPERIMENT

In experiment, we use eye image dataset from Chinese Academy of Science-Institute of Automation (CASIA) version 1.0 which consists of 350 eye images taken from 50 different persons. Seven eye images are taken from each person. Each class consists of seven eye images, so that the total number of eye images used in the experiment is 50 x 7 = 350. All eye image is grayscale, and has size 320 x 280 pixels.

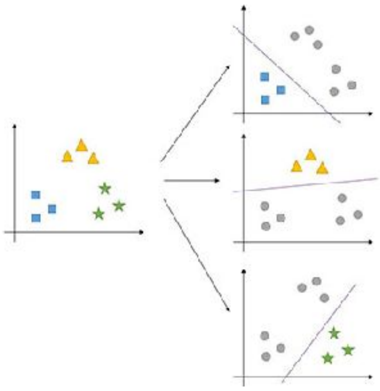
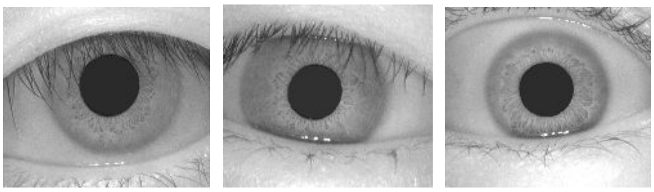
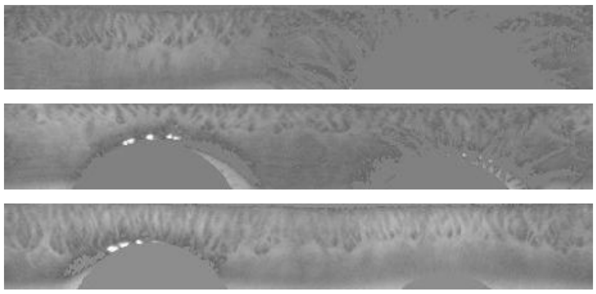


Fig. 5. Illustration of SVM Multiclass

All eye images are pre-processed to localize only iris region and is normalized from polar to spatial coordinate. The pre-processing produces 350 normalized iris images; each has size 512 x 64 pixels. Fig. 4 shows three examples of eye image taken from three different persons (a) and their corresponding normalized iris image (b). The first, middle, and last row images in Fig. 4(b) are the preprocessing results of the left, middle, and right eye images in Fig. 4(a), respectively. As shown in Fig. 4, each eye image has different eyelashes, eye orientation, and eyelid. Reliability of preprocessing step in localizing iris region greatly affects performance of the iris recognition system.



(a)



(b)

Fig. 6. Examples of (a) Three eye images, and (b) Three corresponding normalized iris images

In this study, all normalized iris image are then decomposed using wavelet transform up to eight levels. Four descriptors, i.e. mean, standard deviation, skewness and kurtosis are computed from each sub-image obtained from wavelet decomposition. Thus, each iris image has feature vector with size equal to 16, 32, 48, 64, and 80; for 1, 2, 3, 4, and 5 decomposition levels, respectively. Table I shows values of three feature vectors of the iris images in Fig. 4(b). There are 32 values in the table, which indicates that the iris image is decomposed up to two levels. From upper to lower, the iris images in Fig. 4(b) are named Eye_1, Eye_2, and Eye_3, respectively. All 32 texture descriptors are shown in the texture descriptor column. As shown in Min-Max column, the value range of texture descriptors is quiet vary. In addition, descriptor per each texture column is also vary. Thus, value normalization for each column is required in order to equalize contribution of each feature component.

TABLE I. EXAMPLE OF THE FEATURE VECTOR

Eye Image	Texture Descriptor	Min-Max
Eye_1	[256.2,2.5334,2.1185,0.73486,5.4436, 1.5024,1.2989,0.58891,-1.1278,0.18685, -0.094151,0.11292,7.6714,5.3221,7.3769,6.9161,512.4,5.8982,5.0259,3.4404,10.337,3.2718, 3.1128, 1.8951,-0.80905,0.3266,0.014613, 0.22352,5.7373, 4.2594,5.4294,6.943]	min= -1.1278 max = 512.4
Eye_2	[259.49,3.5107,2.4995,0.95056,7.8823,2.7872,1.7576,0.84886,0.83741,0.36704,-0.21132,0.012385,19.81,14.802,12.154,4.8104,518.98,8.8291,6.3018,4.2749,14.908,7.5043,3.829,2.8327,0.21239,0.50812,0.019878,-0.063733,9.4608,5.4072,6.2352,4.9899]	min = -0.2113 max = 518.98
Eye_3	[286.8,3.3793,2.8762,0.87018,6.3889,2.3589,1.6766,0.94627,1.9246,-0.39779, -0.24174, -0.2612,23.476,10.885,15.999, 13.913, 573.6,9.2972,7.7635,4.2052,11.42,5.1392, 4.3675,2.4426,1.1876,0.28202,-0.41492,-0.22491, 17.933,9.4926,6.9312,6.5186]	min = -0.4149 max = 573.6

