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Zernike's feature descriptors for Iris Recognition with Neural Network

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ABSTRACT

The IRIS recognition is becoming popular and gaining the inclusion in the wide applications ranging from the public databases to device authentication. Iris recognition plays an important role to improve efficiency in biometric identification due to its reliability in highly secured areas. Such as In Airports And Harbors, Access Control In Laboratories And Factories traditional issue is focused on full fingerprint images matching and face detection are used for identification of humans, but iris recognition system is more reliable and gives more accurate results for the identification. Iris recognition works on pattern recognition. In iris recognition the signature of the new iris pattern is compared against the stored pattern after computing the signature of new iris pattern and identification is performed. The IRIS features are extractor using the circular boundaries from the given sample, where the chances of wrong iris extraction are more and which minimize the accuracy of iris recognition system. The rotational features for IRIS region are controlled by using the rotation detector Zernike moments, which normalize the rotational effect in the rotated samples in order to correctly localize the IRIS feature. The IRIS region of interest recognition is performed using the circular transformation as per defined for the Hough transformation. The proposed model in combination utilizes the probabilistic neural network (PNN) classification, and has been assessed for the accuracy measures on the basis of various parameters of accuracy. The proposed model has been found efficient and effective for the IRIS based authentication application in our experimental testing of the proposed model.

***Keywords*: IRIS Recognition, PNN classification, ZERNIKE, Binary feature mask.**

I. INTRODUCTION

IRIS recognition is the elementary feature to recognize totally different individuals. In 1960, a first semi-automatic system for IRIS recognition was developed by Woodrow W. Bledsoe. This system needs an administrator to seek out features.A fully automatic IRIS recognition System was developed in1977. In this system all measurements were taken confidentially. This distance of the eyes, chin width, nose width upper lip, lower lip and other native features were extracted from these measurements. The three steps to IRIS detection and recognition procedure are:

II. LITERATURE REVIEW

Doyle *et al.* (2015) [7] discussed whether or not the correct segmentation of the iris region was needed as to achieve the correct detection of textured or unsmooth contact lenses. Along with primary issue, they also discussed whether or not an associate degree algorithmic program trained on the pictures get from one device can well generalize to the pictures get from a unique device and how better a detector generalizes to a full of textured contact lenses that are not seen in training information. The experimental results shows that correct iris segmentation weren't needed. The results showed that due to sensor specific features trained model do not generalize with the same accuracy to another different sensor.

Gale *et al.* (2014) [10] provided review on advance strategies of feature extraction in iris recognition system. Iris recognition is one in all the foremost correct biometric identification system. The authors have given a summary of the newest analysis of feature extraction of iris recognition. He presents the analysis of various feature extraction methods which were based on CASIA database with the use of Local Binary Pattern and combined LVQ classifier.

Han *et al.* (2014) [21] worked on Iris Recognition based on Local Mean Decomposition. In general, an iris recognition algorithm includes four basic steps: image quality assessment, image preprocessing, image feature extraction, and image matching. Author proposes an iris image matching and recognition method based on local mean decomposition (LMD). The LMD is a multi-resolution decomposition technique employed as a low-pass filter and utilizes discriminating features for iris recognition. To evaluate the performance of this novel approach, several similarity measures were used to assess the results based on experiments using both the CASIA and ICE iris image databases.

Santos *et al.* (2012) [6] developed methodology a novel fusion of several recognition techniques to see the problems of non-cooperative iris recognition using non-ideal visible-wavelength pictures clicked in unrestricted environment. Main motive of research was with the use of new techniques increasing system usability, and new approaches have rapidly emerged. The hardiness of this approach was verified by freelance evaluation within the NICE.II iris-recognition contest, this method placed third rank among the seventy participants.

III. EXPERIMENTAL DESIGN

The angular shift measurement has been incorporated using the Zernike moments algorithm, which is based upon the radial polynomial based rotation estimation method. The angular rotation is estimated by using the hierarchical evaluation of radial polynomials.

3.1 Zernike Moments

It is a method of feature extraction using which global features like amplitude and angle can be extracted from the input image. It was Tagve who first introduced the set of orthogonal Zernike moments for analyzing an image. Zernike moments are sets of orthogonal functions having rotational invariant property. These can be made translational and scale invariant as well as hence can be made suitable for a large number of applications.

Even with a few data points, Zernike moments work as accurate descriptors. Zernike moments can be calculate by using the following equations

$$A_{min=}m+n/n \int_x\int_y f(x,y)\ [V_{min}(x,y)]+dxdy. \qquad (1.1)$$

Where $x^2+y^2<=1$, and n is the order of the object, m is the number of moments of an object, the angle and amplitude calculated from Zernike Moments is used to recognize the right image.

3.2 Artificial Neural Network (Ann)

ANN is a data processing model on the lines of the human nervous system. In the human nervous system, neurons are basic units that convey nerve impulses to and from the brain. The information is passed from one neuron to another to tackle a specific situation.

