Australian Journal of Basic and Applied Sciences, 9(11) May 2015, Pages: 411-416

ISSN:1991-8178

Australian Journal of Basic and Applied Sciences

Journal home page: www.ajbasweb.com

IRIS Recognition System Using Neural Network and Image Data Partitioning Techniques

[1]D. Elantamilan, [2]V. Saishanmuga raja and [3]S.P. Rajagopalan

[1]*Research Scholar, Dr. M.G.R Educational and Research Institute University, Department of Computer Applications, Faculty of Humanities and Science, Chennai, India.*
[2]*Assistant Professor, Dr. M.G.R Educational and Research Institute University, Department of Computer Science and Engineering, Faculty of Engineering and Technology, Chennai, India.*
[3] *Professor Emeritus, Dr. M.G.R Educational and Research Institute University, Department of Computer Applications, Faculty of Humanities and Science, Chennai, India.*

ARTICLE INFO

Article history:
Received 12 March 2015
Accepted 28 April 2015
Available online 5 May 2015

Keywords:
Iris Recognition, Image Data Partitioning, Feedforward Neural Network.

ABSTRACT

In this paper, we propose a method for personal identification based on iris recognition system using Feed forward Neural Network. This paper presents an efficient iris image pre-processing method and the design and training of Feed forward Neural Network. Also different image data partitioning methods are proposed and explored. The process of iris recognition consists of localization of the iris region and generation of data set of iris images followed by iris pattern recognition. Brain Maker simulations were used to measure the accuracy of the system. We also experimented with various number of hidden layers, number of neurons in each hidden layer, input format (binary vs. analog), percent of data used for training versus testing. The recognition and Performance of the system is validated using CASIA version 3 interval dataset. The recognition system achieved high accuracy using simple data pre-processing and a simple neural network.

© 2015 AENSI Publisher All rights reserved.

To Cite This Article: D. Elantamilan, V. Saishanmuga raja and S.P. Rajagopalan., IRIS Recognition System Using Neural Network and Image Data Partitioning Techniques, ***Aust. J. Basic & Appl. Sci.,*** *9(11): 411-416, 2015*

INTRODUCTION

With fast development of iris image acquisition technology, iris recognition is expected to become a fundamental component of modern society, with wide application areas in national ID card, banking, e-commerce, welfare distribution, biometric passport, and forensics, etc. Since 1990s, research on iris image processing and analysis has achieved great progress.

Related works have been done in the medicine's domain (determination of some possible health conditions (Demea, 2005), in biometrics domain (identification and recognition of a person (John Daugman, 2004)) and others. Biometrics plays an important role in public safety and to accurately identify each individual to distinguish them from each other (Melin & Castillo, 2005). The traditional methods normally make use of magnetic cards or cards with some bar codes printed on it. The major problem in these types of methods is that the cards should be carried along where ever a person goes. There are many chances of the cards may be stolen or misplaced. Of late there are many instances of replication of finger prints and magnetic cards and their misuse have come into light. The department of cyber crime has a tough time in cracking the cases and tracking the culprits.

The human iris is unique and cannot be duplicated or imitated, since it is impossible to extract an iris image without the knowledge of a person (Raja & Rajagopalan, 2013). 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 (John Daugman, 2004). From the birth of a person until death, the patterns of the iris are relatively constant over a person's lifetime (Demea, 2005). Because of this uniqueness and stability, iris recognition is a reliable human identification technique. The process of iris recognition consists of iris image capturing, pre-processing, and recognition of iris region in eye image. The iris image preprocessing includes localization. In practice, the identification process starts when an image of the eye from a person located in front of the digital camera is taken. In the process of image acquisition $Tx = f(£x)$, a digital representation of the biometrics Tx is obtained from a real biometric $£x$.

The next step is segmenting the iris image, which identifies the area of interest: the iris texture.

Corresponding Author: D. Elantamilan, Research Scholar, Dr. M.G.R Educational and Research Institute University, Department of Computer Applications, Faculty of Humanities and Science, Chennai, India.

