IRIS Pattern Recognition Using Self-Organizing Neural Networks

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Abstract
With an increasing emphasis on security, automated personal identification based on biometrics has been receiving extensive attention over the past decade. Iris recognition, as an emerging biometric recognition approach is receiving interest in both research and practical applications. Iris is a kind of physiological biometric feature. It contains unique texture and is complex enough to be used as a biometric signature. Compared with other biometric features such as face and fingerprint, iris patterns are more stable and reliable. This paper describes an iris recognition system, composed of iris image acquisition, iris image preprocessing, neural network training process and pattern matching. In this paper a digitally captured iris image is acquired and is then preprocessed. This is needed to remove the unwanted parts that are usually captured along with the iris image, to prevent effects due to a change in camera-to-face distance and also due to non-uniform illumination. The image thus obtained is trained using self organizing map (SOM) and finally decision is made by matching.

1. INTRODUCTION
Reliable automatic recognition of persons has long been an attractive goal. As in all pattern recognition problems, the key issue is the relation between inter-class and intra-class variability. Objects can be reliably classified only if the variability among different instances of a given class is less than the variability between different classes. The iris recognition algorithm is explained in [1] by comparing the results of 9.1 million eye images from trials in Britain, the USA, Japan and Korea. The randomness and uniqueness of human iris patterns were investigated in [2] by mathematically comparing 2.3 million different pairs of eye images. The phase structure of each iris pattern was extracted by demodulation with quadrature wavelets spanning several scales of analysis. The resulting distribution of phase sequence variation among different eyes was precisely binomial revealing 244 independent degrees of freedom. The coupling of wavelet image coding is discussed in [3] along with a test of statistical independence on extracted phase information , in order to obtain a demonstrably robust and reliable algorithm for recognizing stochastic patterns of high dimensionality. The results from the 200 billion irises cross are presented and compared in [4] that could be performed within a database of 6,32,500 different iris images, spanning 152 nationalities. Each iris pattern was encoded into a phase sequence of 2048 bits using the Daugman algorithms. Empirically analyzing the tail of the resulting distribution of similarity scores enables specification of decision thresholds, and prediction of performance, of the iris recognition algorithms if deployed in identification mode on national scales. The following four advances in iris recognition are presented in [5].More disciplined methods for detecting and faithfully modeling the iris inner and outer boundaries with active contours, leading to more flexible embedded coordinate systems; Fourier-based methods for solving problems in iris trigonometry and projective geometry, allowing off-axis gaze to be handled by detecting it and "rotating" the eye into orthographic perspective; statistical inference methods for detecting and excluding eyelashes; and exploration of score normalizations, depending on the amount of iris data that is available in images and the required scale of database search**.** The statistical variability that is the basis of iris recognition is analyzed in [6] using new large databases.

2. METHOD AND MATERIAL
The fig. 1.1 below shows the block diagram for an IRIS recognition system.

From the fig. 1.1 it can be observed that the first and foremost step in the iris recognition system is the acquisition of the input Image. The input Image is given to the database using a web cam. This Image is then checked to confirm whether it is an iris Image or not. The Image is then pre-processed and trained using SOM. The trained Image is then matched with an input data Image using Manhattan Distance. The final result of matching is then displayed. Each block of Fig 1.1 is explained in detail:

2.1 Image Acquisition
One of the major challenges of automated iris recognition is to capture a high-quality image of the iris while remaining non-invasive to the human operator. The iris is relatively small, dark object and that human operators are very sensitive about their eyes, this matter requires careful engineering. The following are factors to be considered while acquiring an iris image:-

(i) It is desirable to acquire images of the iris with sufficient resolution and sharpness to support recognition.

(ii) It is important to have good contrast in the interior iris pattern without resorting to a level of illumination that annoys the operator, i.e., adequate intensity of source (W/cm2) constrained by operator comfort with brightness (W/sr-cm).

(iii) These images must be well framed (i.e. centered) without unduly constraining the operator (i.e., preferably without requiring the operator to employ an eye piece, chin rest, or other contact positioning that would be invasive).

(iv) Artefacts in the acquired images due to secular reflections, optical aberrations, etc. should be eliminated as much as possible.

