EXTRACTION OF TEXTURE FEATURES FROM LOCAL IRIS AREAS BY GLCM AND IRIS RECOGNITION SYSTEM BASED ON KNN

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Biometric systems are systems that enable individuals to be recognized in electronic environment using some physical and behavioral characteristics. Iris recognition system is one of the effective biometric recognition systems. The main goal of this study is recognition of the human from the iris images according to the local texture structures. The digital iris images were derived from CASIA database. The texture features were extracted from the four local iris regions of segmented image by using Gray Level Co-Occurrence Matrix (GLCM). Totally 88 parameters were extracted for each image as a feature vector. Then, the obtained feature vectors were classified by using k-Nearest Neighbor (k-NN) classifier and the average performance of each system were compared according to different k values (1, 3, 5, 7 and 9). Finally, the best average performance among system architectures of iris recognition system was observed as 85 % in k=1 neighbor structure of k-NN classifier.

Key words*: Systems, Iris Recognition; Image Processing; Classification; k-NN; GLCM*

1. Introduction

The importance of the security in many areas has enabled the development of different systems related to this subject. There are several types of systems that individuals can use to promote themselves. The most commonly used methods are ID cards, special passwords, etc. However, there are some disadvantages of these methods in case ID cards can’t be found or the passwords are forgotten. That’s why; increasing security doubt has revealed various security systems in recent years. One of these systems is biometrics systems that can detect identity in electronic environment [1].

Biometrics is the science of verifying identity by analyzing biological data. It is used for automated systems that are developed to detect the identity by recognizing the individual's measurable physical and behavioral characteristics. In summary, biometrics expresses measurable biological traces of the person and it can be physical such as fingerprints, retinal vessels, face, eyes and hands, or behavioral such as signature and writing rhythm.

Among all these physiological properties, iris patterns have a structure of perfect and complex tissues. The iris texture is well preserved from the outside and the copying, recording and copying of the iris tissue is very difficult. These texture properties vary from person to person. Each iris has its own unique structure and it provides a complex system that is stable and does not change over its lifetime [2-3].

Nowadays, the architectural structure of iris recognition systems is generally similar. Obtaining the texture features from preprocessed images and the evaluation of the results by using different classification techniques are a common path in studies. The use of various feature extraction and classification methods makes the applications of iris recognition systems different.

Considering literature studies on iris recognition systems; extensive research has been conducted in this field and various approaches have been presented. Most of these studies are based on the last fifteen years [4-13]. The first successful iris recognition system was proposed by J.Daughman in 1993 [14]. Although this work was published many years ago, it still maintains its scientific value as it provides solutions to every part of the iris recognition system.

In the process of extracting feature vectors from iris images, different feature extraction methods such as Laws Texture Energy Measurements (TEM) [15], Gabor Wavelet Transform (GWT) [16], Wavelet Packet Transformation (WPT) [17], Discrete Wavelet Transform (DWT) [18], Principal Component Analysis (PCA) [16], Independent Component Analysis (ICA) and Gray Level Co-Occurrence Matrices (GLCM) [19] were used. Furthermore, classifiers such as k- Nearest Neighbor (k-NN) method [15], Artificial Neural Networks (ANN) [8] and Support Vector Machines SVM [20] were used for the classification of iris images.

In this study, a common feature extraction technique GLCM was applied to the iris texture area with different approach. Instead of using all iris texture area, the texture features were extracted from only four local iris regions. Thus, fewer texture areas were used in order to extract the feature vectors from the iris textures. Finally, a feature vector with 88 parameters were calculated for each image and obtained feature vectors were used for the proposed iris recognition sys tem.

2. Material and Method

2.1. Data Collection

The database used in this study was obtained from the CASIA iris database (http://biometrics.idealtest.org/). Six iris images with 3 left and 3 rights were used for each person. Our dataset includes iris images of 20 persons. A total of 120 images constitute the entire iris data set used in the study. Sample iris patterns for different persons are shown Fig.1.

