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IDENTIFICATION OF VAGINA AND PELVIS FROM IRIS REGION USING ARTIFICIAL NEURAL NETWORK

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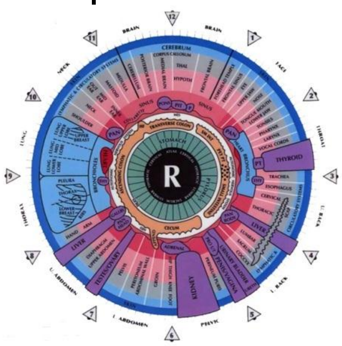
Graphical abstract



Abstract

Iris recognition not only can be used in biometrics technology but also in medical application by identifying the region that relates to the body part. This paper describes a technique for identification of vagina and pelvis regions from iris region using Artificial Neural Network (ANN) based on iridology chart whereby the ANN process utilized Feed Forward Neural Network (FFNN). The localization of the iris is carried out using two methods namely Circular Boundary Detector (CBD) and Circular Hough Transform (CHT). The iris is segmented based on the iridology chart and unwrapped into polar form using Daugman's Rubber Sheet Model. The vagina and pelvis regions are cropped into pixel size of 40x7 for feature extraction using Principal component Analysis (PCA) and classified using FFNN. In the experiments, 15 pelvis and 20 vagina regions are used for classification. The best result obtained gives overall correct identification from localization using CBD and CHT of about 67% and 81% respectively. From the experiments, it is observed that vagina and pelvis regions are able to be identified even though the results obtained are not 100% accurate.

Keywords: Artificial neural network, circular boundary detector, circular hough transform, daugman's rubber sheet model, principle component analysis,pelvis,support vector machine, vagina.

1.0 INTRODUCTION

Biometrics accurately identifies a person and able to distinguish one from another [1]. For this purpose, various physiological characteristics of human such as face, facial thermo grams, fingerprint, iris, retina, hand geometry and others are used. Iris recognition is becoming a popular topic in research and practically because it is one of the biometrics recognition in human identification. The characteristics are different among individual such as the iris contains art of patterns for each person and stable with age. The iris of human does not change which means that the iris is stable [2].

In biometrics, it has been proven that iris pattern is the best parameter for a person's identification and has also been established in medical area. The closely relationship between iris pattern and status of health is founded by previous study [3]. In this study the cholesterol presence is detected by constructing the histogram of the region of interest and applying Otsu's threshold method. From the study it is observed that the procedure in differentiating the iris region is not conducted to prove that iris has different regions that are related to human body parts as claimed by the iridologist. Due to this a research work is carried out to show the significance difference between each region of the iris. Iridologist used Iridology technique to detect health status on pattern and color of iris. The iridology chart shown in Figure 1 illustrates the iris regions that relate to the human body parts [4].

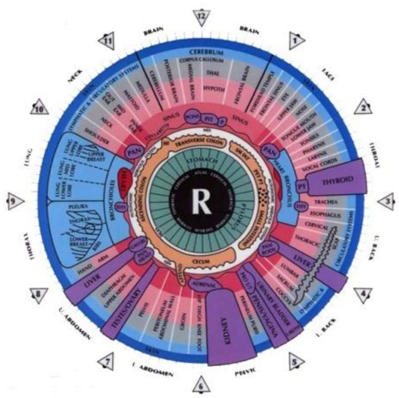


Figure 1 Iridology chart of right eye

Iris patterns are different in texture and due to this the regions of vagina and pelvis are selected for study. CHT and CBD are the proposed methods that have been introduced earlier to produce high accuracy in localizing the iris [5, 6]. Both CBD and CHT techniques are used in this study in order to make comparison in terms of classification accuracy of the vagina and pelvis regions. PCA is used to extract features from the cropped regions of vagina and pelvis and the normalized features are the input to the FFNN [5]. Classification accuracy is calculated and compared to measure the performance. The database for both of these techniques is obtained using iridology digital camera from healthy married women free from Human Papilloma Virus (HPV) of ages 25 to 50 years as in [6].

2.0 CIRCULAR HOUGH TRANSFORM

CHT is one of the proposed methods that are used to localize the iris boundary. The function of this technique is to isolate features of a particular shape within an image and used to find curve of shape such as lines, circles, ellipses and any other arbitrary shape [7]. CHT has been recognized as robust technique to detect feature boundary without affected by image noise. The iris circle shape and the parameters are defined using the circle equation as in [6]. When the formation of circular shape is qualified, the area of iris is detected on the image and used for testing at the region of interest. The center coordinates and the radius are detected automatically using this method whereby the circle forms automatically on the iris image [5].

