Offline Signature Recognition and Verification Based on Artifical Neural Network

Mohammed A. Abdala * & Noor Ayad Yousif**

Received on: 29/9/2008
Accepted on:31/12/2008

Abstract

In this paper, a problem for Offline Signature Recognition and Verification is presented. A system is designed based on two neural networks classifier and three powerful features (global, texture and grid features). Our designed system consist of three stages: the first is pre-processing stage, second is feature extraction stage and the last is neural network (classifiers) stage which consists of two classifiers, the first classifier consists of three Back Propagation Neural Network and the second classifier consists of two Radial Basis Function Neural Network. The final output is taken from the second classifier which decides to whom the signature belongs and if it is genuine or forged. The system is found to be effective with a recognition rate of (%95.955) if two back propagation of the first classifier recognize the signature and (%99.31) if all three back propagation recognize the signature.

Keywords: Signature Recognition, Signature verification, Features Extraction, Neural networks.

نظام تمييز وتحقيق التواقيع باستخدام الشبكات الذكية

الخلاصة

تم في هذا البحث، طرح مشكلة التعرف عل التواقيع وتميزها. النظام المصمم مبني على مصنف متكون من مرحلتين وثلاث مراحل من استخراج الخصائص حيث تشمل خصائص شاملة وخصائص بنوية وخصائص شبكية. النظام المصمم يتكون من ثلاث مراحل وهي معالجة الصورة، استخراج الخصائص ومصنف الشبكات الذكية والتي تتكون من مصنفين، المصنف: الأول يتكون من ثلاث شبكات (Back Propagation) اما المصنف الثاني فيتكون من شبكتين (Radial Basis Function). الاخراج النهائي للنظام ياخذ من المصنف الثاني والذي يقرر من هو صاحب التوقيع وهل هو مزور ام أصلي. لقد أثبتت النتائج بان النظام فعال حيث وصلت نسبة التمييز إلى (95.955%) في حالة تعرف شبكتين من المصنف الأول على التوقيع و كانت نسبة التمييز (99.31%) في حالة تعرف الشبكات الثلاثة للمصنف الأول على التوقيع.

Symbol

P_d, Co – occurrence matrix;
q_k, The gray scale of the pixel in the image;
Radbas, Transfer function of the radial basis neuron;
T, Threshold value;
V(j), Maximum vertical projection;

Greek Symbols

δ_k, Back propagation error;
η, Learning rate;

Cy, Vertical center of the signature;
Cx, Horizontal center of the signature;
C_n, Cross point;
E_n, Edge point;
f_{max}, The maximum input;
f_{min}, The minimum input;
H(i), Horizontal projection;
I (i, j), The gray level of the pixel;
Max, Desired maximum gray level rang of the output image;
Min, Desired minimum gray level rang of the output image;

*Information Technology Department, University of Nahrain, Baghdad, Iraq.
** Control and Systems Engineering Department, University of Technology/Baghdad, Iraq.

1. Introduction:

Signature is a special case of handwriting that can be considered as an image. There is a growing interest in the area of signature recognition and verification (SRVS) since it is one of the important ways to identify a person. Recognition is finding the identification of the signature owner. Verification is the decision about whether the signature is genuine or forged. Forged images can be classified into three groups [1]:

- Random images: are formed without any knowledge of the signer's name or signature shape.
- Simple images: produce by people knowing the name of the signer's but without any example of the signature.
- Skilled images: are produce by people looking at the original signature image and try to imitate it as closely as possible.

SRVS are often categorize into two major classes: on-line and off-line SRVS. The difference between the off-line and on-line lies in how data are obtained. In the on-line SRVS data are obtained using special peripheral device, while in the off-line SRVS images on the signature written on a paper are obtained using scanner or a camera [2]. In this research, an approach for off-line signature recognition and verification is proposed. The designed system consist of three stages: the first stage is pre-processing stage which applied some operations and filters to improve and enhance signature image. The purpose of the pre processing stage is to determine the best signature image for the next stage which is feature extraction stage, choosing the right feature is an art more than a science. Three powerful features are used: global feature, texture feature and grid information feature [3]. The three features are calculated for each signature image and enter to the last stage which is neural network stage. Neural network consist of two-stage classifiers: the first classifier stage contain three back propagation (BP) neural networks, each one of the three BP takes its input from one of the three features and trained individually of each other. Each BP have two outputs that enter as an input to the second stage classifier. The second stage classifier consists of two radial basis function (RBF) neural networks. It is the task of the second classifier (RBF) to combine the result of the first classifier (BP) to make the final decision of the system [4].