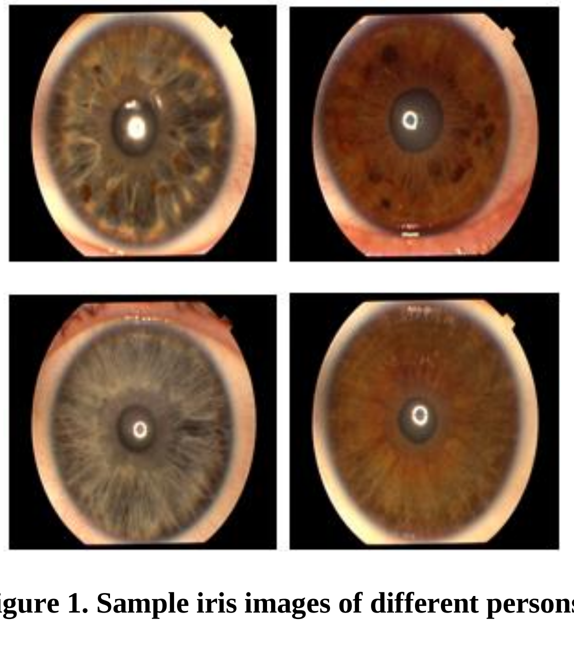

Figure 1. Sample iris images of different persons

2.2. Image Processing

Before the feature extraction process, the all images were-processed in this stage. The scale of the images used in the application is 576x768 pixels. Since the images used in this study are in 3D PNG format, they were converted to 2-D grayscale format by using MATLAB 2011a program. The pupil and sclera area of each image were then left out by segmentation process so that only iris tissue remained in all images.

2.2.1 Image Segmentation

Since the inner and outer boundary of an iris can be nearly modelled as circle, the centre coordinate (xc, yc) with inner radius r_i and outer radius r_o of the circle can be calculated for each iris image. Assume all the iris images have approximately the same standartization and localization, then the area between inner and outer boundaries (r_i<area<ro) can be segmented by using MATLAB 2011a. Some of the segmented iris images used in the study are shown in Fig. 2.

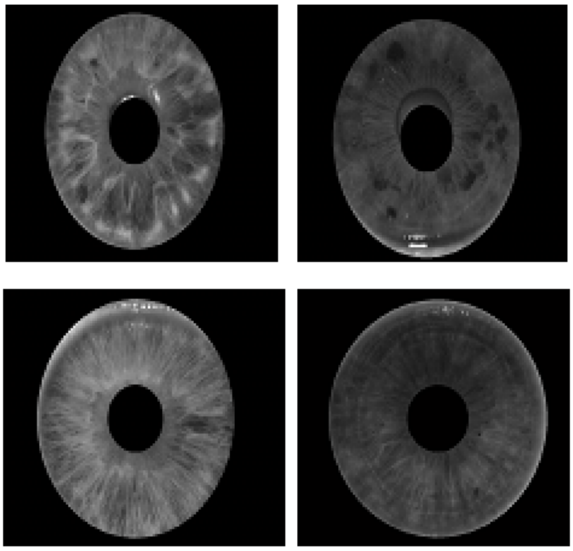

Figure 2. Sample segmented images

2.3. Feature Extraction

In this phase, GLCM was applied to the different local iris regions of the segmented image as shown in Fig. 3. The texture features obtained from the four different local iris areas were observed most suitable parameters by checking intra correlation among the local iris regions. Thus, the parameters were added consecutively and a feature vector with length of 4x22= 88 features (22 features for each local iris area) was constructed for each image. Calculation details were explained in a thirth section.

2.3.1 Gray Level Co-Occurence Matrix (GLCM)

GLCM is a feature extraction method proposed by M. Haralick and it defines the relationship between two neighboring pixels in a grayscale image [21]. The first of these pixels is known as the reference pixel, and the second as the neighboring pixel. The distribution in the matrix is adjusted according to the distance between the pixels and the angle. This matrix is a square matrix of N size and it predicts a function which represents joint probability distribution of grey level pairs in an image [22].

