© June 2018 | IJIRT | Volume 5 Issue 1 | ISSN: 2349-6002

Robust Security Using Neural Network Algorithms for Iris Recognition

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Abstract- **This paper introduces an iris classification system using FFNNGSA and FFNNPSO. The use of both methods has not been done before in iris recognition. This iris identification system consists of localization of the iris region, normalization, feature extraction and then classification as a final stage. A Canny Edge Detection scheme and a Circular Hough Transform are used to detect the iris boundaries. After that the extracted IRIS region is normalized using Daugman rubber sheet model. Next, Haar wavelet transform is used for extracting features from the normalized iris region then the feature matrix is reduced using the principle component analysis (PCA). Finally, both particle swarm optimization (PSO) and gravitational search algorithm (GSA) are used for training a forward neural network to get the optimum weights and biases that give minimum error and higher recognition rate for the FFNN in iris classification. These optimization techniques used in classification strengthen the work. The results showed that training the feed forward neural network by GSA is better than training it by PSO in an iris recognition system.**

Index Terms- **Canny Edge Detection; Circular Hough transform Normalization; Particle swarm optimization; Gravitational search algorithm; Principle component analysis.**

I. INTRODUCTION

Biometric is an automated methodology to uniquely identify human based on their physiological and behavioural characteristics. A lot of biometric characteristics have been proposed for authentication purpose. Traditionally, the biometric method can be categorized into two types: behavioural-based method and physiological based method. In behavioural based method perform task of authentication based on their behavioural characteristics, such as, keyboard typing, signature, gait and voice. the main problem with behavioural based method they all have large variation, can't cope with and can be difficult to measure because of influences such as illness or stress. The Implementation of behavioral based method less cost. Physiological-based method perform authentication by means of his and her physiological characteristics such as, face, fingerprint, hand geometry, iris or DNA. In general physiological based methods are more stable than methods in behavioral category because non-alterable of physiological based method.

II. IRIS BIOMETRICS

The idea of using iris as a biometrics is over 100 years old. However the idea of automating iris recognition is more recent. In 1987, flom and safir obtained a patent for an unimplemented conceptual design of automated iris biometrics system. Image processing techniques can be used to extract unique iris pattern from a digitized image of the eye, and encode it into a biometrics template, which can be stored in a database later. This biometrics template contains an objective mathematical representation of unique information stored in the iris, and comparisons to be made between templates. When a subject wishes to be identified by an iris recognition system eye is first photographed and then a template is found and the subject is identified, or no match is found and subject remains unidentified. In addition, iris recognition system works in the two modes: verification and identification.

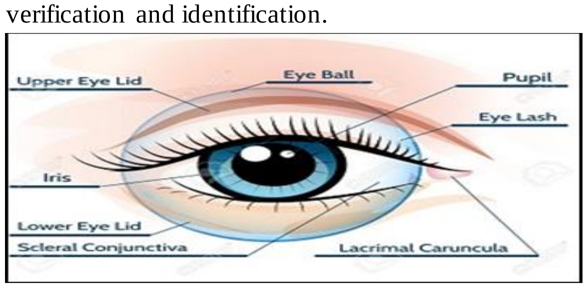


Fig.1: Eye Anatomy

III. METHODOLOGY

In the proposed system, the given input image is pre-processed for enhancing the quality of image by applying, e.g. histogram equalization. The next stage is called "segmentation" which is the isolation of the iris portion from the eye image. It is a technique required to isolate and exclude the artifacts as well as locating the inner and the outer boundaries of the iris. The third stage is normalization. The normalization process output is iris regions that have the same constant dimensions, so that two iris images of the same person under different conditions will have characteristic features at the same spatial location. The fourth stage is extracting the features of the iris and pupil from the segmented image using Haar wavelet transform and reducing the feature vector (output of wavelet transform) using PCA. After that these extracted features are fed to Feed-Forward Neural Network (FFNN) for training purpose. While training, the parameters of the FFNN are optimized using either PSO or GSA to get the optimum weights and biases that give the best recognition rate. The block diagram of the proposed Iris Recognition System.