2. Pre-processing Stage:

Signature image may contain some amount of noise therefore; certain pre-processing are needed to reduce its effects. The term noise is to be understood as anything that prevents recognition system from fulfilling its objective. The pre-processing filters consist of six filters: converting colored image to gray scale image, image enhancement, noise reduction, image trimming, size normalization and signature thinning filters.

2.1 Converting Colored Image to Gray Scale Image:

In present technology colors are used in capturing device. A color image consists of coordinate matrix and three color matrix. Color matrices are known as Red (R), Green (G) and Blue (B). The designed system is based on gray scale images; therefore, colored image must be converted to gray scale using the equation below [5]:

$$G=0.299*Red+0.5876*Green+0.14*Blue \quad ..(1)$$

2.2 Image Enhancement:

Light and camera cause Characteristics can case problem in the image such as poorly lighted image or image with bad contrast. This filter attempts to enhance the brightness and contrast of image by using simple linear mapping function [6]:

$$E(k) = \frac{(\max - \min)}{(f_{max} - f_{min})} (q_k - f_{min}) + \min \quad \ldots(2)$$

Where:

max, min are the desired maximum gray level.

f_{max} , f_{min} are maximum and minimum of input image and q_k represent the gray scale of the pixel in the image.

2.3 Noise Reduction

The purpose of applying this filter is to eliminate noise as much as possible; therefore, two different types of filters are used:

a) Threshold Filter: This filter is used to convert image to black (0) and white (255). The goal is to remove unnecessary information by using specific threshold as [7]:

$$b(i,j)=\begin{cases}255 \text{ if } & I(i,j)\geq T\\ 0 \text{ if } & I(i,j)<T\end{cases} \quad \text{.... (3)}$$

Where
I (i, j) is the gray level of the pixel and T is a specific threshold value.

b) Salt and Pepper Filter: This filter is applied only on black / white image. The goal of applying this filter is to eliminate all single white pixel on black background (salt noise) and all single black pixels on white background (pepper noise).

2.4 Image Trimming:

The capture image may contain the signature and the area surrounding the signature which is empty of data. Thus, the signature must be separated from its background by tracing image from outside margins towards inside.

2.5 Size Normalization:

Signature dimension may vary due to the scanning and capturing process. Furthermore, width and height of signature vary from person to person and sometimes even for the same person. The image size is adjusted so that a few rows are added to the signature image to facilitate the calculation of the next step.

2.6 Signature Thinning:

This filter aims to reduce the width of the signature from several pixels to a single pixel. This process is performed on binary image. So the image is convert to binary using specific threshold as shown:

$$V(i,j)=\begin{cases}1 \text{ if } & I(i,j)\geq T\\ 0 \text{ if } & I(i,j)<T\end{cases} \quad \text{.... (4)}$$

Where T is a desired threshold.
Thinning process is applied to every pixel in the image until skeleton image is acquires skeletonization makes the feature extraction more efficient [8].

3. Feature Extraction:

This stage converts each image into a set of binary features. In our system, three group of features (global feature, grid information and texture feature) are used, each signature image has its own features.

3.1 Global Feature:

Provide information about specific cases concerning the structure of the signature. Global features contain 8 elements for each signature image which are:

a) Signature Height: The height of the signature can be considered as a way of representation, height-to-width ratio.

b) Image Area: Image area is the number of black pixels in the signature image.

c) Maximum Vertical Projection: The vertical projection of the skeletonized signature image is calculated by summing all the pixels along the columns. The vertical projection is define as [6]:

$$V(j)=\sum_{i} I(i,j) \quad \text{.... (5)}$$

d) Maximum Horizontal Projection: The horizontal projection of the skeletonized signature image is calculated by summing all black pixels along the rows, the horizontal projection is define as [6]:

$$H(i)=\sum_{j} I(i,j) \quad \text{.... (6)}$$

e) Vertical Center of the Signature: The vertical center of the signature Cy is given by [9]:

$$Cy= \frac{\sum_{y=1}^{y\,max} y \sum_{x=1}^{x\,max} b(x,y)}{\sum_{x=1}^{x\,max} \sum_{y=1}^{y\,max} b(x,y)} \quad \dots (7)$$

f) Horizontal Center of the Signature: The horizontal center Cx is given by [9]:

$$Cx= \frac{\sum_{x=1}^{x\,max} x \sum_{y=1}^{y\,max} b(x,y)}{\sum_{x=1}^{x\,max} \sum_{y=1}^{y\,max} b(x,y)} \quad \dots (8)$$

g) Number of Edge Point (En): An edge point is defined as a signature point that has only one 8-neighbor.

h) Number of Cross Point (Cn): Cross point is a signature point that has at least three 8-neighbors as shown in figure (1).