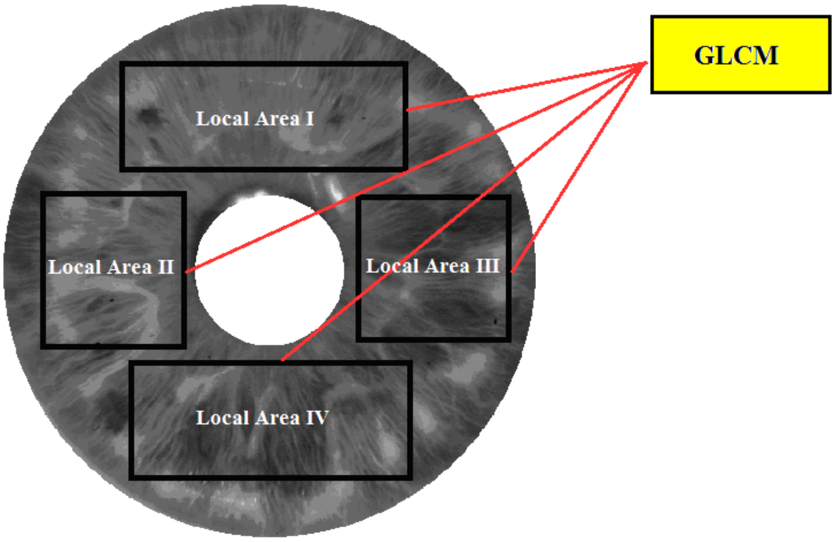

Figure 3. Extraction of the texture features from iris local areas.

In addition to the distance between pixels, it is also necessary to know the directions of the pixel pairs. The most common known directions are 135, 90, 45, 0 and the symmetrical similarities of these angles [23] . An example of a co-occurrence matrix is given in Fig. 4. Here, the number of gray levels, the distance (d) between the pixels and the direction angle (theta) were chosen 8, 1 and 0, respectively. Since the (1,1) pixel pair at the coordinates I (1,1) and I (1,2) in the image matrix (I) is repeated once, the value of the pixel pair in the co-occurrence matrix (f) becomes f (1,1) = 1. Similarly, since the (6,2) pixel pair is repeated 3 times in the matrix I, the value of the pixel pair (6,2) in the matrix f will be f (6,2) = 3. These steps are repeated for the other pixel pairs in the image matrix and the co-occurrence matrix of the entire image is calculated by this way [23].

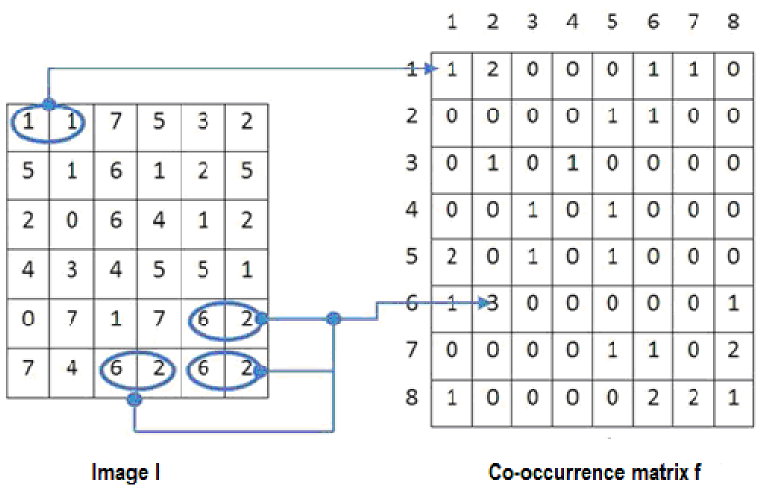

Figure 4. Obtaining co-occurrence matrix

2.3.1.1 GLCM Textural Features

In this study, 22 texture features (four of them from Matlab Image Processing Toolbox) that contain information about the image were calculated from the each local iris area. These parameters are; Autocorrelation, Sum of Squares: Variance, Sum Variance, Sum Average, Ccorrelation (Matlab), Correlation, Cluster Prominence, Cluster Shade, Dissimilarity, Energy (Matlab), Entropy, Homogeneity (Matlab), Homogeneity, Maximum Probability, Sum Entropy, Difference Variance, Difference Entropy, Information Measure of Correlation 1,Information Measure of Correlation 2,Inverse Difference Normalization and Inverse Difference Moment Normalization.

