IRIS RECOGNITION USING BPNN ALGORITHM

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Abstract
The Human Iris is one of the best biometrics features in the human body for pattern recognition. This paper provides a walkthrough for image acquisition, image segmentation, feature extraction and pattern forming based on the Human Iris imaging. It also shows recognition using Backpropagation Neural Network on classifying the patterns formed in the first part of the paper and properly verifies one's identity.

***Keywords-** Back-propagation Neural Network, Biometric Identification, Image Segmentation, Iris Recognition,*

II. INTRODUCTION

Iris recognition is one of important biometric recognition approach in a human identification is becoming very active topic in research and practical application. Iris region is the part between the pupil and the white sclera. This field is sometimes called iris texture. The iris texture provides many minute characteristics such as freckles, coronas, stripes, furrows, crypts, etc. These visible characteristics are unique for each subject. Such unique feature in the anatomical structure of the iris facilitates the differentiation among individuals. The human iris is not changeable and is stable. From one year of age until death, the patterns of the iris are relatively constant over a person's lifetime. Because of this uniqueness and stability, iris
recognition is a reliable human identification technique. Iris recognition consists of the iris capturing, pre-processing and recognition of the iris region in a digital eye image. Iris image pre-processing includes iris localization, normalization, and enhancement. Each of these steps uses different algorithms. In iris localization step, the determination of the inner and outer circles of the iris and the determination of the upper and lower bound of the eyelids are performed. A variety of techniques have been developed for iris localization. In this paper we have used rectangular area technique for iris localization. The next step in the recognition process is the normalization of the captured iris image. The normalized image is then enhanced and the final output is given to neural network for efficient recognition.

II. WORKING PRINCIPLE

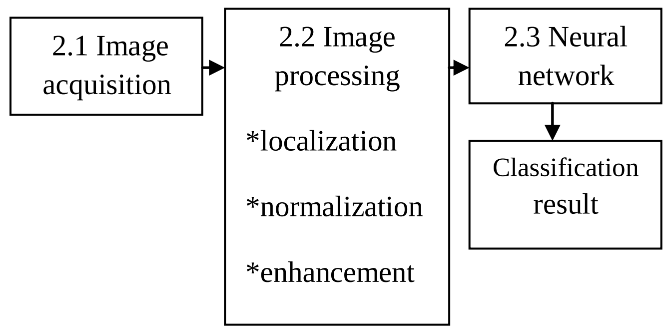


Fig 1: Generic block diagram [4]

2.1. Image acquisition:

The types of images in which we are interested are generated by the combination of an "illumination" source and the reflection or absorption of energy from that source by the elements of the "scene" being imaged. Figure: 2 show the components of a single sensor. Perhaps the most familiar sensor of this type is photodiode, which is constructed of silicon materials and whose output voltage waveform is proportional to light. The use of a filter in front of a sensor improves selectivity. In order to generate a 2-D image using a single sensor, there has to be relative displacements in both the x- and y-directions between the sensor and the area to be imaged. [2]

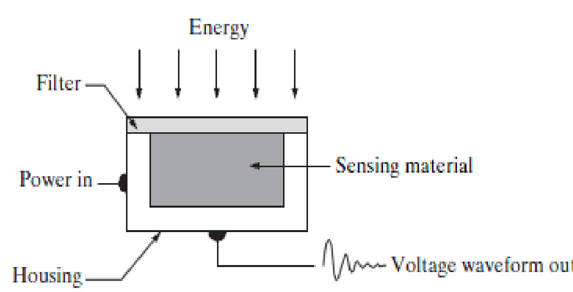


Figure 2: Single Imaging Sensor.

The basic idea behind sampling and quantization is illustrated in Figure: 3. As an example the first figure shows a continuous image, f(x, y), that we want to convert to digital form. An image may be continuous with respect to the x- and y-coordinates, and also in amplitude. To convert it to digital form, we have to sample the function in both coordinates and in amplitude. Digitizing the coordinate values is called sampling. Digitizing the amplitude values is called quantization. The one-dimensional function shown in the second figure is a plot of amplitude (gray level) values of the continuous image along the line segment AB as in first figure. The random variations are due to image noise. To sample this function, we take equally spaced samples along line AB, as shown. The digital samples resulting from both sampling and quantization [7] are shown in the fourth figure. Starting at the top of the image and carrying out this procedure line by line produces a two-dimensional digital image. This is shown in the diagram alongside.