3.2 Grid Information Feature:

Grid information concerned with the overall appearance information of the signature. The skeleton image is divided into 96 rectangular segments, (12 X 8), for each segment the area (sum of foreground pixels) is calculated. The result is normalized so that the lowest value (for the rectangular with smallest number of black pixels) will be zero and highest value (for the rectangular with highest number of black pixels) will be one. The result is 96 values for each signature image. A representation of a signature image and the corresponding grid feature image is shown in Figure (2).

3.3 Texture Feature [3]:

To extract texture feature, Co-occurrence matrix is used. The signature image is binary therefore; the Co-occurrence matrix is 2x2 and describes the transition of black and white pixels. The Co-occurrence matrix P_d is defined as:

$$P_d= \begin{pmatrix} P00 & P01 \\ P10 & P11 \end{pmatrix} \quad \dots (9)$$

Where:

P00 is the number of times two white pixels occurs separate by distance.

P01, P10 is the number of times a combination of white and black pixel occurs separate by distance and P11 is the number of times two black pixels occurs separate by distance. Since P01 and P10 is equal then only one of them is calculated, P00 will be not important since the signature is in black and background is white so it will not be important. The signature image is divided into six rectangular segments (3x2). For each segments the P(0,0), P(1,1), P(0,1) and P(-1,1) matrices are calculated and P01 and P11 elements of these matrices used as texture features. Thus, 48 features are as a texture features (six segments × four matrices × two elements). Figure (3) shows the designed system.

4 Neural Network Design:

The last stage of our system is the neural network (classifier) stage. It consists of two stage classifiers, the first classifier stage contains three back propagation (BP) neural network [10] and the second classifier stage contain two radial basis function (RBF) neural networks [11].

4.1 First Classifier Stage:

This classifier consists of three BP neural networks. Each one of the three BP neural networks has the unique design that is different from the other two networks. Each group of the three feature sets is entered to one of the three BP neural networks and trained individually of the other two. Each BP neural has two outputs that enter as an input to the second classifier stage. The BP is designed to minimize the error between actual output and desired output by updating weights in the backward pass. Each network consists of input layer, hidden and output layer. The three back propagation neural networks are:

NN1: It is the first BP neural network of the first classifier stage, it has 8 inputs, 24 classifier and two outputs (Out 11 and Out

12). The input of this neural came from global features, the learning rate (η) used to train this NN is 0.5 and the activation function that used to train this NN is Trainlm as shown in figure (4).

NN2: It is the second BP neural network of the first classifier stage. It has 48 inputs , 48 hidden neurons and two outputs (Out21 and Out22). Input of this BP came from texture features. The learning rate (η) used to train this NN is 0.005 and the activation function used to train this NN is Trainscg as shown in figure (5).

NN3: it is the third BP neural network of the first classifier stage. It has 96 inputs, 96 hidden neurons and two outputs (Out31 and Out32). Input of this neural came from grid information feature. The learning rate (η) used to train this NN is 0.005 and the activation function used to train this NN is Trainscg as shown in figure (6).

4.2 Second Classifier Stage:

The second stage classifier consists of two radial basis function (RBF) neural networks. The RBF are feed forward architecture with hidden nonlinear layer and linear output layer. Each RBF have three input from first classifier stage (output of the first classifier) and a single output. The final output of the first classifier RBF1 indicate whether the signature is recognized (output = 1) or (output = 0) if not recognized while the output of the second RBF2 indicate the data base number for the signature if it is recognized. The structure of RBF neural network is shown in figure (7).