Some of the mathematical expressions of these parameters are given in detail as below [24]-[25].

- Autocorrelation= $\sum_i \sum_j (ij).f(i,j)$
- Sum of Squares: Variance = $\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (1-\mu)^2 f(i,j)$
- Sum Variance= $\sum_{i=1}^{2N} (1-\mu)^2 f(i,j)$
- Sum Average= $\sum_{k=2}^{2N} k \sum_{ij} f(i,j)$
- Entropy= -$\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \left(f(i,j) \right) \log f(i,j)$
- Cluster Shade= $\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \left\{ i + j - \mu_x - \mu_y \right\}^3 \log f(i,j)$

Lastly, the parameters derived from 4 different local iris sections were added in sequence and a feature vector with length of 4x22= 88 parameters was created.

2.4. Classification

In the classification step, it is aimed to match the patterns to the nearest classes according to their feature spaces with minimal error. The performance of the classifier depends on well-defined properties.

Classifiers can be examined in two groups, traditional and intelligent. Traditional classifiers are built on Bayesian decision theory which is a statistical method. K nearest neighbors (kNN), Fisher's linear classifiers, maximum likelihood, binary tree method and multivariate Gaussian models are as an example of traditional classifiers. In this study, kNN method was used for the iris recognition system.

2.4.1 K- Nearest Neighbor (k-NN) Algorithm

KNN is a nonparametric algorithm and it can be used for both classification and regression in the pattern recognition applications. Non-parametric means that no assumption has been made about the basic data or its distribution. The k-NN is one of the simplest algorithms in machine learning. It is simpler and takes less time when compared to the other classifiers (ANN, SVM etc.) [26].

In this method, data classification is made according to a majority vote of its neighbors and the data is appointed to the most common class among its k nearest neighbors. For example, if k equal to 1, then the data will be assigned to the class of that 1- nearest neighbor. The essential thing is that before classifying, the properties of each class are clearly specified in advance.

In addition, the performance of the system is affected by factors such as the similarity measure, the number of sufficient behaviors in the sample set, and the threshold value. However, the most important control parameter is the number of nearest neighbors (k). The given pattern is classified by looking at the distances to the nearest neighbor k [27].

One of the different parameters used in this algorithm is distance measurement. In the study, the nearest neighbors were calculated using the Euclidean distance. Euclidean distance between two sample points is shown in Eq. (1).

$$d(x_r, x_s) = \left[\sum_{i=1}^{p} c_i (x_{ri} - x_{si})^2 \right]^{1/2} \tag{1}$$

The function learned in the k-NN algorithm can be discrete and real valued. In discrete valued functions x_r is the sample point to be classified and x_s is the learning point. Weights equal to 1 at an ordinary Euclidean distance (c_i=1, i=1, 2, …, p) [28].

2.5. Architecture of the Proposed System

The structure of the system designed for the iris recognition is shown in Fig. 5. The pupil and sclera area of each image were left out by segmentation and the local iris regions with at least 60% of the iris texture constructed the input matrix of the system. The system includes preprocessing, feature extraction and classification steps. The texture features were extracted from four local iris regions of segmented image by using GLCM. Totally 88 parameters were extracted for each image as a feature vector and a single output was taken from the system to test whether the iris images were matched correctly.