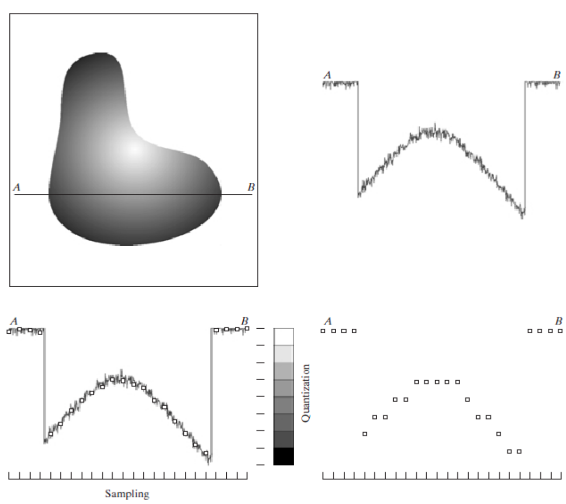


Figure 3: (a) Continuous image. (b) A scan line from A to B in the continuous image, use to illustrate the concepts of sampling and quantization. (c) Sampling and quantization. (d) Digital scan line. [2]

Step 1: Sampling

$$X_s(f) = f_s \sum_{n=-\infty}^{\infty} X(f-f_s)$$

Or

$$X_s(f) = X(f) \circledast (f) \ldots. (1)$$

Step 2: Quantization

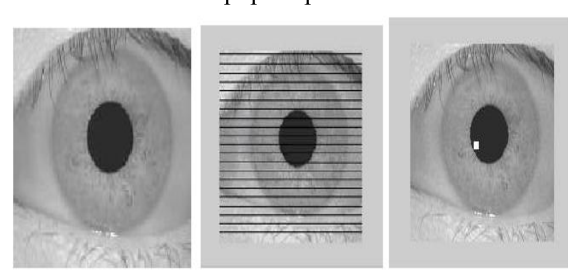
$$n = 2^b$$

$$x_q[k] = x[k] + e_q[k] \ldots.. (2)$$

2.2 Image processing:

2.2.1 Image localization:

An eye image contains not only the iris region but also the pupil, eyelids, sclera, and so on. For this reason, at first step, segmentation will be done to localize and extract the iris region from the eye image. Iris localization is the detection of the iris area between pupil and sclera [4][5]. So we need to detect the upper and lower boundaries of the iris and determine its inner and outer circles. To find the boundary between the pupil and iris, we must detect the location (centre coordinates and radius) of the pupil. The rectangular area technique is applied in order to localize pupil and detect the inner circle of iris. The pupil is a dark circular area in an eye image. Besides the pupil, eyelids and eyelashes are also characterized by black colour. In some cases, the pupil is not located in the middle of an eye image, and this causes difficulties in finding the exact location of the pupil using point-by- point comparison on the base of threshold technique. We are looking for the black rectangular region in an iris image. Choosing the size of the black rectangular area is important, and this affects the accurate determination of the pupil's position.



(a) (b) (c)

Fig 4: (a) Iris image, (b) The lines that were drawn to detect rectangular areas, (c) The result of detecting of rectangular area.[4]

Searching starts from the vertical middle point of the iris image and continues to the right side of the image. A threshold value is used to detect the black rectangular area. Starting from the middle vertical point of iris image, the grayscale value of each point is compared with the threshold value. Grayscale values within the pupil are very small. So a threshold value can be easily chosen. If grayscale values in each point of the iris image are less than the threshold value, then the rectangular area will be found. If this condition is not satisfactory for the selected position, then the search is continued from the next position. This process starts from the left side of the iris, and it continues until the end of the right side of the iris. In case the black rectangular area is not detected, the new position in the upper side of the vertical middle point of the image is selected and the search for the black rectangular area is resumed. If the black rectangular area is not found in the upper side of the eye image, then the search is continued in the down side of image. At first step, the points located in the boundary of pupil and iris, in horizontal direction, then the points in the vertical direction are detected In Figure: 4, the circle represents the pupil, and the rectangle that is inside the circle represents the rectangular black area. The border of the pupil and the iris has a much larger grayscale change value. Using a threshold value on the iris image, the algorithm detects the coordinates of the horizontal boundary points of (x1, y1) and (x1, y2), as shown in figure. The same procedure is applied to find the coordinates of the vertical boundary points (x3, y3) and (x4, y3). After finding the horizontal and vertical boundary points between the pupil and the iris, the following formula is used to find the centre coordinates (xp, yp) of the pupil.[2]