3.0 CIRCULAR BOUNDRY DETECTOR

Circular Boundary Detector is another proposed method that is used to localize the iris boundary. The function of this technique is to produce a circular template on the eye image so that the boundaries of iris and pupil can be detected. The Circular Boundary Detector technique is also not affected by image noise since the formation of the circles is dependent on the selected radius based on pixel size. The localization process starts by selecting two points on the iris region. (*a*,*b*) is the first point for the center of the iris and (x,y) is the second point for the radius of the iris. The iris circle shape is defined using the circle equation as in [6].

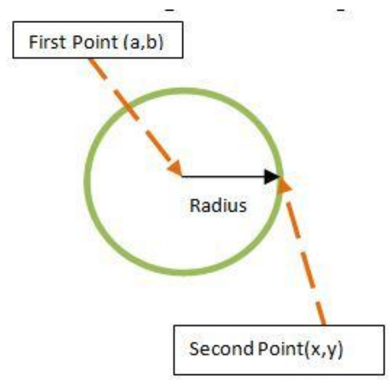


Figure 2 Circular formation using CBD

The circle as in Figure 2 is formed automatically on the iris image even though the coordinates of the circle center and the circumference are selected manually but the construction of the circular boundary is based on the computation of the rest of x and y coordinates as angle θ varies from 0° to 360° [6].

4.0 DAUGMAN'S RUBBER SHEET MODEL.

To obtain a fixed number of features from the iris regardless of its spatial resolution, normalization of the segmented iris region is conducted. A fixed dimension coordinate system is mapped which is invariant to size changes. The different sizes of iris will be produced due to variation of pupil dilation. The rubber sheet model is an algorithm used to transform iris from circle (circular) to rectangular (polar form). This algorithm was developed by John G. Daugman [2]. This algorithm maps the coordinates of each point from the segmented iris region to polar coordinates (θ, r) where r ranges from 0 to 1 and θ ranges from (0, 2π). The process is shown in Figure 3.

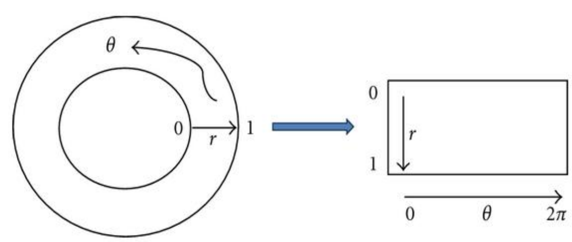


Figure 3 Transformation of iris from circular to polar using rubber sheet model algorithm

The unwrapping of the iris region in Cartesian coordinates (x,y) to the normalized polar is represented as,

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta) \qquad \text{(Eq. 1)}$$

with,

$$x(r,\theta) = (1-r)x_p(\theta) + rx_i(\theta) \qquad \text{(Eq. 2)}$$

$$y(r,\theta) = (1-r)y_p(\theta) + ry_i(\theta) \qquad \text{(Eq. 3)}$$

where I(x,y) is the original iris image, ($x_p(\theta)$, $y_p(\theta)$) is the coordinate of pupil boundary points and ($x_i(\theta)$, $y_i(\theta)$) is the outer perimeter of the iris bordering the sclera [8].

5.0 PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is a statistical technique that is normally used for pattern recognition for data selection in the system and reduction of high data dimensions. This technique shows that the data of image processing can produce best performance [9]. By finding the eigenvalues and eigenvectors, PCA finds the variances and coefficients of the dataset. The rows are in the order of the amount they contribute to the total variation where rows whose contribution to total variation is less than the maximum fraction of variance are removed. PCA determines the eigenvectors and eigenvalues from the covariance matrix. The covariance of random variables (dimensions) is represented as,

$$cov(x,y) = \sum_{i=1}^{N} \frac{(x_i-\bar{x})(y_i-\bar{y})}{N} \qquad \text{(Eq. 4)}$$

where $\bar{x}$ is mean of (x), $\bar{y}$ is mean of (y) and N is the dimension of dataset. Matrix D, that is D(i,j) = cov(i,j) is the covariance matrix and it centers data by subtracting the mean of each sample vector [9]. The eigenvectors are ordered by eigenvalues from highest to lowest. This causes the component to be sorted in order of significant and construct a feature vector. The selected eigenvectors are taken from the list of eigenvectors and form a matrix in the columns. The eigenvalues will be removed when it is below than one and greatest information is provided by the largest eigenvalues and the information from the data is not affected when the eigenvalues are removed. The equation of eigenvectors and eigenvalues are represented as,

$$DE_i = E_i E_v \qquad \text{(Eq. 5)}$$

where E_i is an eigenvectors, E_v is an eigenvalues. The variable D is the covariance matrix [9].