Neural networks have proven their efficiency in number of applications such as categorization, prediction, pattern recognition and control. The recent solution to improve the NN convergence speed proposed by NN researchers is coupling the NN with Particle Swarm Optimization (PSO) to form Particle Swarm Optimization Feed-forward Neural Network (FFNNPSO). The function of PSO in NN is to get the best set of weights where all the particles are trying to move or fly to get the best solution. The application of FFNNPSO in solving

A) IMAGE ENHANCEMENT

Image enhancement is a technique in image processing that uses in preparing an image for a particular application. The outputs of the process usually bring out details information that is suitable for a specific application. There is no general best theory for image enhancement. An enhancement technique that gives a high performance in one application might not be useful in another application. Generally, there are two approaches in image enhancement: spatial domain method and frequency domain method. In this paper, we have studied only an image enhancement in a spatial domain. Let be an input image and be a processed image, a spatial domain process will be expressed as

$$S = T[r]$$

A histogram equalization technique is a cumulative distribution transformation function. It is a process of transforming an original image into equally likely intensity optimization problems is scarce. However, FFNNPSO had been successfully applied in solving classification problems in the medical domain. Also, FFNNGSA was applied to train NN for classifying fingerprint, face and cancer data sets. It was proved that FFNNPSO is more efficient and effective compared to Genetic Algorithm Back propagation Neural Networks (FFNNGA) in solving the classification problems using universal XOR, Cancer and Iris data set.

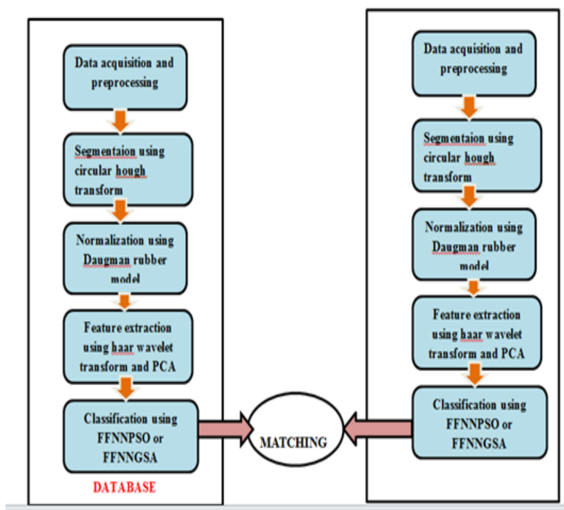


Fig2. Block diagram

image. The transformed image tends to have a higher contrast than an original image. Let be a probability of occurrence of gray level image, r_k , which can be given by

$$p_r(r_k) = \frac{n_k}{n} \quad K= 0,1,2,\ldots\ldots L-1$$

where is a number of gray level. The transformation function of histogram equalization can be written as

$$S(K) = \sum_{j=0}^{k} p_r(r_j)$$

B) SEGMENTATION

The general Hough transform can be used to detect geo-metric shapes that can be written in parametric form such as lines, circles, parabolas, and hyperbolas The circular Hough transform can be used to detect the circles of a known radius in an image. The equation of a circle can be written as

$r^2 = (x a)^2 + (y b)^2$

Where r is the radius of the circle and a and b are the center coordinates. In parametric form, the points on the equation of a circle can be written as follows:

x = a + r cos (ɵ)

y= b + r sin (ɵ)

For every point where the perimeter of a drawn circle passes, the coordinate was incremented by 1. This was done for every circle drawn to create an accumulation array. A circle is indicated by peaks in the accumulation array (Hough space) . Detection of circles using this transformation requires knowledge of the radius. As we don't know the definite radius. The transform is computed by drawing circles of a given radius at every point in the edge image.

The circular detection of the iris includes finding the outer iris boundary and the inner iris boundary. After edge detection, each edge point is taken as a center of a circle of radius R written onto an accumulator array which counts the number of circles passing through the coordinates of each edge point and finds the highest count. The coordinates of the center of the circles are the coordinates with the highest count.

C) $(x - x_c)^2 + (y - y_c)^2 = r^2$

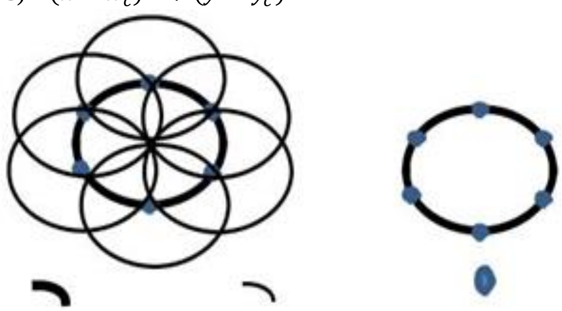


Fig 3The Circular Hough Transform

D) FEATURE EXTRACTION

Thus each image can be represented after applying a combination between the 3rd and the 4th level Haar wavelet: (1) cD3h and cD4h (2) cD3v and cD4 v (3) cD3d and cD4d. All these matrices are combined to build one single vector characterizing the iris patterns. The resultant vector is called the feature vector. All mapped images have fixed size for the feature vector. This feature vector has a size of 360elements resulted from the above 6 matrices. After that afeature vector of 71 elements resulted from a reductionusing PCA of the wavelet feature vector by getting theEigen values and Eigen vectors of the wavelet vector.