This process may include additional processing methods that are designed to provide an image in a suitable form for further analysis. Isolation of distinctive features and the encoding phase is a process that allows the biometrics' digital template *Tx* to be obtained. The resulting template is compared to those in a database in mode called 1 : *N* to search for the pattern that best matches the template using a decision threshold *t* which is chosen based on the assumed security strategy. In the simplest case, a minimum-distance classifier can be used for data-mining in the database *D*, which generates the lowest similarity score *s*1..*N* = *s* (*Tx*,*T*1..*N*) according to the criterion

$$S \le t \Rightarrow match$$

$$S > t \Rightarrow notmatch \quad (1)$$

Artificial Neural Network :

An Artificial Neural Network (ANN) is an information processing system that is inspired by the way biological nervous system works, such as the brain processing information. The key element of this paradigm is the structure of the information processing system. It consists of a large number of highly interconnected processing elements (neurons) work to solve specific problems. ANNs, like people, learn by example (Raja & Rajagopalan, 2013). An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons.

A neural network is a system of parallel processors connected together as a directed graph. Schematically, each processing element (neuron) of the network is represented as a node. These connections provide a hierarchical structure trying to emulate the physiology of the brain for processing new models to solve specific problems in the real world. What is important in developing neural networks is their useful behavior by learning to recognize and apply relationships between objects and patterns of objects specific to the real world. In this respect neural networks are tools that can be used to solve difficult problems (Fallahnezhad *et al*., 2001), (Sibai *et al*., 2011) and (Wade *et al*., 2010). Artificial neural networks are inspired by the architecture of the biological nervous system, which consists of a large number of relatively simple neurons that work in parallel to facilitate rapid decision-making (Zeng & Liu, 2004).

The ANN is a universal computation algorithm that has the ability to compose complex hypotheses that can explain a high degree of correlation between features without any prior information from the data set (Cartwright, 2008a)

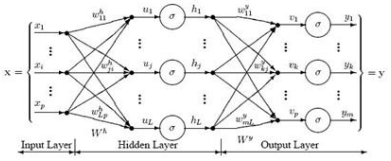

Fig. 1: A Neural Network with Hidden layers.

A neural network is created and the iris images are given as the inputs. Here the Artificial Neural Network has to compare the scanned iris image with the stored image and identify the person from the image. For doing this the nodes in the neural network has to learn and store the features of the iris each time an image is being given as input. Aim of this study is to make Neural Network learn faster and accurately identify the person. In some cases if the nodes are forced with a mass data, the network instead of learning may adopt rote learning or memorize. This is just like the children resort to repeat what they read from the book verbatim from their memory instead of acquiring the abstract of the concept and interpret in their own way.

Preprocessing And Segmentation:

After storing the eye images in the database, the images for generic information from the pupil and iris are observed. To extract the exact image of iris the unwanted components around the iris has to be removed. For doing this the author have the following stages in his experiments.

In preprocessing stage, several methods were implemented for feature extraction and noise removal in order to extract the iris from the captured image. In the process of segmentation, it may be necessary to use certain algorithms whose task is to further prepare the image for processing by the feature extraction algorithms.

When we started collecting iris images for training and testing the neural network, we decided to select iris images of the same color in order to create more difficult situations for our recognition system to achieve higher accuracy rate. We collected and pre-processed brown-colored iris images of different persons from the iris database CASIA version 3 interval dataset (CASIA, 2010). The iris images were between 400 Kb and 500 Kb and were not ready for processing but had to be pre-processed. For instance the white sclera and black pupil are visible in all the images. Additionally, the relevant

content of the binary iris image were not ready to be fed to an artificial neural network for processing. Thus four pre-processing steps were taken:

1. Edit each image with Adobe Photoshop to convert it from png to jpeg (JPEG Specifications, xxxx) format needed by the program in step 2. JPEG is a common format used for graphic images and has high resolution as it can support millions of colors. In addition, it is the most common format for storing and transmitting photographic images on the World Wide Web.
2. On each image, run a Java program to extract the 100 _ 100 RGB (Red, Blue & Green) values (Lin, xxxx) from the iris image's jpg file.
3. For each image, store 100 _ 100 RGB pixel values in a Microsoft Excel spreadsheet. Next, in the spreadsheet, RGB values of sclera pixels close to 0 were replaced by 0. RGB values of pupil pixels close to FFFFFF were also replaced by 0. The replacement of RGB values of sclera and pupil pixels by 0 was done to avoid processing these non-iris areas. RGB values in row/column strips and blocks were then summed.
4. The Excel spreadsheet content was converted to a .dat file input into the NetMaker (IEEE Expert Staff, 1992) application which generated the input files for the BrainMaker artificial neural network simulator (IEEE Expert Staff, 1992).

The first three steps are data pre-processing steps while the fourth step is a BrainMaker pre-processing step. As we are going to use artificial neural network for iris recognition, we manually manipulated the images. But the first three pre-processing steps that require manipulation of the iris image can be simply automated. A published Java program to generate a file with the RGB values of all pixels was used for automation. Since the program expected a jpeg image for input, we removed the unwanted pixels in the images using Photoshop by cutting a slight portion from the top and bottom of the images and saved them as jpg files. The Java program converted each pixel into a 6 hex digit RGB value given by

rgbValue = src.getRGB(j,k)+0xFFFFFF+1

Iris Image Data Partitioning:

In this section, we describe how we converted a matrix of RGB values into data ready for neural network processing (Sibai *et al*., 2011). After completion of the pre-processing step, we obtain a matrix of RGB values each with six hexadecimal numbers ''R1R0G1G0B1B0'' where R1R0 represent the hexadecimal red value, G1G0 represent the hexadecimal green value, and B1B0 represent the hexadecimal blue value. For simplicity, we treat the 6 hexadecimal digits as one number in the order generated by the Java program thus giving more weight to the red component of the pixel's RGB value. In theory, it is fair to treat red, green and blue colors with equal weights but as our results with concatenating the RGB numbers into one number were satisfactory, we did not experiment with uniform color weights.

As it is desired to reduce the cost of the artificial neural network, and as BrainMaker limits the number of neurons per layer, the iris image's RGB matrix had to be partitioned to reduce as much possible the number of values fed as input to the neural network. For that purpose, we considered three simple data partitioning techniques as shown in **Fig.2**.

1. Horizontal strip partitioning (rows).
2. Vertical strip partitioning (columns).
3. Block partitioning.

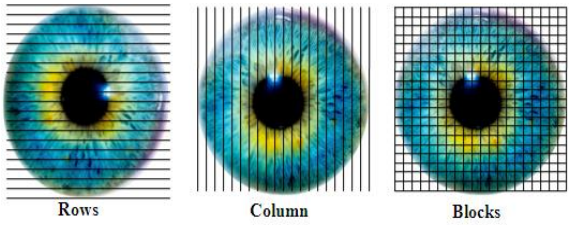

Fig. 2: Data partitioning techniques: horizontal (left), vertical (middle), block (right).

In horizontal strip (row) partitioning, we divided the RGB matrix into r (=10, 25) horizontal strips and summed all the RGB values of all pixels falling in one horizontal strip. When r was set to 10 (25), and as the image contains 100 _ 100 pixels, each horizontal strip contained the RGB values of 100/10 (25) = 10 (4) rows of 100 pixels each, and a 1000 (400) RGB values were summed into one number representing that horizontal strip. Similarly, in vertical strip (column) partitioning, we divided the RGB matrix into c (=10, 25) vertical strips and summed all the RGB values of all pixels falling in one vertical strip. When c was set to 10(25), and as the image contains 100 _ 100 pixels, each vertical strip contained the RGB values of 100/10 (25) = 10 (4) columns of 100 pixels each, and 1000 (400) RGB values were summed into one number representing that vertical strip.

In block partitioning, the image was divided into b (=16, 25) square blocks. When b was set to 16 (25), and as the image contains 100 _ 100 pixels, each block consists of 25 _ 25 (20 _ 20) pixels whose RGB values were summed into one number per block. Each horizontal/vertical strip or block was

thus represented by one number which was fed as one input into the artificial neural network for identifying a match/no match of the presented iris image.