For the present work, digitally captured images of eyes with good resolution and illumination were acquired. For the sake of visual distinction, four iris images of different colours were collected and stored. These collected images were further cropped to get iris images of size 135 x 147 without losing the characteristics. Here we are using a 4 Mega Pixel Camera to capture iris Image and an image cropping software to get the required size of image.

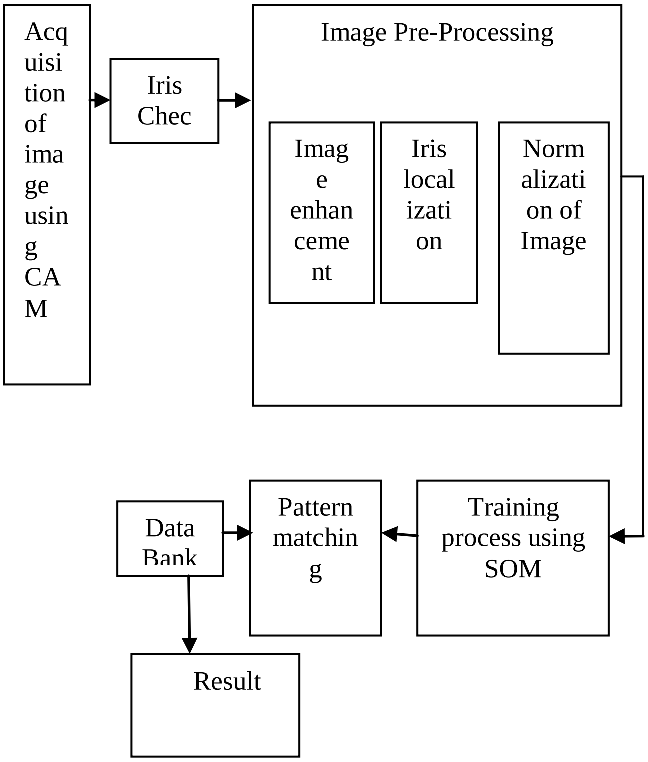

Fig. 1.1 Block Diagram for an IRIS Recognition System

2.2 IRIS Checking

Recognition systems are usually used for user verification and authentication. Thus, it is important to feed the correct input to the system. So, before executing the main recognition program, it is necessary to check if the input is appropriate or not. In this paper, an efficient technique is used to identify whether the input image is an iris or not. The checking process consists of two main steps:-

(i) Block matching approach

(ii) Checking RGB value of pupil.

2.2.1 BLOCK MATCHING APPROACH:-

The human iris, an annular part between the pupil and white sclera, has an extra ordinary structure and provides many interlacing minute characteristics such as Freckles, coronas, Stripes, Furrows, crypts and so on. These visible characteristics, generally called the texture of the iris are unique to each person. Individual differences that exist in the development of anatomical structures in the body result in such uniqueness.

However, the iris is a textural image which contains repetitive patterns across it. So, a pattern at one position of the iris should match with the patterns present at the other locations in the iris. This property of the iris was used for the checking process. The various steps involved in this checking process are explained in detail below.

(i) The RGB image was converted to grey scale eliminating hue and saturation information while retaining the luminance. The input RGB image was of class uint8. So, the output grey image was of the same class as the input image.

(ii) The center of the image was located. A 20x20 sub image block was selected such that it contained a part of the iris pattern excluding the pupil. This sub image was used as the test image for checking.

(iii) This test image was compared with subsequent 20x20 sections of the original image. The count was increased every time a section matched with the test image.

2.2.2 CHECKING RGB VALUE OF PUPIL:

The second step of the checking process was to find the RGB value of the central portion, i.e., the pupil. The pupil is the central dark portion of the eye. It is a dark colored circle in the eye which is surrounded by the iris. The RGB value of the pupil is usually below 60. The centre of the image was first located. Its RGB value was found out and checked whether less than 60.

Affirmative results of the block matching approach and RGB value of pupil, together confirmed that the given input image was that of an iris.

