Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 11, Issue 4, December 2020: 2391-2396
DOI: 10.53555/tojqi.v11i4.10096

Research Article

Asian & Non-Asian Iris Image Optimum Classifier Using Generalized Feed Forward Neural Network

V.L Agrawal[1*]

Abstract:

Analysis of iris pattern has been the focused of researches, mostly in biometric authentication. The researchers state that the iris contains unique patterns to each person and stable with age. Therefore, iris has been used as recognition of a person. Iris recognition is one of the most reliable methods for identification of individuals. However, there are many parameters which can attenuate the accuracy and reliability of iris recognition systems. The iris recognition system's reliability can be challenged and the accuracy of biometrics recognition systems can be degraded due to the several different abnormalities in the pattern of iris tissue. The main purpose of is to find appearance primitives of iris images firstly, compact and yet discriminative visual features, we call them Iris-textons here, are automatically learned from a set of training images. Main purpose of this work images are classified into two ethnic categories, Asian and non-Asian human iris images. Classification of Asian and non-Asian iris images is an essential research topic as it may be advantageous in monitoring biometric authentication. Therefore the need for fast, automatic, less expensive and accurate method to classify Asian and non-Asian iris images is of great realistic significance.

Index Terms: Mat Lab, Nuero Solution Software, Microsoft excel, Various Transform Techniques.

I. INTRODUCTION

Iris biometrics offers high accuracy in applications such as secure access to bank accounts at ATM machines, national border controls, and secure access to buildings and passports control etc. Biometric methodology both, physical characteristics category contains iris, fingerprints, retina, hand geometry, and face characteristics and behavioural characteristics include voice, online signature, gait and keystroke pattern - is very convenient in comparison with pins, passwords and other tokens. Iris recognition is one of the most reliable methods for identification of individuals. However, there are many parameters which can attenuate the accuracy and reliability of iris recognition systems. Identifying or verifying one's identity using biometrics is attracting considerable attention in these years. Biometrics authentication uses information specific to a person, such as a fingerprint, face, utterance, or iris pattern. Therefore, it is more convenient and securer than the traditional authentication methods. Among all the biometrics authentication methods, iris recognition appears to be a very attracting method because of its high recognition rate. The iris of human eye is the annular part between the black pupil and the white sclera, in which texture is extremely rich. Some examples are shown in Fig. 1. Iris texture is random and unique to each subject, so iris recognition has become one of the most important biometric solutions for personal identification. Since Daugman's first iris recognition algorithm, there have been many schemes for iris representation and matching in literature. All these method regard iris texture as phenotypic feature. That is to say, the iris texture is the result of the developmental process and is not dictated by genetics. Even the genetically identical irises, the right and left pair from any given person have different visual appearance. However, through investigating a large number of iris images of different races, Asian and non-Asian, we found that these iris patterns have different

[1]*Faculty, Electronic and Telecommunication Department, HVPM'S College of Engineering and Technology (India)

visual appearance. Fig. 1 shows some typical iris examples, the first column is from Asian, and the second column is from non-Asian. These images have very different visual appearance. For an iris image from Asian, the inner 1/2 annular part of iris region often provides more texture information than the outer 1/2 annular part and the main patterns are spots and blocks.

However for an iris image from non-Asian, the above two parts provide almost the same texture information and the main patterns are capillary like patterns. We have an intuitive assumption that the iris patterns are both a phenotypic feature and a genotypic feature. Iris texture of different race is consisted of different appearance primitives. Motivated by this assumption, we try to find out the differences of visual appearance in different ethnicity and do ethnic classification (also called race classification) based on iris texture.

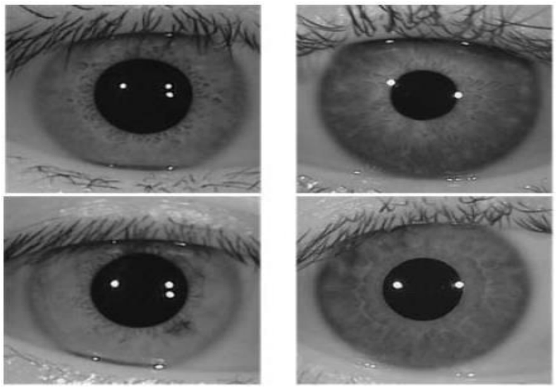


Figure1.CASIA iris images. The first column is from Asian, the second column is from non-Asian.

In this chosen work, we Applied a novel algorithm for automatic ethnic classification based on discriminative appearance primitives of iris images. The main purpose of this work is to find compact and yet discriminative visual features, we call them Iris-Textons here, are automatically learned from a set of training images. Then the Iris-Texton histogram was used to represent the visual appearance of iris images. Finally, all images are classified into two ethnic categories, Asian and non-Asian, through neural networks. This work is expected to be used for coarse classification in an iris recognition system. It will speed up iris matching on a very large scale iris database, which includes a lot of Asian and non-Asian users.