6.0 ARTIFICIAL NEURAL NETWORK (ANN)

A Feed forward Neural Network (FFNN) is the fundamental architecture of ANN which consists of series of layers. It also has a connection from the network input at the first layer and has connection from the previous layer and at each subsequent layer. For the final layer, it produces an output of the network. FFNN or Multi-Layer Perceptron (MLP) with one hidden layer has been proven for approximating any function with reliable accuracy provided it satisfies the related condition [10]. The characteristic of MLP is a nonlinear activation function in its hidden layer and showing a high degree of connectivity between the layers that is determined by the weights of the network.

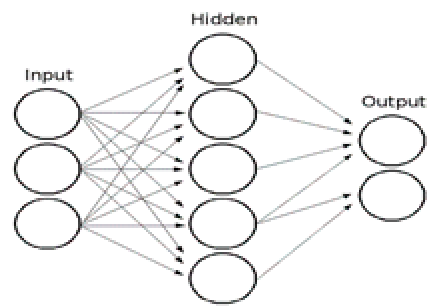


Figure 4 3 layer structure of multilayer perceptron

Figure 4, shows the 3 layer MLP. First layer shows the input layer. The middle layer is a hidden layer and the last layer shows the output layer. The MLP works by propagating on a layer-to-layer basis from the input signal towards the output signal. The signals given to a layer and outputs a value to the next layer in each layer process. The weight value is attached to the layer in each interconnection. To adjust the strength of the signal propagating through the layer, the weight is used [10]. MLP activation function TANSIG approximates the sigmoid activation function and it is commonly used in the hidden layer. It can also be used for the output layer in pattern classification problems. The input active range of **tansig** between negative one and positive one and apart from the range it will be squashed to within these limits. The equation of **tansig**, hidden layer and output layer can be expressed as;

$$tansig(n) = \frac{e^{cn} - e^{-cn}}{e^{cn} + e^{-cn}} \qquad \text{(Eq. 6)}$$

where, c=1 and n=output value. The value from the input hidden layer, H_1 can be obtained from,

$$H_1 = tansig(b_I * W_{I_0 \rightarrow H_1} + \sum_{i+1}^{N} I_i * W_{I_i \rightarrow H_1}) \qquad \text{(Eq. 7)}$$

$$O_1 = tansig\,(b_H * W_{H_0 \rightarrow O_1} + \sum_{i+1}^{M} H_i * W_{H_i \rightarrow O_1}) \quad \text{(Eq. 8)}$$

where, W_{Ho} is the weight between hidden and output layer, W_{Hi} is the weight between input and hidden layer and b_H is the bias [11].

7.0 METHODOLOGY

The block diagram of the process used to differentiate between iris pattern of vagina and pelvis region is shown in Figure 5

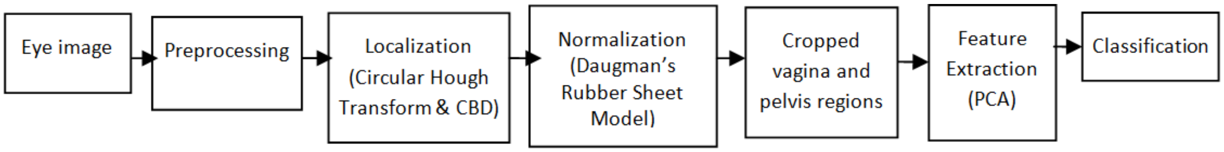
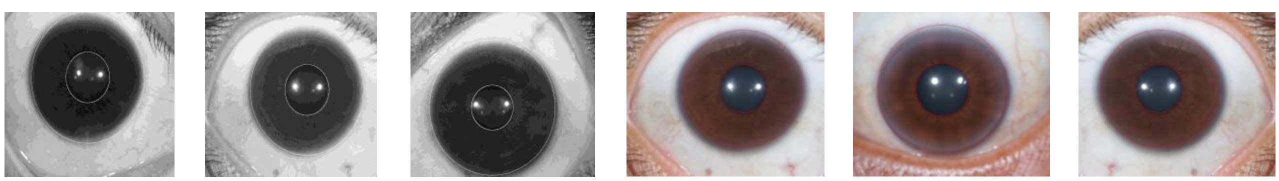