2.3 Image Pre-Processing

An iris image contains not only the region of interest (iris) but also some irrelevant parts (e.g. eyelid, pupil etc) a change in the camera-to-eye distance may also result in variations in the size of the same iris. Furthermore, the brightness is not uniformly distributed because of nonuniform illumination. Therefore, the original image needs to be preprocessed to localize iris, normalize iris and reduce the influence of the factors mentioned above. Such pre-processing is detailed in the following subsections:-

2.3.1 IMAGE ENHANCEMENT

2.3.1.1 Contrast Adjustment

The cropped image as shown in fig. 1.2 was converted to grey image. The intensity values of this image were then adjusted and limits were found to contrast stretch an image. This process maps the values of an intensity image to new values such that values between low intensity input and high intensity input map values between low intensity output and high intensity output. Values below low intensity input and above high intensity input are clipped i.e., values below low intensity input map to low intensity output and those above high intensity input map to high intensity output.

2.3.1.2 Image Filtering

The image was filtered using an 'unsharp filter' and the filtered image shown in figure 1.3 was obtained. The unsharp masking consists of generating a sharp image by subtracting from an image a blurred version of itself. Using frequency domain terminology, this means obtaining a high pass-filtered image by subtracting from the image a low pass-filtered version of itself. That is, input image and then taking the inverse transform of the product. Multiplication of the real part of this result by (-1) gives us the unsharp filtered image fun(x, y) in spatial domain.

Fig.1.2 Contrast Adjusted Image

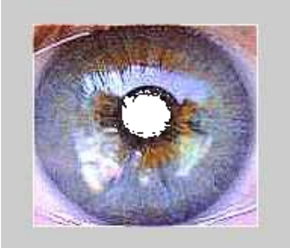

Fig. 1.3 Filtered Image

2.3.2 IRIS LOCALIZATION

2.3.2.1 Thresholding

It is of great importance to convert the grey image to binary for the effective extraction of the iris. Thresholding technique facilitates the efficient conversion of grey to binary. The masking function is constructed on the basis of maximum magnitude, called thresholding. There are three basic ways to threshold the transformed image.

(i) A single global threshold can be applied to all sub images.

(ii) A different threshold can be used for each sub image.

(iii) The threshold can be varied as a function of the location of each co-efficient with the subimage.

In the first thresholding approach, the level of compression differs from image to image depending on the number of coefficients that exceed the global threshold. Hence, this method was employed for the conversion.

The simplest of all thresholding techniques is to partition the image by using single global threshold T. Segmentation is then accomplished by scanning the image pixel by pixel and labeling each pixel as object or background, depending on whether the grey level of that pixel is greater or less than the value of T. The objects of interest in this case are darker than the background, so any pixel with the grey level<=T was labeled black (0) and any pixel with grey level>T was labeled white (255). The image as shown in fig. 1.4 is obtained.

The threshold was specified by using the following algorithm to obtain T automatically.

$$f_{hp}(x,y) = f(x,y) - f_{lp}(x,y) \qquad (1.1)$$

Unsharp filtering generalizes this by multiplying f(x, y) by a constant A>=1.

$$f_{un} = A\, f(x,y) - f_{lp}(x,y) \qquad (1.2)$$

Thus, unsharp filtering gives us the flexibility to increase the contribution made by the image to the overall enhanced result. This equation (2) may be written as:

$$f_{un}(x, y) = (A-1)\, f(x, y) + f(x, y) - f_{lp}(x,y) \qquad (1.3)$$

Substituting equation (1) in equation (3) we obtain:

$$f_{un}(x, y) = (A-1)\, f(x, y) + f_{hp}(u, v) = (A-1) + H(x, y) \qquad (1.4)$$

This result is based on a high pass rather than a low pass image. When A=1, unsharp filtering reduces to regular high pass filtering. As A increases past 1 the contribution made by the image itself becomes more dominant. Unsharp filtering can be implemented with the composite filter

$$H_{un}(u,v) = (A-1) + H_{hp}(u,v) \qquad (1.5)$$

With A>=1. The process consists of multiplying this filter by the transform of the input image and then taking the inverse transform of the product. Multiplication of the real part of this result by (-1) gives us the unsharp filtered image fun(x, y) in spatial domain.

1.Select an initial estimate for T.

2. Segment the image using T. This produces two groups of pixels: G1 consisting of all pixels with grey level values>T and G2 consisting of values<=T.