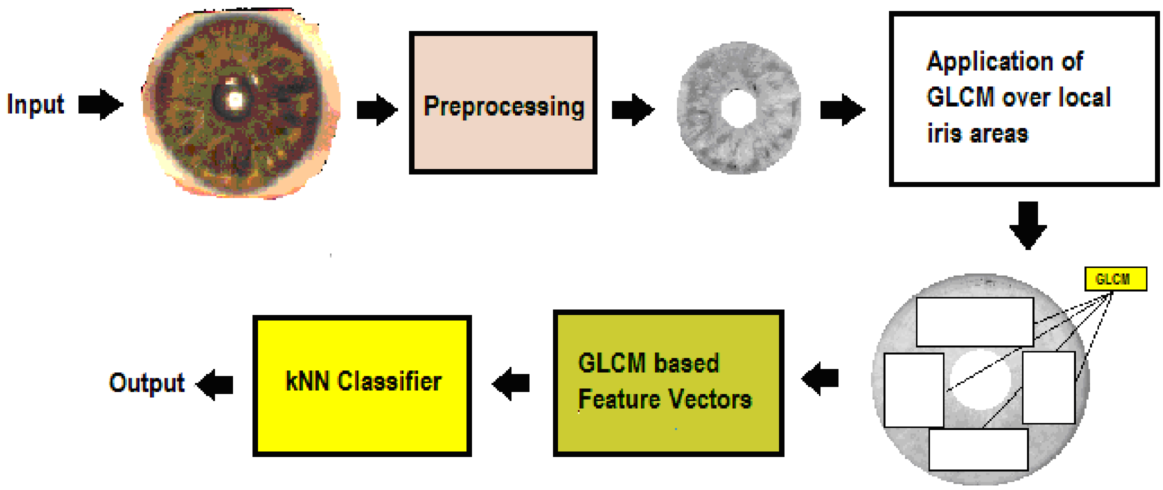

Figure 5: General structure of the Proposed Iris Recognition System

The k-NN algorithm was used for the classification of the images. The training process was done to access the best performance of each system structure. Performances of different k-NN classifiers were calculated by the ratio of the number of correctly detected patterns to the total test pattern number and all the obtained performance results were presented in the result section. In this study, 120 images belonging to 20 individuals were used and each sample was alternately placed in the training and test data set with leave-one-out cross-validation.The performance of the each system was calculated by Eq. (2).

$$\textit{Performance} = (\#\ \textit{of correctly detected patterns} / \#\ \textit{of total test patterns}) \times 100 \qquad (2)$$

3. Results

The average performance of the iris recognition system was given in Tab.1. Here, the nearest neighbor number (k) was taken in the range [1-9] and leave-one-out cross-validation was performed to show the average performance value of each structure. Finally, the average performance of the each system was measured between [49- 85%] and the best performance among the all system architectures was observed as 85 % in k=1 neighbor structure of k-NN classifier as shown in Tab.1.

Table 1: Average performance results for the different k of the K-NN classifier

Nearest Neighbor Number (k)	*Correctly Detected Average Pattern Rate*	*Average Performance*
1	**(102/120)**	**% 85**
3	(95/120)	% 79.16
5	(71/120)	% 59.16
7	(60/120)	% 50
9	(60/120)	% 49.16

4. Conclusion

As a result, the iris recognition system is designed according to the iris texture characteristics of different persons. The texture features were extracted from the four local iris regions of segmented image by using GLCM and the obtained feature vectors were then classified by k-NN classifier. At the initial stage of the analysis, the iris recognition system was trained with training sets and their performances were evaluated with test sets. Then, the average performance of each system was compared according to different k values. Finally, the highest average performance value among the system architectures was observed as 85 % in k=1 neighbor structure of k-NN classifier. Considering the literature studies, some of the main approaches to iris recognition through machine learning techniques are listed in Tab.2.

Table 2: Comparison of different approaches to iris recognition by machine learning techniques.

#	Authors-Years	Dataset	Features	Performance (%)	Classification Technique
1	Saminathan et al, 2015	Casıa-IRISV1	Intensity Image	98.5	LS-SVM
2	Abiyev and Altunkaya, 2008	Casıa-IRISV1	Intensity Image	99.25	Neural Network
3	Fasca et al, 2012	Proprietary	LBP and HOG	91	Back Propagation Neural Network
4	Liam et al, 2002	Proprietary	Intensity Image	83	Self-Organizing Map (SOM) Neural Networks
5	Nie et al, 2014	UBIPr	-	50.1	RBM Feature Learning
6	J.K Pillai et al, 2013	Notre Dame	Daugman's İris Code	87.82	Kernel Learning Framework for cross-sensor Adap.

The performance value of this system architecture **85 %**, which was designed using GLCM-based features, was found to be in an acceptable range when compared to performance of other iris recognition systems in the literature **[50% -99%].**

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