$$H_4 = \frac{1}{\sqrt{4}} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ \sqrt{2} & -\sqrt{2} & 0 & 0 \\ 0 & 0 & \sqrt{2} & -\sqrt{2} \end{bmatrix}$$

E) SUPERVISED LEARNING

Recognizing hand-written digits, pattern recognition, regression. Labeled examples (input , desired output) Neural Network models: perceptron, feed-forward, radial basis function, support vector machine Supervised learning is the machine learning task of inferring a function from supervised training data. The training data consist of a set of training examples. In supervised learning, each example is a pair consisting of an input object (typically a vector) and a desired output value (also called the supervisory signal). A supervised learning algorithm analyzes the training data and produces an inferred function, which is called a classifier (if the output is discrete, see classification) or a regression function (if the output is continuous, see regression). The inferred function should predict the correct output value for any valid input object. This requires the learning algorithm to generalize from the training data to unseen situations in a "reasonable" way (see inductive bias).

F) TRAINING PROCESS

Gradient descent, also known as steepest descent, is the simplest training algorithm. It requires information from the gradient vector, and hence it is a first order method.

Let denote f(wi) = fi and ∇f(wi) = gi. The method begins at a point w0and, until a stopping criterion is satisfied, moves from wi to wi+1 in the training direction di = -gi. Therefore, the gradient descent method iterates in the following way:

wi+1 = wi - gi•ηi, i=0,1,...

The parameter η is the training rate. This value can either set to a fixed value or found by one-dimensional optimization along the training direction at each step. An optimal value for the training rate obtained by line minimization at each successive step is generally preferable. However, there are still many software tools that only use a fixed value for the training rate.

The next picture is an activity diagram of the training process with gradient descent. As we can see, the parameter vector is improved in two steps: First, the gradient descent training direction is computed. Second, a suitable training rate is found.The gradient descent training algorithm has the severe drawback of requiring many iterations for functions which have long, narrow valley structures. Indeed, the downhill gradient is the direction in which the loss function decreases most rapidly, but this does not necessarily produce the fastest convergence. The following picture illustrates this issue.

G) MULTI LAYER FEED-FORWARD

Input Layer - The activity of the input units represents the raw information that is fed into the network. Hidden Layer - The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. Output Layer - The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

Feed-forward NNs allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward NNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down.

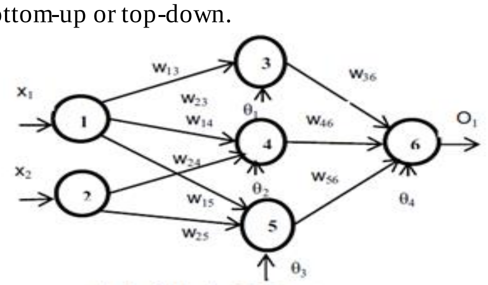


Fig 4.Multi layer feed forward

H) IMAGE PROCESSING TOOLBOX IN MATLAB

Image processing toolbox provides a comprehensive set if reference- standard algorithms, functions, and apps for image processing, analysis, visualization, and algorithm development. It can perform image analysis, image segmentation, image enhancement, noise reduction, geometric transformations, and image registration. Image processing toolbox supports a diverse set of image types, including high dynamic range, giga pixel resolution, embedded ICC profile, and topographic.

Visualization functions and apps explore images and videos, examine a region of pixels, adjust color and contrast, create contours or histograms, and manipulate regions of interest. The toolbox supports workflows for processing, displaying, and navigating large images.

Oculus Rift

At the top of the price range, Oculus Rift plans on being the gold standard of Virtual Reality HMDs. Specifically designed for video gaming, it has a high field of view, delivering the very best in immersive virtual experiences.