3. Compute the average grey level values µ1 for the pixels in regions G1 and G2.

4. Compute the new threshold value T=1/2(µ1+ µ2).

Repeat steps 2 to 4 until the difference in T in successive iterations is smaller than the predefined parameter T_o. The parameter T_o is used to stop the algorithm after changes become small in terms of this parameter.

Fig. 1.4 Threshold Image

2.3.2.2 IRIS extraction

The grey filtered image is resized to the dimension 192x192. If the specified size does not produce the same aspect ratio as the input image has, the output image is distorted. Nearest neighbor interpolation method fits a piecewise constant surface through the data values. The value of an interpolated point is the value of the nearest point.

For the purpose of recognition, only the iris ring should be extracted while the pupil has to be removed. This was carried out by identifying the lower pixel values (<=15) of the pupil in the resized, filtered grey image and converting them into higher pixel values (=255). This image was then converted to a binary image using the thresholding technique mentioned above. Thus, the iris was extracted and the image shown in figure 1.5 is obtained.

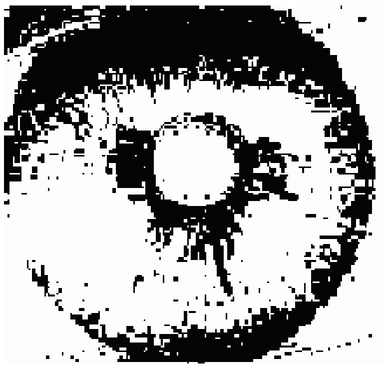

Fig. 1.5 Extracted Iris Image

2.3.3 NORMALIZATION

Irises from different people may be captured in different size, and even for irises from the same eye, the size may change because of illumination variations and other factors. Such elastic deformation in the iris texture will influence the results of iris matching. For the purpose of achieving more accurate iris recognition results, it is necessary to compensate for such deformation. Here, the iris ring was unwrapped anti-clockwise to a rectangular texture block with a fixed size (64x512) by a linear mapping. This was done by creating sub images each of dimensions 64x64 (as shown in Fig.1.6) in a counter clockwise manner and then arranging these sub images to form the final rectangular vector image of size 64x512 (as shown in Fig. 1.7). The normalization can thus reduce to a certain extent the distortion of the iris caused by pupil movement.

Fig. 1.6 Formation of sub-images (64x64 each)

Fig. 1.7 Normalized vector image (64x512).

2.4 Training process Using SOM

2.4.1 SOM ARCHITECTURE

The principal goal of the self-organizing map is to transform an incoming signal pattern of arbitrary dimension into a 1-D or 2-D discrete map, and to perform this transformation adaptively in a topologically ordered fashion.

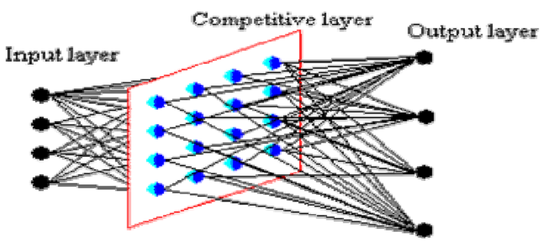

Fig. 1.8 Architecture of SOM

The self organizing map as shown in fig. 1.8 proceeds first by initializing the synaptic weights in the network. This can be done by assigning them small values picked from a random number generator. Once the network has been properly initialized there are three essential processes involved in the formation of the self organizing map. They are:

(i) Competition process

(ii) Cooperation process

(iii) Synaptic adaptation process.

2.4.1.1 Competitive process

For each input pattern, the neurons in the network compute their respective values of a discriminant function. This function provides the basis for competition among the neurons. The particular neuron with the largest value of discriminant function is declared winner of the competition. Let m denote the dimension of input space (data). Let an input pattern (vector) selected at random from the input space be denoted by

$$X=[x_1, x_2, \ldots x_m]^T \qquad (1.6)$$

The synaptic weight vector of each neuron in the network has the same dimension as the input space. Let the synaptic weight vector of neuron j be denoted by

$$W_j= [w_j1, w_{j2}, \ldots w_{jm}]^T, \qquad (1.7)$$

j=1, 2,…..l

Where, l = number of neurons in the network.