Our data partitioning techniques are characterized by simplicity and fast processing (summing), compared to more complicated techniques based on wavelets, and are key to reducing the system cost.

Experimental Methodology:

As the NetMaker accepts DAT files as inputs, these DAT files containing the sums of RGB values in the various strips and blocks previously discussed were prepared for that purpose. Neural network training and testing experiments were conducted for two different data encodings: binary and analog. In binary coding, each sum is converted into 6 bits for both horizontal and vertical strip partitioning and 4 bits for block partitioning. These numbers are governed by the maximum number of neurons per layer (=64) acceptable by the BrainMaker simulator. For that reason, for horizontal or vertical partitioning, we limited the number of neurons in the input layer of the simulated artificial neural networks to 60 analog inputs (one RGB sum per neural network input) and 60 binary inputs (10 RGB sums of 6 bits each). As the RGB sums are very large integer numbers we divided these numbers by a large constant (1 billion) to convert them into real numbers under 10.0. In analog coding, each of these real numbers was fed to a neural network input. In binary coding, the real number was truncated and converted into the closest whole number under 10 and represented by a 6-bit binary number when the image is divided into horizontal or vertical strips. For instance, if the RGB sum of a horizontal strip, vertical strip or lock, is 6311370815, it is then divided by 1000000000 to yield 6.311370815 which is then approximated to 6 which is then represented by 000110.

All in all, 6 DAT files were prepared: (1) horizontal strip (row) partitioning scenario with binary values, (2) horizontal strip (row) scenario with analog values, (3) vertical strip (column) with binary values, (4) vertical strip (column) scenario with analog values, (5) block partitioning scenario with binary values, and (6) block partitioning scenario with analog values. Each DAT file contains the RGB sum information for 60 iris images and each image information is mapped to a unique value that is used to distinguish the irises.

Training and Testing Neural Network:

Iris recognition experiments using neural network BrainMaker software were performed then in two steps: training and testing. The DAT files were provided for the NetMaker application hich prepared the input files required by the BainMaker simulator and which provided the capability to set (i) T_r, the percentage of images for training the network and (ii) T_e, the percentage of images to test the network, where $T_r + T_e = 100\%$. We later experimented with these percentages, setting (T_r, T_e) to (25%, 75%), (75%, 25%), and (50%, 50%) and discovering that with a total of 60 iris images, (T_r, T_e) = (25%, 75%) – i.e. 15 images for training and 45 images for testing which resulted in the best artificial neural network accuracy.

Input files for neural network were created by NetMaker: the definition file, the training fact file, and the testing fact file. The first two files are used to train the neural network while the third one is used in the testing phase, where images are fed into the neural network and the network determines if they match or do not match the iris image which the network was trained to recognize. After generating the files required by NetMaker, the NetMaker application was started to train the network first and then to test it. In the training phase, 15 iris images were used; one was presented to the artificial neural network as the image to ‘‘memorize’ while the remaining 14 images were presented as false iris images. In the testing phase, 45 iris images including the true image which the network was trained to ‘‘memorize’’ and 44 false images were presented to the neural network which the network is expected to indicate with an output of 1 if the input image matches the true memorized iris image, and with an output of 0 when there is no match.

This process was repeated for various neural network topologies based on the same feedforward neural network with a number of neurons in the first layer matching the number of RGB sums (in analog values) or 6 times the number of RGB sums (in binary coding, where a RGB sum is converted into 6 bits, 1 bit per neural network input). This process of training and testing was repeated for the different horizontal strips (with 10 or 25 horizontal strips), vertical strips (with 10 or 25 vertical strips), and block partitioning (with 16 or 25 blocks). After trials and errors of the percentage of iris images used for training and for testing, the results of 15 iris images used for training and 45 images used for testing which has yielded the best iris recognition accuracy by the feedforward artificial neural network is presented in the next section.