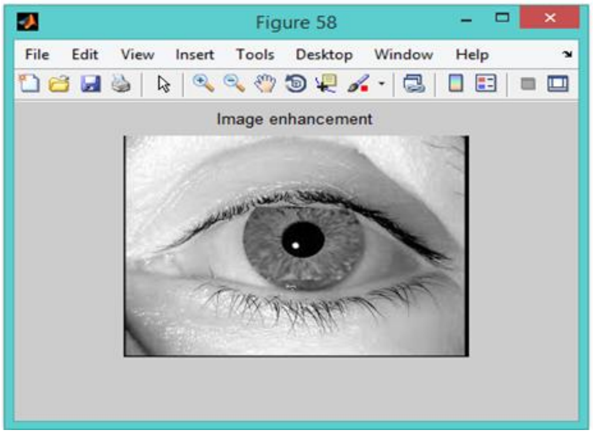
I) NN TOOL

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network.

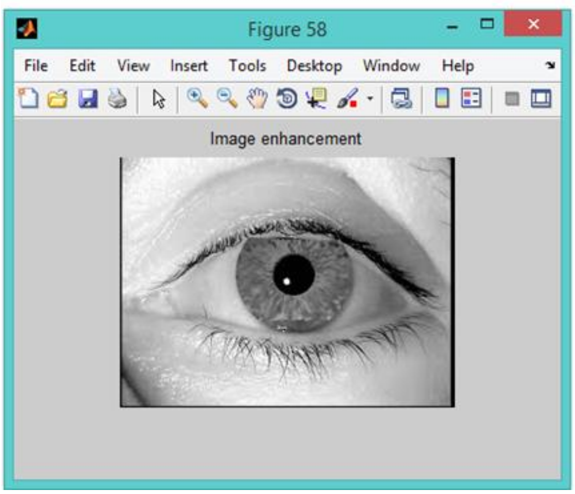
Many algorithms exist for determining the network parameters. In neural network literature the algorithms are called learning or teaching algorithms, in system identification they belong to parameter estimation algorithms. The most well-known are back-propagation and Levenberg-Marquardt algorithms. Back-propagation is a gradient based algorithm, which has many variants. Levenberg-Marquardt is usually more efficient, but needs more computer memory. Here we will concentrate only on using the algorithms.

III. RESULTS

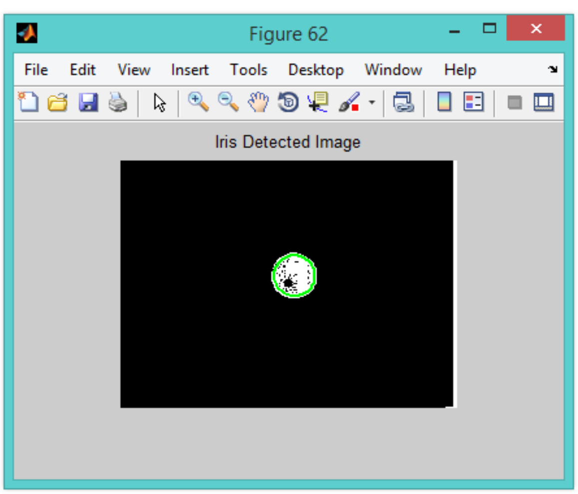
we evaluate the proposed iris image is available databases. The software MATLAB was used to extract code from iris images and inbuilt used histogram equalization for reducing unwanted noise. The major advantage of our system is create a robust security by generating and features has been extracted to match.