.II. RESEARCH METHODOLOGY

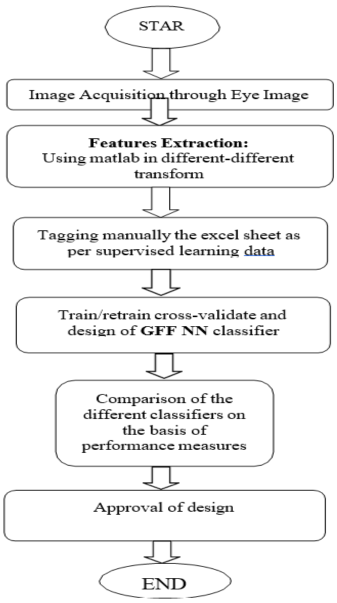
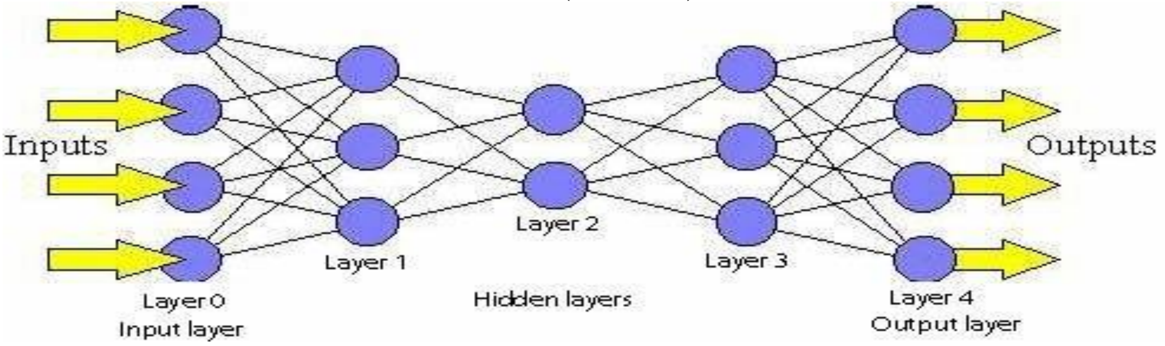


Figure 2. Methodology of work.

NEURAL NETWORK

Following Neural Networks is tested:

Generalized Feed-Forward Neural Networks (GFF NN):



In theory, a MLP can solve any problem that a generalized feed-forward network can solve. In practice, however, generalized feed-forward networks often solve the problem much more efficiently. Without describing the problem, it suffices to say that a standard MLP requires hundreds of times more training epochs than the generalized feed-forward network containing the same number of processing elements.

Feed-forward networks have the following characteristics:

1. Perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world, and hence are called hidden layers.
2. Each perceptron in one layer is connected to every perceptron on the next layer. Hence information is constantly "fed forward" from one layer to the next., and this explains why these networks are called feed-forward networks.
3. There is no connection among perceptrons in the same layer.

Learning Rules used:

1) Momentum

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

2) Conjugate Gradient

CG is the most popular iterative method for solving large systems of linear equations. CG is effective for systems of the form A=xb-A (1) where x _is an unknown vector, b is a known vector, and A _is a known, square, symmetric, positive- definite (or positive-indefinite) matrix. (Don’t worry if you’ve forgotten what “positive-definite” means; we shall review it.) These systems arise in many important settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis, circuit analysis, and math homework.

a. Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

b. It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in n-space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector.

3) Quick propagation

Quick propagation (Quickprop) is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimize Back-propagation; the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

4) Delta by Delta

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in n-space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector.

III. SIMULATION RESULTS

1) COMPUTER SIMULATION

In this Project,156 images have been used which consist of two types of iris images therefore the dimension of the matrix is obtained as 156X(128+7).Out of 156 images 60% used for training & 40% used for cross-validation.

The simulation of best classifier along with the confusion matrix is shown below :