$$x_p = (x_3 + x_4)/2 \; , \; y_p = (y_3 + y_4)/2 \; \ldots\ldots\ldots (3)$$

$$r_p = \sqrt{(x_c - x_1)^2 + (y_c - y_1)^2} \; , \text{ or } \; r_p = \sqrt{(x_c - x_3)^2 + (y_c - y_3)^2} \quad \ldots\ldots (4)$$

$$DL_i = \sum_{i=10}^{y_p-(r_p+10)} (S_{i+1} - S_i), \qquad DR_j = \sum_{j=y_p+(r_p+10)}^{right-10} (S_{j+1} - S_j) \ldots\ldots\ldots\ldots\ldots (5)$$

$$S_j = \sum_{k=j}^{k+10} I(i,k), \; y_s = (L + R)/2, \; r_s = (R - L)/2 \quad \ldots\ldots\ldots\ldots (6)$$

2.2.2 Image normalization:

The irises captured from the different people have different sizes. The size of the irises from the same eye may change due to illumination variations, distance from the camera, or other factors. At the same time, the iris and the pupil are non concentric. These factors may affect the result of iris matching. In order to avoid these factors and achieve more accurate recognition, the normalization of iris images is implemented. In normalization, the iris circular region is transformed to a rectangular region with a fixed size. With the boundaries detected, the iris region is normalized from Cartesian coordinates to polar representation. [4][5]

$\theta \in [0, 2\Pi]$, $r \in [R, R_L(\theta)]$;

$x_i = x_p + r.\cos(\theta)$, $y_i = y_p + r.\sin(\theta)$….(7)

2.2.3 Image enhancement:

Image enhancement is basically improving the interpretability or perception of information in images for human and providing `better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified. The choice of attributes and the way they are modified are specific to a given task. Moreover, observer-specific factors, such as the human visual system and the observer's experience, will introduce a great deal of subjectivity into the choice of image enhancement methods. There exist many techniques that can enhance a digital image without spoiling it. The enhancement methods can broadly be divided in to the following two categories:

1. Spatial Domain Methods
2. Frequency Domain Methods

In spatial domain techniques, we directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. In frequency domain methods, the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value (intensities) of the output image will be modified according to the transformation function applied on the input values. Image enhancement simply means, transforming an image f into image g using T. (Where T is the transformation. The values of pixels in images f and g are denoted by r and s, respectively. As said, the pixel values r and s are related by the expression,

$$s = T(r) \;\ldots\ldots (8)$$

Where T is a transformation that maps a pixel value r into a pixel value s. The results of this transformation are mapped into the grey scale range as we are dealing here only with grey scale images. So, the results are mapped back into the range [0, L-1], where L=2k, k being the number of bits in the image being considered. So, for instance, for an 8-bit image the range of pixel values will be [0, 255]. I will consider only gray level images. The same theory can be extended for the color images too. A digital gray image can have pixel values in the range of 0 to 255.[6]

2.2.3.1 Histogram processing:

The histogram of a digital image with intensity levels in the range [0, L-1] is a discrete function.

$$g(x, y) = T[f(x, y)] \ldots\ldots (9)$$

$$h(r) = nk$$

{K^{th} intensity value} {Number of pixels in the image with intensity $r_{k.}$ }

Histograms are frequently normalized by the total number of pixels in the image. Assuming an M x N image, a normalized histogram.

$P(r_k) = n_k / MN, \quad k = 0, 1\ldots, L-1$

is related to probability of occurrence of r_k in the image.