5 Training Phase:

In this phase, the features computed earlier are fed into the neural network stage of our system as inputs. In the designed system, 205 signatures are collected from 41 persons (5 signatures taken from each person). From these, 164 signatures (4 signatures from each person) are used to train the system. The second classifier (RBF) collects the output of the first classifier (BP) to give the final decision of the system. The system recognize the signature if two of the back propagation neural networks of the first classifier stage recognize the signature. The RBF neural network (second classifier) is responsible for giving the final decision, the mean square error of the first classifier stage is 10^{-7}, figure (8) shows the convergence of competitive learning algorithm for the first back propagation neural network (NN1) of the first classifier, the number of epochs required to train the NN1 is 618 epochs. Figure (9) shows the convergence of competitive learning algorithm for the second back propagation neural network (NN2) of the first classifier, the number of epochs required to train the NN2 is 4278 epochs. Figure (10) shows the convergence of competitive learning algorithm for the third back propagation neural network (NN3) of the first classifier, the number of epochs required to train the NN3 is 2783 epochs.

6 Testing Phase and Result:

In the testing phase, 148 signature images were used to test the system. 82 signatures belong to the same 41 persons (fifth signature image and one signature image previously used in the training phase) and 66 forged signatures from other persons. The identification rate is %100 for the trained signatures. The tested signatures have an identification rate of %95.955 when at least two NNs recognize the signature as shown n table (1).

The identification rate increase to %99.31 when all three BP neural networks recognize the tested signature as shown in table (2).

7 Conclusion:

In this work, we present an offline signature recognition and verification system based on two stage classifiers. The designed system consist of three stages which is pre-processing, feature extraction and neural network stage. In order to make the right decision the signature image must pass through three stages. The system recognize the signature if two BP neural network of the first classifier recognize it and the identification rate is %95.955,

while the identification rate reaches %99.31 if all the three BP neural network of the first classifier recognize the signature. Despite the variation in the used signature, some signatures from different signers can be close enough to each other so that the system may not make the right decision in recognizing them. The system failed to recognize the rotated signature. Signature involve in many area of the human lives so many research has been done over the years to solve the signature recognition and verification problem. These research vary in their recognition rate, one of the research [12] used linear vector quantization neural network (LVQ-NN). A 30 signature from 15 person where used in the training phase and 15 signature in the testing phase. The recognition phase is %100 for the original signature but the recognition rate decrease when the signature is rotated.

Reference:

[1] Edson J. R. Justino, Flavio Bortolozzi and Robert Sabourin, "Off Line Signature Verification Using HMM for Random, Simple and skilled forgeries", IEEE Sixth International Conference on Document Analysis and Recognition, Vol. 1, pp. 105-110, 2001.

[2] Yu Qiao, Xiaoou Tang and Jianzhuang Liu, "Offline Signature Verification Using Online handwriting Registration", Department of Information Engineering, The Chinese University of Hong Kong, IEEE, pp.1-8, 2007.

[3] H. Baltzakis, N. Papamarkos, "A new signature verification technique based on a two-stage neural network classifier", Engineering Application of Artificial Intelligence, Vol.14, pp.95-103, 2001.

[4] Ben Krose and Patrick van der Smagt, "An Introduction to Neural Networks", Institute of Robotics and System Dynamics, University of Amsterdam, 8th edition, 1996.

[5] Cemil Oz, Fikret Ercal and Zafer Demir, "Signature Recognition and Verification with Artificial Neural Network Using Moment Invariant Method", Springer, Vol.3497, pp.195-202, Berlin/Heidelberg, 2005

[6] Scott Umbaugh, "Computer Vision and Image processing: A Practical Approach using CVIP Tools", Prentice-Hall, Inc., USA, 1998.

[7] Jerry Gibson and Al Bovic, "Hand Book of Image and Video Processing", Academic Press Series in Communications, Networking, and Multimedia, Al Bovik, Canada, 2000.

[8] R.Gonzalez & Richard Woods, "Digital Image processing", Prentice Hall, Inc, 2nd Edition, New Jersey, 2002.

[9] Emre Ozgunduz and M. Elif Karslıgil, "Off-line Signature Verification and Recognition by Support Vector Matching", Computer Engineering Department, Yıldız Technical University, Yıldız, Istanbul, Turkey, 2003.

[10] Ahmed Faris Al-Moli, "Image Compression Using Back Propagation Neural Network", M.Sc. Thesis University of Technology, Baghdad, Iraq, 1995.