RESULTS AND DISCUSSION

We have given three main data partitioning scenarios: horizontal strip (rows), vertical strip (columns), and blocks, and each scenario is repeated with different partition sizes (10, 15 & 20). It is expected that the accuracy of the iris recognition by the artificial neural network may differ across different scenarios. Table 1 shows the accuracy of iris recognition under each experiment when the images are divided into 10 horizontal strips, 10 vertical strips, or 16 blocks.

Table 2 shows the accuracy results when the images are divided into 25 horizontal strips, 25 vertical strips, or 25 blocks. Analyzing the results in the two tables, it is clear that the results obtained by dividing the images into fewer partitions are better than the results obtained after dividing the images into a large number of partitions. As each neuron in the input layer of the feedforward neural network interconnects to all neurons in the hidden layer, 10 partitions seems to capture the features of the iris better than the 25 partitions case where iris features may be diluted and therefore lost among the higher number of partitions.

Comparing the accuracy of horizontal strip partitioning versus vertical strip partitioning versus block partitioning from Table 1, the block partitioning outperformed other partitioning techniques. Since the experiments were conducted on 100 x 100 pixel images, there is no improvement in accuracy in horizontal and vertical partitioning. So in either type of strip partitioning, there is no extra iris feature information preserved. However with block partitioning, the detailed iris features were better preserved.

The best accuracy (95.56%) was obtained with 10 block partitioning with 10 neurons in the input layer and 10 neurons in the hidden layer and 1 hidden layer only. When the number of neurons in the hidden layer was increased to 50 neurons, the accuracy reduced to 84.44%. This accuracy result was obtained with 1 or 2 hidden layers of 50 neurons each. Also increasing the number of hidden layers from 1 to 2 reduced the accuracy. When binary coding is used and due to the discarded fraction and insufficient number of bits, we obtained poor accuracy.

From the literature survey done, we compared our proposed method with the existing methods. The accuracy 95.56% of our proposed method exceeds the results obtained by Wildes (1997) (84.49%), Masek (83.92%), Liam *et al*., (2002) (64.64%), and are close to those obtained by Xu *et al*., (2008) (98.42%). The comparison of the accuracy is shown in the Table 3.

Table 1: Experiments results with 10 Horizontal, Vertical strips and Blocks.

Experiment Description	No.of Hidden Layers	No. of Neurons	Correctly recognized	Incorrectly recognized	Accuracy (%)
(Horizontal Partitioning) Analog input	1	10	33	12	73.33%
(Vertical Partitioning) Analog input	1	10	27	18	60.00%
(Block Partitioning) Analog input	1	10	43	2	95.56%
(Block Partitioning) Analog input	1	50	38	7	84.44%
(Block Partitioning) Analog input	1	10	35	10	77.78%
(Block Partitioning) Analog input	2	5,10	33	12	73.33%
(Horizontal Partitioning) Binary input	1	50	27	18	60.00%
(Vertical Partitioning) Binary input	2	25,25	27	18	60.00%
(Block Partitioning) Binary input	2	25,25	26	19	57.78%

Table 2: Experiments results with 25 Horizontal, Vertical strips and Blocks.

Experiment Description	No.of Hidden Layers	No. of Neurons	Correctly recognized	Incorrectly recognized	Accuracy (%)
(Horizontal Partitioning) Analog input	1	25	28	17	62.22%
(Vertical Partitioning) Analog input	1	25	27	18	60.00%
(Block Partitioning) Analog input	1	25	38	7	84.44%
(Block Partitioning) Analog input	1	50	33	12	73.33%
(Block Partitioning) Analog input	2	25,25	26	19	57.78%
(Block Partitioning) Analog input	2	25,50	26	19	57.78%

Table 3: Recognition Performance comparison with existing methods.

Methodology	Accuracy Rate
Wildes	84.49%
Masek	83.92
Liam *et al*	64.64
Proposed Method	95.56

Conclusion:

Iris recognition system is used in places where security is more important. Iris identification is very effective in authentication due to its unique features. In this paper we used a simple feed forward neural network trained with back propagation algorithm. We have described how the iris images are preprocessed and made ready as input for the network. We have chosen 60 iris images from the CASIA version 3 interval dataset. We have made use of three different data partitioning methods: Horizontal strip, Vertical strip and Blocks.

