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Design and Implementation Iris Recognition System Using Texture Analysis

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Abstract

The aim of this work is to produces a technology of recognition and identifies of the person by using the iris. The work was started by reading the images of eyes (UBIRIS database). After that, the iris region localized from the eye image by using the method of image processing. The iris shape is circular so it transfer to rectangular shape and enhance the image and remove the noise like eyelashes and flash of the camera. Then the image quantized from 256 grey levels to 16 grey levels. Four statistical functions used because these functions give us accurate description of iris, the samples had been taken in four angles. The information for each sample is save in database. The last stage is to classify the samples by using neural network. The results will prove that the work have high accurate conclusions.

Introduction

Technologies that exploit biometrics have the potential for application to the identification and verification of individuals for controlling access to secured areas. A lot of biometric techniques are being developed based on different features and algorithms. This includes recognition of voice, fingerprints, hand shape, retinal scans, handwritten signatures, etc. Unfortunately, from the human factors point of view, these methods are highly invasive. Typically, a person is required to make physical contact with a sensing device (e.g. finger or hand contact) or otherwise take some special action (e.g. recite a specific phonemic sequence) [1].Automated iris recognition is yet another alternative pattern for recognition. Interestingly, the spatial patterns that are apparent in the human iris are highly distinctive to an individual [2]. Like the face, the iris is an overt body that is available for remote (i.e. noninvasive) assessment. Unlike the human face, however, the variability in appearance of any one iris might be well enough constrained to make possible an automated recognition system based on currently available machine vision technologies. The possibility that the human iris might be used as a kind of optical fingerprint for personal identification was suggested originally by ophthalmologists. Therefore, the potential of the human iris for such types of problem comes from anatomy of the eye [3].

System proposed

The system proposed is implemented in MATLAB program, consist of the following steps.

1. Image reading

The images will be shown from the database (UBIRIS), 36 persons are used, and each person has 5 images. The lift eye is used for all people because the lift eye is differs from the right. the image being read shown in Figure(1)

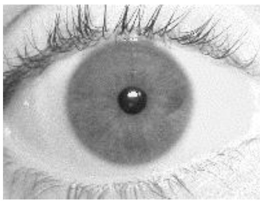

Fig.1 the UBIRIS image

2. Preprocessing

A. Segmentation

As soon as reading the image, the next step is to isolate the iris from the rest of the image, namely, finding both the inner (papillary) boundary and the outer (sclera) boundary.

Daugman made use of integrodifferential operator as shown in equation (1) [5]. The result of application of this equation in (MATLAB) is shown in figure (2)

$$max_{(r,x_0,y_0)} \left| G_\sigma(r) * \frac{\partial \; I_{ave}(r,x_0,y_0)}{\partial r} \right| \qquad (1)$$

Where

$$G_\sigma(r) = \frac{1}{\sqrt{2\pi\,\sigma^2}} \exp\left(-\frac{r^2}{2\sigma^2}\right)$$

$$I_{ave}(r,x_0,y_0) = \oint_{\Gamma(x_0,y_0,r)} \frac{I(x,y)}{2\pi r}\, ds$$

I(x, y) image intensity value at location (x, y).

r the radius of limbic and papillary.

x_0 , y_0 Circular contours

r the radius to search for.

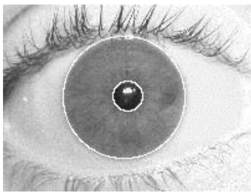

Fig.2 the segmented image

B. Iris Normalization

Once the iris region is successfully segmented from an eye image, the next step is to transform the iris region so that it has fixed dimensions in order to allow comparisons. The homogenous rubber sheet model devised by Daugman as shown in equation (2) which remaps each point within the iris region to a pair of polar coordinates (r, θ), where r is on the interval [0,1] and θ is angle [0,2π] [5] . Figure (3) show iris after normalization.

$$I(x(r, \theta), y(r, \theta)) = I(r, \theta) \qquad (2)$$

Fig.3 the normalized image

C. Enhancement

In the next step, histogram slide technique is use to enhance the image, the technique used to make the image either darker or lighter but retain the relationship between gray-level values as shown in equation (3). Where offset value is the amount to slide the histogram [6]. Figure (4) shows the results.

$$\text{Slide}\,(I(r,c)) = I(r,c) + \text{OFFSET} \qquad (3)$$

Fig.4 the enhanced image

D. Noise Removal

In this step, a clip technique had been used to remove the spike of light and eyelashes on the histogram of the image [6].The proposed clip was 185 for spike and 65 for eyelashes.

E. Brightness

The final step of preprocessing is the brightness. A histogram stretching [6] is use as shown in equation (4). The result is shown in figure (5)

$$(I(x,y)) = \left[\frac{I(x,y) - I(x,y)_{MIN}}{I(x,y) - I(x,y)_{MAX}}\right] [MAX\ MIN] + MIN \qquad (4)$$

Where $I(x,y)_{max}$ the largest gray-level value in the image $I(x,y)$, $I(x,y)_{min}$ the smallest gray-level value in the image $I(x,y)$, *MAX* and *MIN* correspond to maximum and minimum gray-level values possible (for an 8-bit image these are 255 and 0).