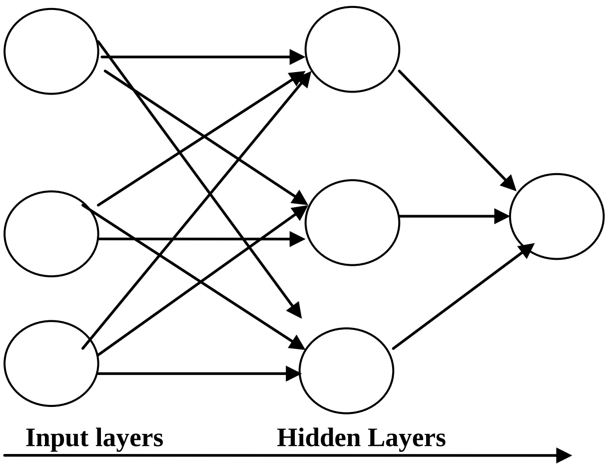

Figure 3.1: Artificial Neural Network

The information passes from one neuron to next, in spite of there being no direct connection between then through of ANN consists of highly weighted interconnected process components (like neurons) that operate in unison to solve a particular problem. Like human beings, ANN's too learn by example. Just as in humans, there occur changes in colligation connections between the neurons, ANN's also learn in a similar way.

Figure 1.3 defines the architecture of artificial neural network. This model has one input layer one output layer and hidden layer. Flow of data is left to right direction.

3.2.1 Architecture of Neural Network:

Artificial Neural Network has the following types:

1. Feed-Forward Networks
2. Feed-Back Networks

1. FEED-FORWARD NETWORKS:

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Feed-Forward neural Networks let signals travel in one direction only i.e., from input to output. In these networks, feed work loops are absent. It means the output of any layer has no effect on that layer. These are simple straight forward networks that relate inputs are widely employed in pattern recognition .The organization of the kind is also stated as bottom-up or top- bottom.

2. FEED-BACK NETWORKS:

Feedback ANNs let signals travel in each direction with the introduction of loop in the network. These network units are very powerful can be very sophisticated. Feedback networks are continuously changing i.e., they are dynamic till an equilibrium is reached. With the change in input equilibrium is re-established. Feedback Networks are also terms as interactive or recurring.

3.2.2. NETWORK LAYERS

The most common sort of ANN is composed of three layers of units. In it a layer of 'input' units connects with a layer of "hidden" units which then connects with a layer of "output" units. The input units stand for the raw data which is given to the network. The activity of each hidden unit is fired by the activities of the input units as well as the biases [weights] on the connections that exist between input units and hidden ones. The behavior of the output units is determined by the activity of the hidden units as well as the basis between the hidden units and output units.

3.2.3. PERCEPTRON

The first work of great importance on neural networks in the 1960s was accomplished by Frank Rosenblatt under the title of 'Perceptron', a label which he himself has coined. The Perceptron resembles an MCP model (having neurons with weighted inputs) with a little extra fixed pre-processing. The units A_1……………… A_j ,A_p are named as association units. Their function is to extract, particular, localized features from the given input pictures. Perceptron follows the basic plan of the sense of sight (i.e, eyes) in mammals. They were primarily put to use for pattern recognition although they can do a lot extra too.

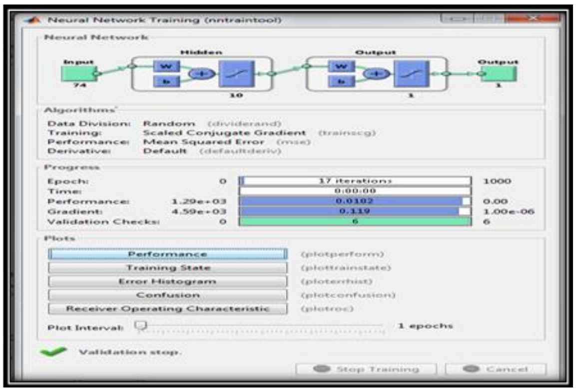

Figure 3.2: Neural Network generated

Figure 5.1 describe that how neural network compute the results. Neural network has one input layer with 74 neurons and 10 hidden layer and one output layer with one neuron.

VI. MULTILAYER PERCEPTRON LAYER (MLP)

A Multilayer Perceptron feed forward neural network is organized in the layers of units (neurons). The input signal travels through this network from left to right i.e., in the forward direction only. Back propagation is the most common learning algorithm used in training MLP. Back Propagation is an efficient method to change the weights in feed forward network. In it the value of Perceptron relies on the weights value of the inputs. A threshold is created during implementation and if the result is greater than threshold value the output is one else zero.

1.8 CORRELATION:

To find the similarity between two images correlation is employed. It is a kind of template matching which yields the matching characteristics of two images by calculating the intensity of a specific pixel .Beside the mean intensity value of the complete image. In it images are matched and compared pixel by pixel and lastly it gives the percentage of matching of the images.