Figure 5 Block diagram of the classification process

Initially, the eye images are obtained from the volunteers and the eye images are cropped and resized from 3888 x 2592 pixels to 601 x 501 pixels [6]. CHT and CBD technique was used to localize the inner and outer boundaries. The localized images in circular are transformed to polar form or rectangular shape at normalization stage. The fixed dimension of a normalized image is 128 x 1024 pixels. The localization of inner and outer boundary of iris using CHT and CBD are shown in Figure 6(a)-(c) and Figure6(d)-(f) respectively while Figure 7 shows the normalized iris using Daugman's Rubber Sheet model.



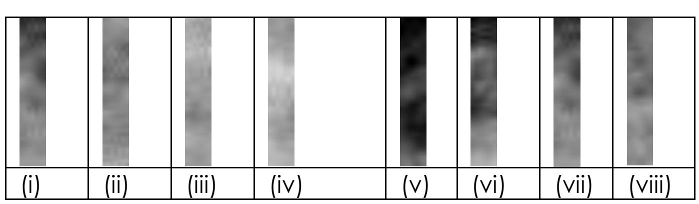
(a) (b) (c) (d) (e) (f)

Figure 6(a)-(c): Localization of inner and outer boundary of iris using CHT

Figure 6(d)-(f): Localization of inner and outer boundary of iris using CBD

Figure 7 Normalized iris using Daugman's Rubber Sheet model

Based on the iridology chart as a reference, selected regions were cropped into regions of interest (ROI). For the study purpose, the selected regions are vagina and pelvis 15 samples of pelvis and 20 samples of vagina are used for classification. The dimension of vagina and pelvis region is 40 x 7 pixels. Several samples of cropped vagina and pelvis are shown in Figure 8(a) and (b) respectively.



(a) (i-iv), vagina regions (b) (v-viii), pelvis regions

Figure 8 Vagina and pelvis cropped at ROI

The pixel values from the ROI of vector size 280 (40x7) are directly processed using PCA and the extracted features of 280 are used as the input to FFNN for classification of vagina and pelvis. The test using FFNN is conducted 10 times and accuracy is considered by averaging the result.

8.0 RESULT AND DISCUSSION

The experiments are conducted on three different sets of train data that are, 3 each vagina and pelvis regions, 5 each vagina and pelvis regions and 7 each vagina and pelvis regions. The overall correct classification when using CBD and CHT on localized iris for the first train data is about 59% and 69% respectively, for the second train data is about 64% and 76% respectively while for 7 each train data is about 67% and 81% respectively. Figure 9 shows the overall correct percentage classification of vagina and pelvis region using CBD and CHT localization techniques. The result shows that CHT technique gives the best accuracy than CBD technique considering 7 train samples each vagina and pelvis that is about 81% overall correct classification. The result for classification using FFNN has similar trend compared to the result using SVM-RBF from previous findings [10].

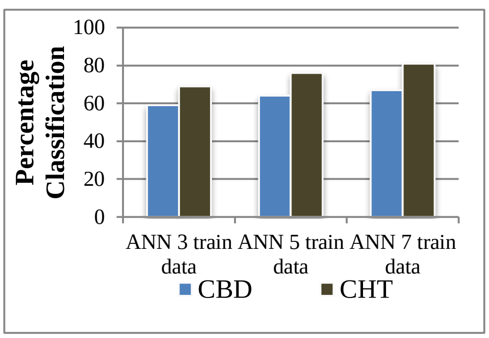


Figure 9 Overall correct classification using CBD and CHT localization techniques

9.0 CONCLUSION AND RECOMMENDATION

It is observed that the result using CHT localization technique obtained the highest overall classification accuracy of about 81% with 7 train samples each of vagina and pelvis regions. Classification using FFNN can be considered among the best classification techniques. The identification of iris regions based on iridology chart has shown promising results since it is able to differentiate between vagina and pelvis regions. This is proven when using CHT or CBD localization techniques with FFNN classifier resulted to more than 50% correct classification. Also, from the above investigation it can be concluded that iris regions are related to human body parts such as heart, kidney, liver and others and these can possibly be differentiated.

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