In experiment, 200 eye images are used for training, and 150 eye images are used for testing. The experiment is performed using Support Vector Machine Classifier with Radial Basis Function (RBF) Kernel. The level of wavelet decomposition is from 1 to 5. Performance of the system is determined by recognition rate, which is computed using (13). In (13), R is recognition rate, N is total number of testing, TT is total number of correct testing.

$$R = \frac{TT}{N} \times 100\% \tag{13}$$

TABLE II. THE RATE RECOGNITION

Level of wavelet decomposition	Recognition rate
1	92.5 %
2	**93.5 %**
3	92.3 %
4	92.1 %
5	91.5 %

Table II shows recognition rate of the system by using 1, 2, 3, 4, and 5 level of wavelet decomposition. The best recognition rate is 93.5%, which is obtained from 2 level of wavelet decomposition. The worst recognition rate is obtained by using 5 level of wavelet decomposition. The result informs that the higher the level of wavelet decomposition, which means the greater the number of texture descriptors, does not assure improvement of recognition rate. Overall, the feature extraction method using statistical moments of wavelet transform is appropriate for iris recognition system.

IV. CONCLUSIONS

In this study, an iris recognition system by using statistical moments of wavelet transform as the method of feature extraction has been developed. From the experimental result, the system achieves good result to recognize persons by using their iris image, with the best recognition rate 93.5%. As future works, more feature extraction methods will be explored in order to improve the recognition rate with acceptable accuracy and time execution.

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REFERENCES

[1] J.Daugman, S.Z.Li, A.K. Jain, “Iris Recognition at Airports and Border Crossing”, Encyclopedia of Biometrics hal 998-1004, Springer-Boston, 2015.

[2] K.Dongik, J.Yujin, T.Kar-Ann, S.Byungjun, K.Jaihie, “An empirical study on iris recognition in a mobile phone”, Expert Systems with Applications Vol.54 hal 328-339, 2016.

[3] Daugman, John G, "Biometric personal identification system based on iris analysis," U.S. Patent 5,291,560, issued March 1, 1994.

[4] Daugman, John, "How iris recognition works," IEEE Transactions on circuits and systems for video technology 14, no. 1 (2004): 21-30.

[5] Boles, Wageeh W., and Boualem Boashash, "A human identification technique using images of the iris and wavelet transform," IEEE transactions on signal processing 46, no. 4 (1998): 1185-1188.

[6] Ma, Li, Tieniu Tan, Yunhong Wang, and Dexin Zhang, "Efficient iris recognition by characterizing key local variations," IEEE Transactions on image processing 13, no. 6 (2004): 739-750.

[7] Hayashi, Nozomi, and Akira Taguchi, "Iris identification using morphological skeleton," In Communications and Information Technologies (ISCIT), 2010 International Symposium on, pp. 713-716. IEEE, 2010.

[8] Bharath, B. V., A. S. Vilas, K. Manikantan, and S. Ramachandran, "Iris recognition using radon transform thresholding based feature extraction with Gradient-based Isolation as a pre-processing technique," In 2014 9th International Conference on Industrial and Information Systems (ICIIS), pp. 1-8. IEEE, 2014.M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

[9] Canny, John, "A computational approach to edge detection," IEEE Transactions on pattern analysis and machine intelligence 6 (1986): 679-698.

[10] Kaur, Navjot, and Mamta Juneja, "A review on iris recognition," In Engineering and Computational Sciences (RAECS), 2014 Recent Advances in, pp. 1-5. IEEE, 2014.

[11] Kerbyson, D. J., and T. J. Atherton, "Circle detection using Hough transform filters," In Image Processing and its Applications, 1995., Fifth International Conference on, pp. 370-374. IET, 1995.

[12] Masek, Libor, "Recognition of human iris patterns for biometric identification," The University of Western Australia 2, 2003.

[13] S. Mallat, "A Wavelet Tour of Signal Processing: The sparse way", Academic Press, 1999.

[14] Gonzalez RC, Woods RE, "Digital image processing", 3rd, Pearson Prentice Hall, 2002.

[15] V. Vapnik, "The Nature of Statistical Learning Theory", NY: Springer-Verlag, 1995.

[16] C.-J. L. Chih-Chung Chang, "A Library for Support Vector Machines," Taipei, Taiwan, 2001.

[17] X. Hou, "Support Vector Machine," github, 25 April 2015. [Online]. Available:http://houxianxu.github.io/support-vector-machine/.[Accessed 23 May 2016]