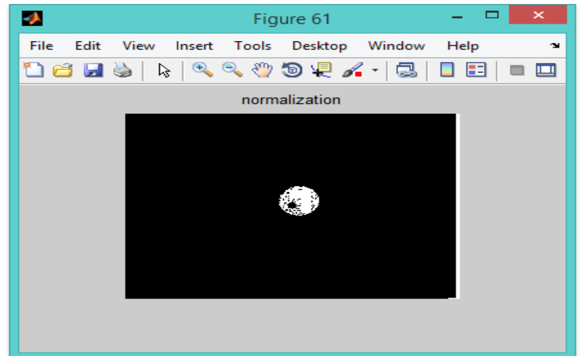
Original image



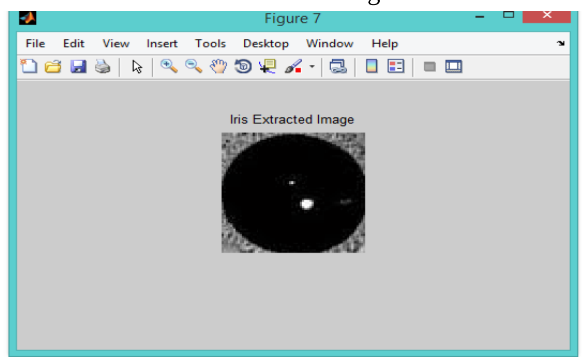
Enhanced image



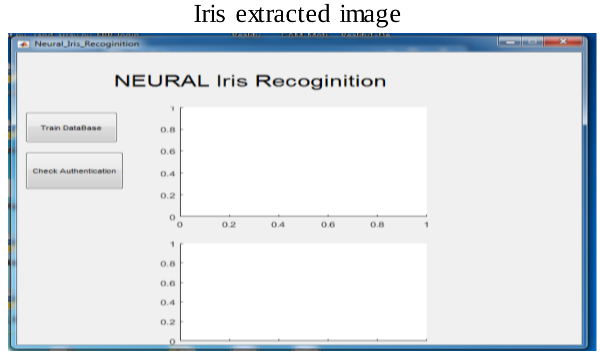
Segmented image



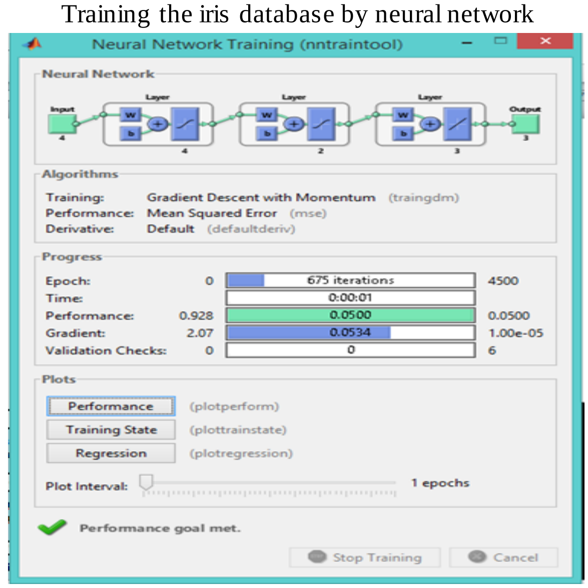
Normalization image



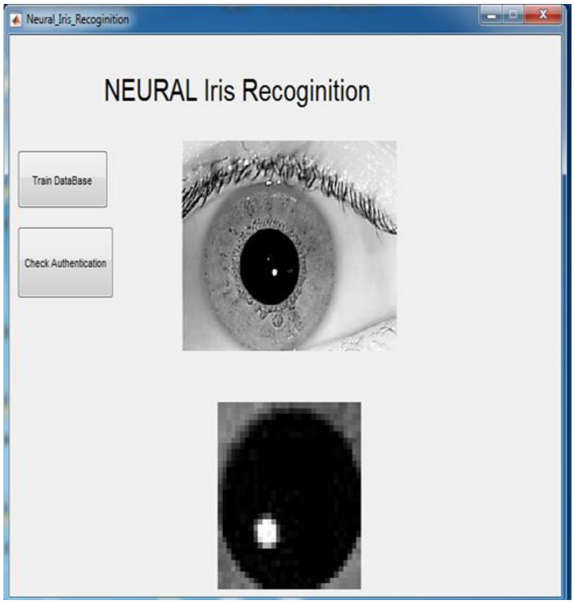
Iris extracted image



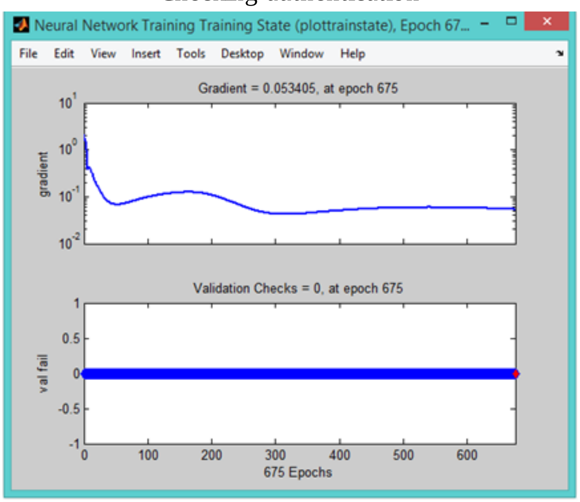
Training the iris database by neural network