V. RESULT ANALYSIS

Testing is done on UBIRIS Database which contains 500 IRIS images of 100 different people, 5 different images for every person. In this network, there is one input layer with seventy four neurons, ten hidden layers and an output layer having one neuron. Max epochs that have been taken are 1000 features which have already been extracted and saved in data set. These features are supplied to input layer of Artificial Neural Network (ANN). Data will be processed for classification in hidden layers. Output layer will provide the result image and identity it according to the target value. Performance of neural network, training state, and confusion matrix and error histogram are used to calculate the results.

Performance plot:

This graph gives performance of the new system and shows MSE of training, validation and testing.

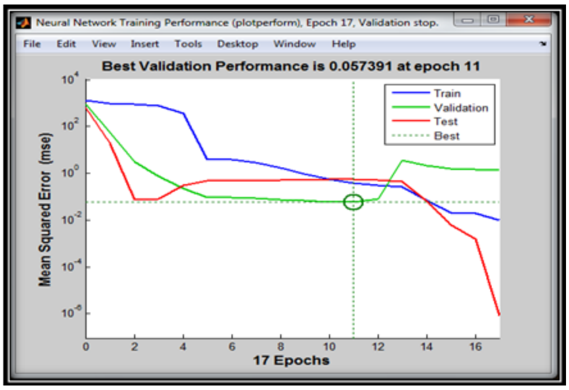

Figure 5.2:Performance plot

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In the figure 5.2 given below, Blue color line represents training. Testing is shown in red color where as validation in green color line. Best match point in this figure meets at 11thepoch. The best validation performance is indicated by the lowest mean square error (MSE).

Confusion matrix:

This matrix is related to the actual and predicted values of the neural network and describes the overall performance of this system for testing, training and validation.

Figure: 5.3: Confusion matrix

In the figure 5.3 green squares contain large no of correct responses where as red squares contain less number of incorrect response. At the right bottom of matrix, Blue Square contains overall performance of system.

Error Histogram:

In this plot training, testing and validation are represented by blue, red and green color respectively.

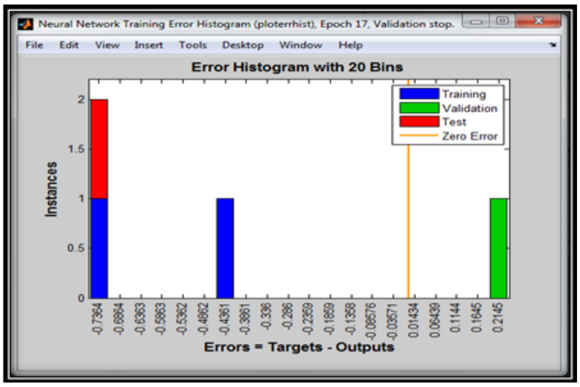

Figure 5.6: Error Histogram

Figure 5.6 shows training and testing error are occurring at first bin in the plot. The validation success point is found in the last entry with value 0.2145, where the match is higher than all other entries. On the 7th entry on index, the training error has been reported.

5.2 Performance parameters results of system

After building IRIS detection and recognition system, to test the performance of overall system on the basis of accuracy, precision, recall and elapsed time. System has been tested 56 inputs testing images in which 50 match correctly match with corresponding image of person and 3 images incorrectly match. Table 5.1 shows the statistical analysis parameters.

Table 5.1: The statistical analysis parameters

True Positive	53
True Negative	0
False Positive	3
False Negative	0

VI. COMPARISON

Proposed technique show better result as compare to existing techniques, when we apply it on a large dataset of images. This technique allows recognition against pose variations and at any angle between -60 degree to +60 degree and provide better recognition rate. The comparison table of existing algorithms and proposed algorithm is as follows.

Table 5.6: Comparison with Zernike moments based model

Database	Method	Rank-one Recognition Rate (Percentage)
UBIRIS.v2	PWMAP/Sparse	49.6
	Zernike+Phase	63
	Proposed	**94.6**
CASIA v4-distance	PWMAP/Fragile Bits	93.8
	Zernike+Phase	95
	Proposed	**98.3**

VII. CONCLUSION

The proposed model is based upon the amalgamation of the features of hessian matrix defined with speeded up robust features (SURF) and fast retina keypoints (FREAK) for the feature representation from the input samples, which belongs to the training or testing models. The angular rotation in the given samples has been measured using the Zernike moments based angular shift detection for the rotated samples. The angular shift normalization model enables the model to correctly extract the IRIS features from the given eye samples. The neural network based classification has been incorporated for the matching of the testing and training samples in order to produce the final result according to the defined decision logic. Proposed algorithm is trained and tested on IRIS sample database which contains higher than 1200 image of more than 240 persons for IRIS recognition and with 5 IRIS images of every person. It was found that proposed system of IRIS recognition provides better accuracy (96.66%) as compared to existing IRIS recognition system.

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