To find the best match of the input vector x with the synaptic weight vector W_j, compare the inner products W_j^TX and select the largest. This assumes that the same threshold is applied to all the neurons; the threshold is the negative of bias.

The best matching criterion, based on maximizing the inner product W_j^TX, is mathematically equivalent to minimizing the Euclidean distance between the vectors X and W_j . If we use the index i(X) to identify the neuron that best matches the input vector X, we may then determine i(X) by applying the condition

$$i(X)=\arg\min_j ||X-W_j|| , \qquad (1.8)$$

j=1,2,……l

The particular neuron i that satisfy this condition is called the best matching or winning neuron for the input vector X.

2.4.1.2 Co-operative Process

The winning neuron locates the center of the topological neighborhood of co-operating neurons. In particular, a neuron that is firing tends to excite the neurons in its immediate neighborhood more than those for that away from it. This observation leads to make the topological neighborhood around the winning neuron i decay smoothly with lateral distance. To be specific, let $h_{j,i}$ denote the topological neighborhood centered on winning neuron i, and encompassing a set of excited neurons, a typical one of which is denoted by j. Let d_{ig} denote the lateral distance between the winning neuron i and excited neuron j. Topological neighborhood satisfies two distinct requirements.

(i) The topological neighborhood h is symmetric about the maximum point defined by

di,jj,i =0.

(ii) The amplitude of the topological neighborhood decreases monotonically with increasing with lateral distance d, decaying to zero for dj,ij,i = ; this is the necessary condition for convergence.

A typical choice of $h_{j,i}$ that satisfies these requirements is a Gaussian function.

$$h_{j,i}(X)=\exp(-d_{j,i}^2 /2\sigma^2) \qquad (1.9)$$

Which is a transmission invariant (i.e., independent of the location of the winning neuron). The parameter α is the "effective width".

For cooperation among neighboring neurons to hold, it is necessary that topological neighborhood $h_{j,i}$ be independent on lateral distance $d_{j,i}$ between winning neuron I and excited neuron j in the output space rather than on some distance measure in the original input space. In two dimensional lattices, it is defined by

$$d_{j,i}^2=\| r_j - r_i \|^2 \qquad (1.10)$$

The unique feature of the SOM algorithm is that the size of the topological neighborhood shrinks with time.

2.4.1.3 Adaptive Process

This last mechanism enables the excited neurons to increase their individual values of the discriminator function in relation to the input pattern through suitable adjustments applied to their synaptic weights. The adjustments made are such that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced. The unit with the smallest distance is that which most closely represents the current input, and is thus considered the winner for that input. The weights of the winning unit are now updated towards that input.

$$W_{winner}=W_{winner} + \beta(x-W_{winner}) \qquad (1.11)$$

Where β is the learning rate and it should be time varying.

Starting from an initial state of complete disorder, SOM algorithm gradually leads to an organized representation of activation patterns drawn from the input space, provided that the parameters of the algorithm are selected properly. The two phases are:

(i) Self – organizing or ordering phase

(ii) Convergence phase

2.4.1.4 Self – Organizing Phase

In this phase, the topological ordering of the weight vectors takes place. The ordering phase may take as many as 1,000 iterations of the SOM algorithm. Careful considerations must be given to the choice of learning-rate parameter and neighborhood function:

The learning rate parameter should begin with a value close to 0.1; thereafter it should decrease gradually, but remain above 0.01.

(ii) The neighborhood function h (j, i) should initially include almost all neurons in the network centered on the winning neuron I, and then shrink slowly with time.

2.4.1.5 Convergence Phase

This phase is needed to fine tune the feature map and therefore provide an accurate statistical quantification of the input space. The convergence phase may have to go on for thousands and possibly tens of thousands of iterations.

(i) For good statistical accuracy, the learning parameter should be maintained during the convergence phase at a small value, on the order of 0.01.

(ii) The neighborhood function should contain only the nearest neighbors of a winning neuron, which may eventually reduce to 1 or 0 neighboring neurons.

2.4.2 TRAINING ALGORITHM

The training algorithm can be written as follows

Step 1: Set topological neighborhood parameters, learning rate, initialize weights.

Step 2: While stopping condition is false, do steps 3 to 9.

Step 3: For each input vector x, do steps 4 to 6.

Step 4: For each j, compute squared Euclidean distance.