2.2.3.2 Histogram equalization:

Histogram equalization is a common technique for enhancing the appearance of images. Suppose we have an image which is predominantly dark [6]. Then its histogram would be skewed towards the lower end of the grey scale and all the image detail is compressed into the dark end of the histogram. If we could `stretch out' the grey levels at the dark end to produce a more uniformly distributed histogram then the image would become much clearer.

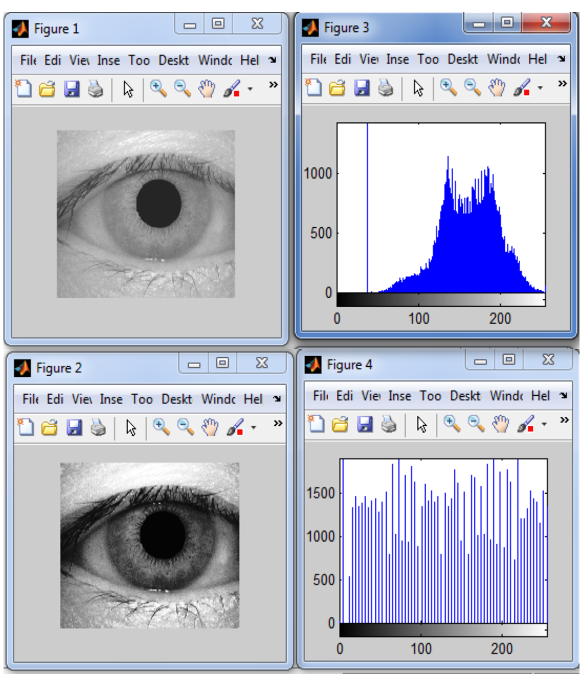


Fig 5: The original image and its histogram, and the equalized versions. Both images are quantized to 64 grey levels.

2. 3. Neural Network:

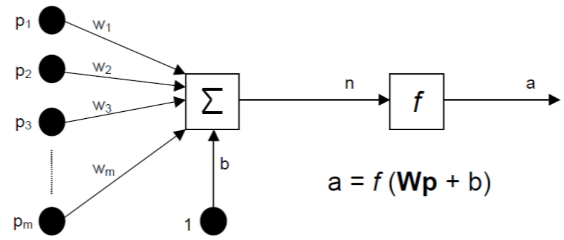


Fig 6: A single neuron example of neural network

Neural Nets are essentially networks of simple neural processors, arranged and interconnected in parallel. Neural Networks are based on our current level of knowledge of the human brain, and attract interest from both engineers, who can use Neural Nets to solve a wide range of problems, and scientists who can use them to help further our understanding of the human brain. Neural Nets can be used to construct systems that are able to classify data into a given set or class, in the case of iris detection, a set of images containing one or more iris, and a set of images that contains non iris. Neural Networks consist of parallel interconnections of simple neural processors. Figure: 6 shows an example of a single neural processor, or neuron [1][7]. Neurons have many weighted inputs, that is to say each input (p1, p2, p3… pm) has a related weighting (w1, w2, w3… wm) according to its importance. Each of these inputs is a scalar, representing the data. In the case of face detection, the shade of GRAY of each pixel could be presented to the neuron in parallel (thus for a 10x10 pixel image, there would be 100 input lines p1 to p100, with respective weightings w1 to w100, corresponding to the 100 pixels in the input image). The weighted inputs are combined together, and if present, a bias (b) is added. This is then passed as the argument to a transfer function (typically a pure linear, hard limit, or log-sigmoid function), which outputs a value (a) representing the chosen classification. The normalized and enhanced iris image is represented by a two-dimensional array. This array contains the grayscale values of the texture of the iris pattern. These values are input signals for the neural network. Architecture of BPNN is given in Figure: 7