[11] L. Fausett, "Fundamentals oF Neural Network", Florida Institute of Technology, Prentice-Hall, Inc, New Jersey, 1994.

Table (1) Results if two BP recognizes the signature.

Description of the signature	No. of signature	Rate %
Total number of tested signatures	148	
Samples that should be accepted	82	
Correct Acceptation (CA)	81	54.72
False Rejection (FR)	1	0.675
Samples that should be rejected	66	
Correct Rejection (CR)	61	41.21
False Acceptation (FA)	5	3.37
Overall rejection rate	%4.045	
Overall identification rate	%95.955	

Table (2) Results if all three BP recognizes the signature.

Description of the signature	No. of signatures	Rate %
Total number of tested signatures	148	
Samples that should be accepted	82	
Correct Acceptation (CA)	81	54.72
False Rejection (FR)	1	0.675
Samples that should be rejected	66	
Correct Rejection (CR)	66	44.59
False Acceptation (FA)	0	0
Overall rejection rate	%0.675	
Overall identification rate	%99.31	

Figures

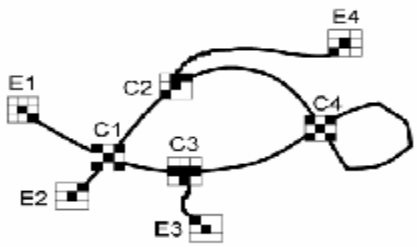

Figure (1) Edge points (E1, E2, E3, E4) and cross points (C1, C2, C3, C4)