3. Feature Extraction

From the statistical point of view, an image is a complicated pattern on which statistics can be obtained to characterize these patterns. The techniques used within the family of statistical approaches make use of the intensity values of each pixel in an image, and apply various statistical formulae to the pixels in order to calculate feature descriptors.

Texture feature descriptors, extracted through the use of statistical methods, can be classified into two categories according to the order of the statistical function that is utilized: First-Order Texture Features and Second Order Texture Features. First Order Texture Features are extracted exclusively from the information provided by the intensity histograms, thus yield no information about the locations of the pixels. Another term used for First-Order Texture Features is Grey Level Distribution Moments. In contrast, Second-Order Texture Features take the specific position of a pixel relative to another into account. The most popularly used of second-order methods is Grey Level Co-occurrence Matrix (GLCM) method [7].The table (1), shows statistical functions were used.

Table (1) statistical functions

Texture feature	Formula
Energy	$\sum_{i,j} P(i,j)^2$
Sum Variance	$\sum_{i} (i + \sum_{j} p_{x+y}(j) * \log(p_{x+y}(j)))^2 p_{x+y}(i)$
Sum Entropy	$\sum_{i=2}^{w} p_{x+y}(i) * \log(p_{x+y}(i))$
Entropy	$-\sum_{i,j} p(i,j) * \log(p(i,j))$

In the system we have 36 persons; five images had been taken for each person. Some of these images were added noise and other rotate to test robust of the system. The original images have size 150*200, while the normalized iris images have size 32*256.By using eq. (2). In the feature extraction, four features had been taken for each iris image in four angles (0˚, 45˚, 90˚, 135˚), so we have 16 features for each iris image. This is in the first case. In the second case the iris image had been divided to four blocks, 4 features for each block in four angles, so we have 64 features for four blocks. In the third case the iris image had been divided to 8 blocks, so we have 128 features. In the last case the iris image had been divided to 16 blocks, so we have 256 features.

4. Probabilistic Neural Network (PNN)

PNN is derived from Radial Basis Function (RBF) Network which is an ANN using RBF. RBF is a bell shape function that scales the variable nonlinearly. PNN is adopted for it has many advantages [8]. Its training speed is many times faster than a BP network. PNN can approach a Bays optimal result under certain easily met conditions. Additionally, it is robust to noise and its simple structure and training manner. The most important advantage of PNN is that training is easy and instantaneous. The speed of PNN is very fast. The network classifies input vector into a specific class because that class has the maximum probability to be correct [9].

PNN has 3 layers, input layer, hidden layer (may be one or more) and output layer. The figure (6) displays the architecture for a PNN that recognizes K = 36 classes according to number of persons represent the output layer (on the right). The input layer (on the left) contains nodes: one for each of the input features of a feature vector **x**. These are fan-out nodes that branch at each feature input node to all nodes in the hidden (or middle) layer so that each hidden node receives the complete input feature vector **x**. The hidden nodes are collected into groups: one group for each of the K classes.

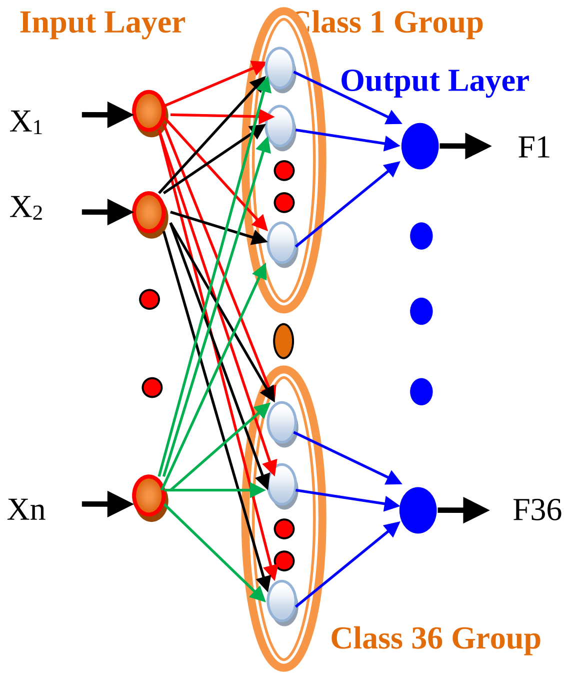

Fig.6 architecture of PNN

The training was for four images while test was for one image selected randomly. The accuracy for each case of the system is lustrated in table (2).

Table (2) experimental results

Cases	No. Of images	Blocks	Feature Vector	Accuracy	Time
case1	180	1	16	61.12%	0.027
case2	180	4	64	88.89%	0.031
case3	180	8	128	99.97%	0.058
case4	180	16	256	100%	0.135

Discussion and future work

The results show in table (2) that when the number of blocks of image increase the accuracy will increase too but the time increases because increase of the processing time on the samples. This work is applied to 36 of persons therefore the accuracy was very high reaches to 100%

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In the future work

1. Increase the number of persons to test the system.
2. Use other methods.

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