Simulation results show that 10 horizontal or vertical partitions (or 16 blocks) resulted in better iris recognition accuracy than 25 horizontal or vertical partitions (or blocks). Block partitioning outperformed the horizontal or vertical strip partitioning methods. It is also evident that one

hidden network layer is best. The proposed method was able to achieve 95.56% accuracy which much improved than the existing methods. Using dissimilar irises of various colors is expected to enhance our artificial neural network's accuracy even further.

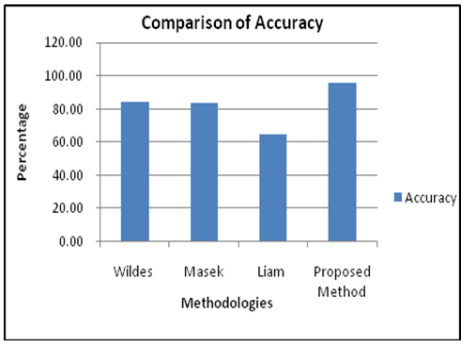

Fig. 3: Recognition Performance comparison with existing methods.

REFERENCES

Demea, S., 2004. "Corelatii intre aspectul irisului si patologia generala" (Correlations between iris aspects and endocrine pathology), PhD Thesis, manuscript sent for publications in Sibiu Medical .

John Daugman, 2004. "How Iris Recognition Works", IEEE Transactions on Circuits And Systems For Video Technology, 14.

Melin, P., O. Castillo, 2005. Hybrid Intelligent Systems for Pattern Recognition. Heidelberg: Springer-Verlag.

Raja, V.S., S.P. Rajagopalan, 2013. "IRIS Recognition System using Neural Network and Genetic Algorithm", International Journal of Computer Applications, 68(20).

Raja, V.S., S.P. Rajagopalan, 2013. "A Comparative Analysis Of Optimization Techniques For Artificial Neural Network In Bio Medical Applications", Journal Of Computer Science, 10(1): 106.

Fallahnezhad, M., M.H. Moradi, S. Zaferanlouei, 2011. A HybridHigher Order Neural Classifier for handling classification problems, Expert Systems with Applications, 38(1): 386-393.

Sibai, F.N., H.I. Hosani, R.M. Naqbi, S. Dhanhani, S. Shehhi, 2011. Iris recognition using artificial neural networks, Expert Systems with Applications, 38(5): 5940-5946.

Wade, J.J., L.J. McDaid, J.A. Santos, H.M. Sayers, 2010. SWAT: A spiking neural network training algorithm for classification problems, IEEE Transactions on Neural Networks, 21(11): 1817-1830.

Zeng, J., Z.Q. Liu, 2004. Type-2 fuzzy hidden Markov models to phoneme recognition, Proceedings of the International Conference on Pattern Recognition (ICRP), Cambridge, 192-195.

CASIA-Iris Version 3 interval dataset.[Online]. Available: http://biometrics.idealtest.org/.

JPEG Specifications. [online]. Available: http://www.jpeg.org/ committee. html

Lin, E., Program for retrieving the RGB values of a jpeg image's pixels. Available: http://www.ericlin2.tripod.com/getrgb/getrgbt.html.

IEEE Expert Staff, 1992. Brainmaker professional. IEEE Expert: Intelligent Systems and Their Applications, 7(2): 70–71.

Wildes, R., 1997. Iris recognition: An emerging biometric technology. Proceedings of IEEE, 85(9): 1348–1363.

Masek, L., Recognition of Human Iris Patterns for Biometric Identification. http://www.csse.uwa.edu.au/opk/studentprojects/labor.

Liam, L., 2002. Iris recognition using self-organizing neural network. Student Conference on Research and Development, 169–172.

Xu, G., Z. Zhang, Y. Ma, 2008. An efficient Iris recognition system based on intersecting cortical model neural network neural network. International Journal of Cognitive Informatics and Natural Intelligence, 2(3).