Figure (2) Grid feature effects

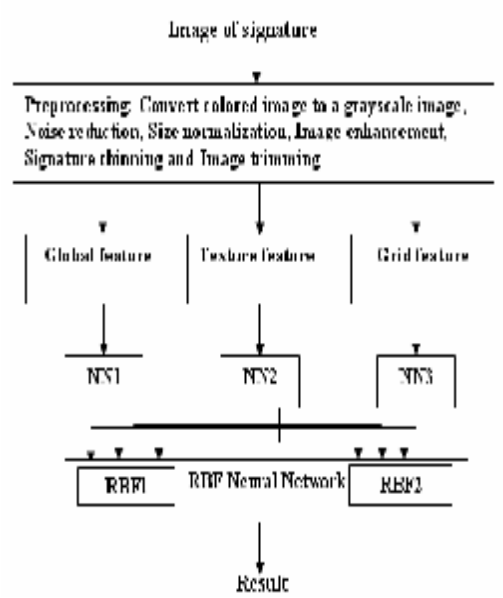

Figure (3) Designed system

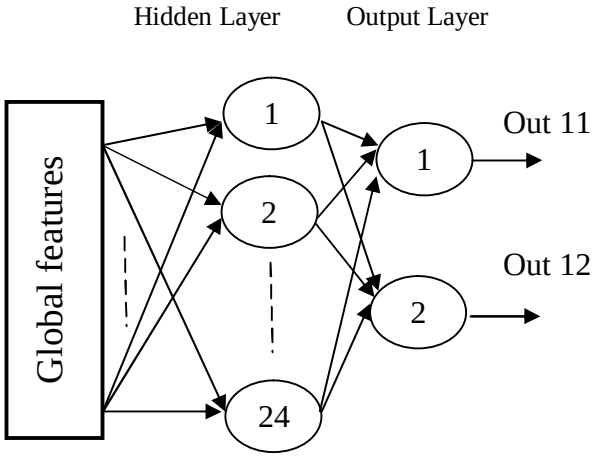

Figure (4) First BP Neural Network

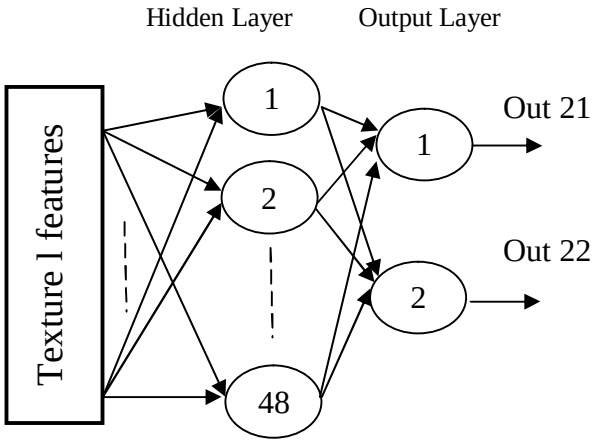

Figure (5) Second BP Neural Network

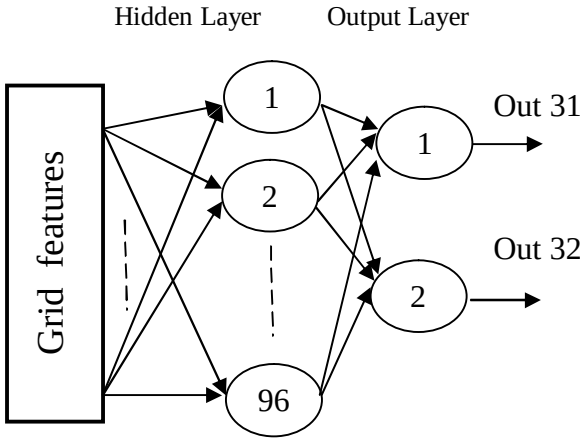

Figure (6) Third BP Neural Network

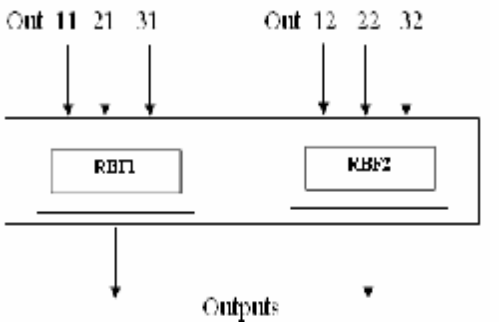

Figure (7) Inputs and output of the radial basis function NN.

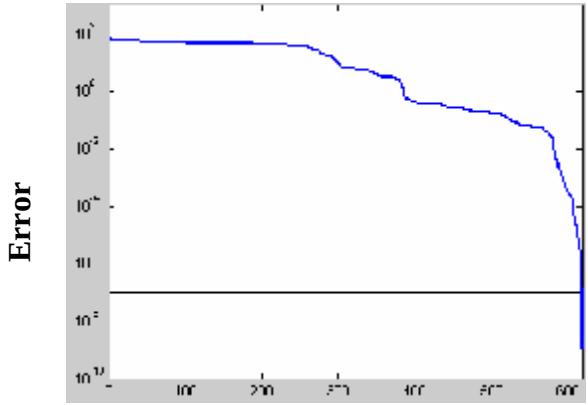

Figure (8) Convergence of NN1

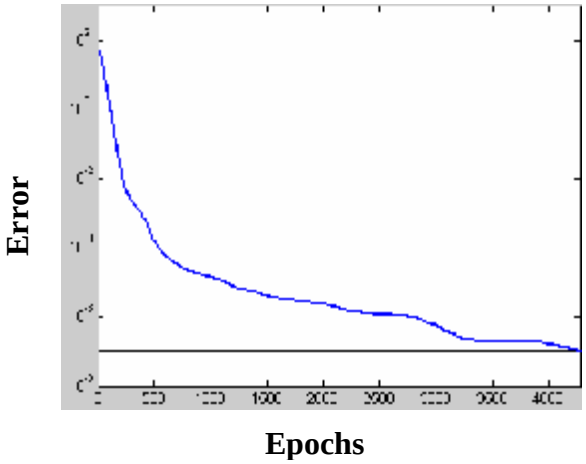

Figure (9) Convergence of NN2

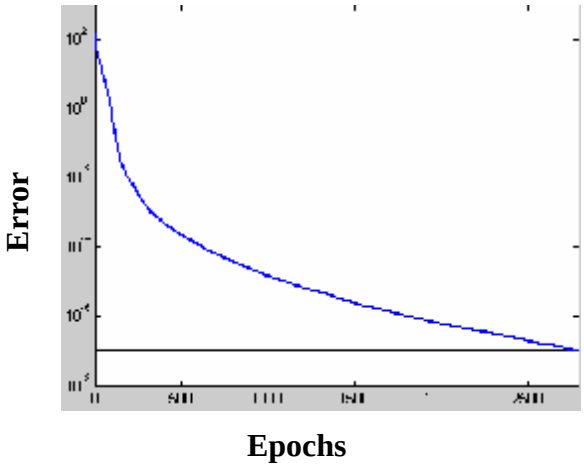

Figure (10) Convergence of NN3