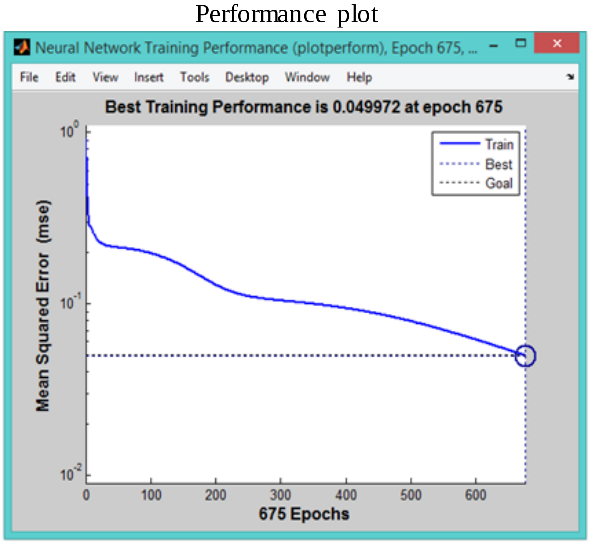
Trained database



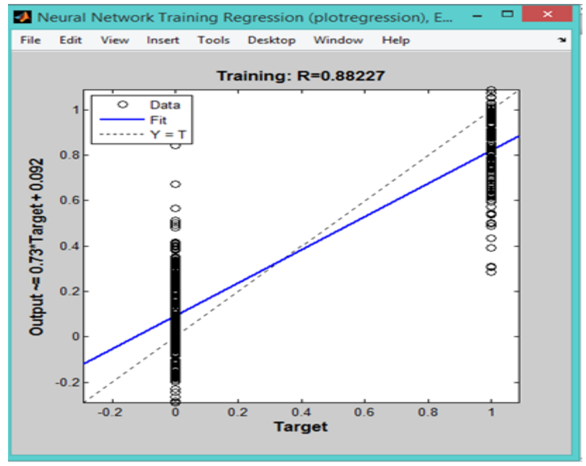
Checking authentication



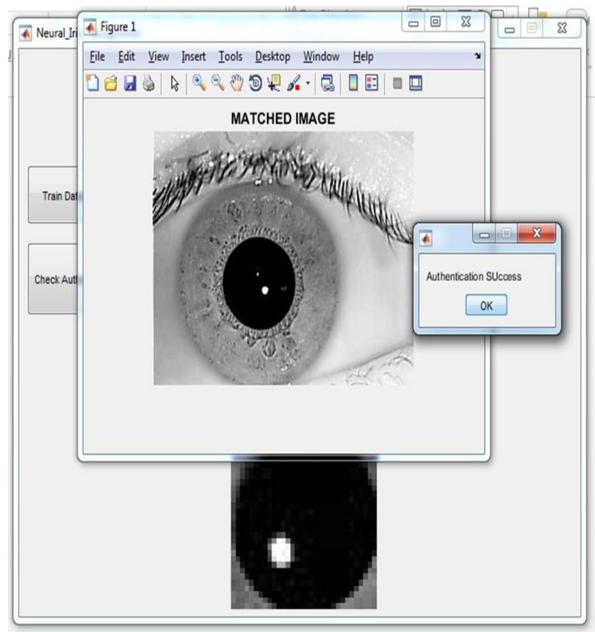
Performance plot



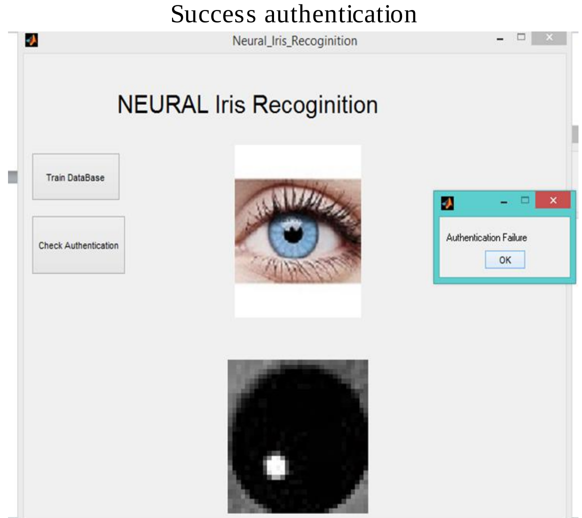
Training plot



Regression plot



Success authentication



Failure authentication

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