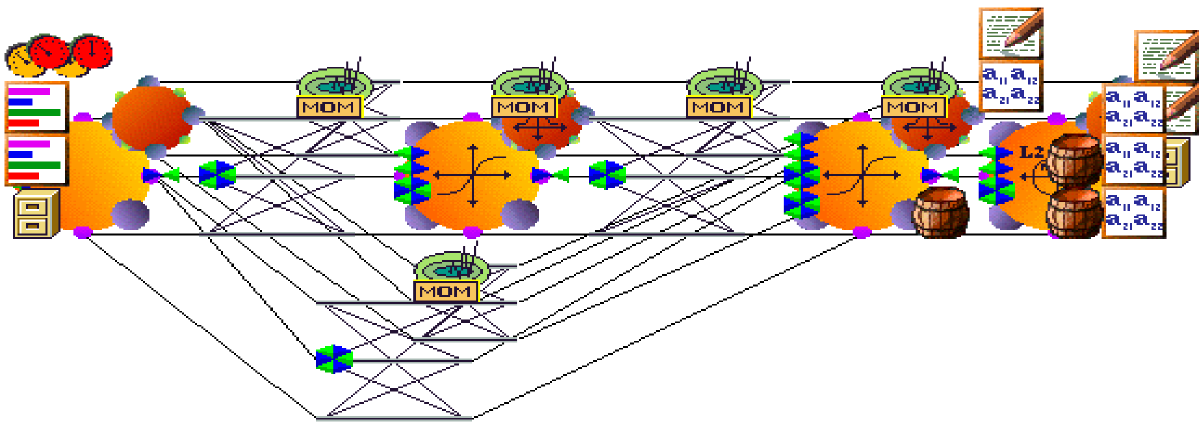


Figure.3 GFF neural network trained with MOM learning rule

2) RESULTS

Performance	NAME(NON-ASIAN)	NAME(ASIAN)
MSE	0.097169713	0.099829093
NMSE	0.392353336	0.40309142
MAE	0.148864877	0.161897135
Min Abs Error	0.004024183	0.003481143
Max Abs Error	1.054794357	1.055555555
r	0.808660352	0.799322593
Percent Correct	97.05882353	89.28571429

TABLE I. Accuracy of the network on CV data set

Performance	NAME(NON-ASIAN)	NAME(ASIAN)
MSE	0.002247006	0.002399528
NMSE	0.009090907	0.009707979
MAE	0.045355328	0.047121003
Min Abs Error	1.92065E-05	0.003705257
Max Abs Error	0.063156199	0.072214062
r	0.999277118	0.998645491
Percent Correct	100	100

TABLE II. Accuracy of the network on training data set

IV. CONCLUSION AND FUTURE WORK

From the results obtained in DCT domain it is conclude that the GFF neural network with Momentum(MOM) learning rule and hidden layer 1 (H1) gives best result of 97.05% (Non-Asian) & 89.28%(Asian) for cross validation (CV) while it gives 100% during training for both Asian & Non-Asian. So overall accuracy is 96.71%.

The accuracy of the system can be further improved with the use of two type of iris images through rigorous training and cross validation. These systems may also be realized in hardware system on chip after thro validation and the systems can be deployed in different Labs.

V. ACKNOWLEDGMENT

Author acknowledge the help of technical staff of college for their support during the work.

REFERENCES

Caiyong Wang , Jawad Muhammad, Yunlong Wang , Zhaofeng He , and Zhenan Sun," Towards Complete and Accurate Iris Segmentation Using Deep Multi-Task Attention Network for Non-Cooperative Iris Recognition,'May 17,2020 at 12:09:07 UTC from IEEE Xplore.

Yong Lu And Haichuan Pan," Application of Iris Images in Racial Classifications Based on Dilate Convolution and Residual Network,'November 29, 2019 fromIEEE Access.

Ayse Eldem, Huseyin Eldemeniz Ustun," A Model of Deep Neural Network for Iris Classification With Different Activation Functions,'978-1-5386-6878-8/18/$31.00 ©2018 IEEE.

Dharanesh C M , Ragvendra Prasad , Chandrashekar M Patil," Feature Extraction & Classification for Personal Identification using Iris,'978-1-5386-3243-7/17/$31.00 ©2017 IEEE.

Dinesh Kumar Vishwakarma,,Divyansh Jain,Shantanu Rajora," Iris Detection And Recognition Using 2 Fold Technique,'ISBN: 978-1-5090-6471-7/17/$31.00 ©2017 IEEE.

Joke A. Badejo, Aderemi A. Atayero, Tunji S. Ibiyemi," A Robust Preprocessing Algorithm for Iris Segmentation from Low Contrast Eye Images,'978-1-5090-4171-8/16/$31.00 ©2016 IEEE.

Renu Sharma, Ashutosh Singh, Akanksha Joshi, Abhishek Gangwar," Robust Iris Classification through a Combination of Kernel Discriminant Analysis and Parzen Based Probabilistic Neural Networks,'978-1-4799-4272-5/14 $31.00 © 2014 IEEE.

Ahmad Nazri Ali," Simple Features Generation Method for SVM based Iris Classification,'978-1-4799-1508-8/13/$31.00

©2013 IEEE.

Atul Bansal,Ravinder Agarwal, R.K. Sharma," SVM Based Gender Classification Using Iris Images,'978-0-7695-4850- 0/12 $26.00 © 2012 IEEE.

P. Mitropoulos, C. Koulamas, R. Stojanovic, S.Koubias, G. Papadopoulos, & G. Karayanis, “Real-time vision system for defect detection and neural classification of web textile fabric,” in Proceedings of SPIE Conference, vol. 3652, pp. 59-69, Jan. 1999, USA.

E. Shady, Y. Gowayed, M. Abouiiana, S. Youssef, and C. Pastore, “Detection and classification of defects in knitted fabric structures,” TextileResearch Journal, vol. 76, pp. 295-300, 2006.