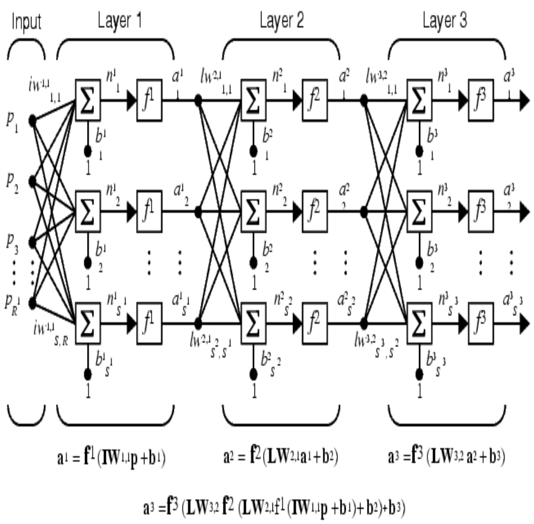


Fig 7: Multilayered neural network. [4]

Two hidden layers are used in the BPNN. In this structure, x1, x2…, xm are grayscale values of input array that characterizes the iris texture information, P1, P2… Pn are output patterns that characterize the irises. The k-th output of neural network is determined by the formula [1]:

$$P_k = f_k\left(\sum_{j=1}^{h2} v_{jk} \cdot f_j\left(\sum_{i=1}^{h1} u_{ij} \cdot f_i\left(\sum_{l=1}^{m} w_{li} \cdot x_l\right)\right)\right) \ldots\ldots (10)$$

In formula 10) Pk output signals of BPNN are determined as:

$$P_k = 1/\left(1 + e^{-\sum_{j=1}^{h2} v_{jk} \cdot y_j}\right) \ldots\ldots (11)$$

2.3.1 Parameters Learning:

At the beginning, the parameters of BPNN are generated randomly. The parameters v_{jk}, u_{ij}, and w_{li} of BPNN are weight coefficients of second, third and last layers, respectively. Here k=1,..,n, j=1,..,h2, i=1,..,h1, l=1,..,m. To generate BPNN recognition model, the training of the weight coefficients of v_{jk}, u_{ij}, and w_{li}. s has been carried out. During training the value of the following cost function is calculated [1].

$$E = 1/2 \sum_{k=1}^{n} (P^d_k - P_k)^2 \quad \ldots\ldots\ldots (12)$$

Here n is the number of output signals of the network and P^d_k and P_k are the desired and the current output values of the network, respectively. The parameters vjk, uij, and wli of neural network are self adjusted. The adaptive learning rate is applied in order to increase learning speed and guarantee convergence. The following strategy is applied for every given number of epochs. [1][7]

IV. TABLES

Methodology	Accuracy rate
Daughman	100%
Boles	92.64%
Li Ma	94.9%
Avila	97.89%
Back Propagating Neural Network	99.25%

Table 1: The recognition performance of comparing with existing methods [4]

IV. CONCLUSION

The neural networks aimed at providing artificial intelligence to the system. Neural networks using back propagation is presented in this paper for personal iris recognition The recognition rate of BPNN system was found to be 99.25%.The identification result obtained using the neural network approach illustrates the success of its efficient use in iris recognition.. A fast iris localization method like rectangular area method is used. Using this method, iris segmentation is performed in short time. The vector as an input signal the back propagating neural network is used to recognize the iris patterns. The BPNN algorithm is preferred over other neural network algorithms because of its unique ability to minimize errors. BPNN is found to be very accurate where recognition is required over other neural networks.

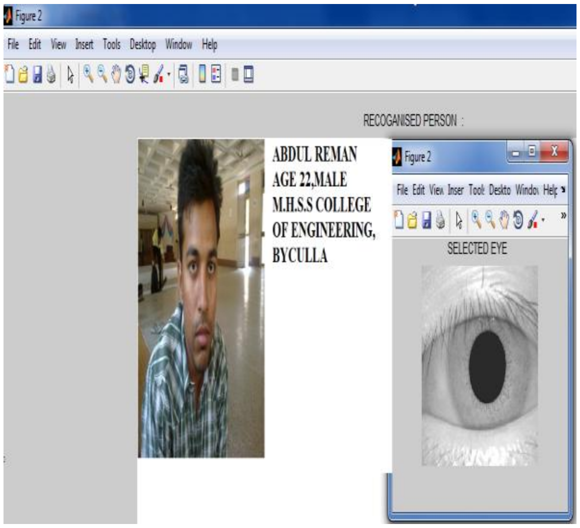


Fig 8: The obtained result on MATLAB

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