$D(j) = (w_{ij} - x_i)^2 \quad i = 1$ to n and j = 1 to m.

Step 5: Find index j, when D (j) is minimum.

Step 6: For all units j, with the specified neighborhood of j, and for all i, update the weights.

Step 7: Update the learning rate.

Step 8: Reduce the radius of topological neighborhood at specified times.

Step 9: Test the stopping condition.

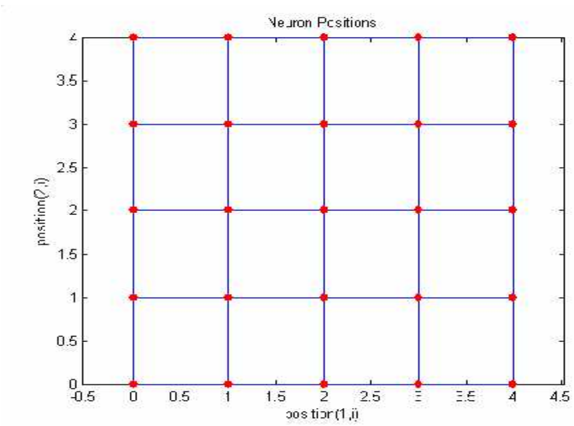

Fig. 1.9 SOM in Physical Space (Grid Topology)

maximum and minimum contrast values were fed as input elements to form a self organizing map of dimensions 5x5 shown in figure 1.9. The distance function used was "Manhattan Distance" while the topology function was "Grid topology". The SOM was trained and the input vectors were plotted with the map that the SOM's weights had formed. The network input for training was a resized image of dimensions 2x520.

2.5 Pattern Matching

The distance between the neurons in the trained network was found by using "Manhattan Distance". For the matching process, a data image was fed which was trained as mentioned above. Its Manhattan Distance was computed and compared with that of the stored, trained iris image. The distances of matching irises were equal while those of non matching irises were found to be different. Thus, the matching process was carried out.

In this paper, an attempt was made to design an iris recognition system using the Self - Organizing Neural Networks. The system was tested by using four different colored irises which were digitally captured. These iris images were processed, enhanced and trained using SOM. An input data image was fed for matching. The recognition system efficiently produced reliable matching results for the same irises and detected different irises. As such the data for authentic and imposters were well separated.

3. CONCLUSION

We tested the performance of our algorithm using a Pentium IV processor and obtained an average of correct recognition of 83%. In the test, there were some irises which were heavily distorted such as half of the iris was covered. For this type of data, the network gave an output of unrecognized pattern rather than matching it with the closest pattern. However, the performance of the recognition system can be improved by acquiring images that are captured by high resolution digital cameras or sensors keeping in mind correct alignment of the input data.

Overall, the iris recognition system performed remarkably well under preliminary testing. As the experiment was conducted on a very small scale one must be cautious in the extrapolation of the results. Nevertheless, the results speak in favor of the iris recognition system as a promising biometric technology.

4. REFERENCES

[1] John Daugman, "How Iris Recognition Works", IEEE Trans. On Circuits and Systems for Video Technology, Vol.14, No.1, pp 21-30, Jan 2004.

[2] John Daugman, Cathryn Downing"Epigenetic Randomness, Complexity and Singularity of Human iris Pattern", Proceedings of The Royal Society, pp 1737-1740, April 2001.

[3] John Daugman, "Demodulation by Complex-Valued Wavelets for Stochastic Pattern Recognition", International Journal of Wavelets, Multiresolution and Information Processing, Vol. 1, No.1, pp 1-17, Jan 2003.

[4] John Daugman, "Probing the Uniqueness and randomness of Iris Codes: Results from 200 Billion Iris Pair Comparisons", Proceedings of the IEEE, Vol.94, No.11, pp 1927-1935, Nov 2006.

[5] John Daugman, "New Methods in Iris Recognition", IEEE Trans. On Systems, Man and Cybernetics-Part B: Cybernetics, Vol.13, No.5, pp 1167-1175, Oct 2007.

[6] John Daugman, "The Importance of Being Random: Stastical Principles of iris Recognition", The Journal of Pattern Recognition Society, Vol.36, pp 279-291, 2003.