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EFFECT OF THE TRESHOLDING TO SIGNATURE VERIFICATION USING ARTIFICIAL NEURAL NETWORK

Serdar ÇİKOĞLU* Fevzullah TEMURTAŞ Nejat YUMUŞAK****
*Gebze Endüstri Meslek Lisesi, Bilgisayar Bölümü, Gebze, İzmit, Türkiye
**Sakarya Üniversitasi, Bilgisayar Mühendisliği Bölümü, Sakarya, Türkiye

ABSTRACT

In this study, signature verification has been done using artificial neural networks. In signature verification process firstly, signatures have been normalized and thresholded in order to prevent the noises in background. Then the features used in artificial neural network's learning have been extracted. Signatures have been differentiated using five features such as signature density, horizontal relative difference between signature centers, vertical relative difference between signature centers, signature width, signature height. 15 features have been formed from these features using three different threshold calculations. So three types of articial neural network model using this 5,10 and 15 feature for signature verification have been used. Effects of this thresholds were investigated on learning performance of the neural network by using 3 different tresholding (185,170,150).

Key Words : Artificial Neural Networks, Signature Verification, Tresholding

YAPAY SİNİR AĞI İLE YAPILAN İMZA TANIMAYA EŞİKLEMENİN ETKİSİ

ÖZET

Bu çalışmada, yapay sinir ağı kullanılarak imza tanıma işlemi gerçekleştirilmiştir. İmza tanıma işleminde, öncelikle imzalar normalize edilmiş ve arka planda oluşan gürültü ve kirlilikleri gidermek için eşiklenmiş ve ardından yapay sinir ağı eğitiminde kullanılacak özellikler elde edilmiştir. İmzalar, imza yoğunluğu, imzanın merkezler arası göreli yatay farkı, imzanın merkezler arası göreli dikey farkı, imzanın genişliği, imzanın yüksekliği olmak üzere 5 özelliğine bakılarak, birbirlerinden ayırt edilmişlerdir. Bu beş özellik üç farklı eşikleme değeri için hesaplanarak toplam 15 özellik haline getirilmiştir. Böylece 5, 10 ve 15 özelliği giriş olarak kullanan üç tip yapay sinir ağı modeli imza tanıma için kullanılmıştır. Ayrıca yapay sinir ağı yapısının öğrenme performansına; eşiklemenin etkisi 3 değişik (185, 170, 150) eşikleme ile bakılmıştır.

Anahtar Kelimeler : Yapay Sinir Ağları, İmza Tanıma, Eşikleme

1. INTRODUCTION

Signature are used everday to authorise the transfer of funds of millions of people. For example; bank checks, credit cards and legal documents all require our signatures. Forgeries in such transactions cost millions of dollars each year. By forgery is meant copying, falsifying, or altering any kind of written or printed matter for the purpose of defraunding others. Signature verification is the process carried out to determine whether a given signature is genuine or forged[1].

1.1 SIGNATURE VERIFICATION AND IT' S IMPORTANCE

Signature is a special sign for a person. An other expression, signature is used to determine a writing's owner. It may be a sign or a name. Every kinds of official or special documents consist of a signature to be acceptable. For this reason, signatures give responsibilities and provide rights to people. Signatures on documents are meant that every responsibilities are accepted by people. Unacceptable documents do not consist of a signature. Only, signed documents are acceptable[2].

1.2 SIGNATURE VERIFICATION

Human handwritings are among the most complicated objects to recognize. They comprise some of the areas where humans possess monopoly and computers have treaded little on. Signatures form a special class of handwriting in which legible letters or words may not be exhibited. They provide secure means for authentication, attestation and authorization in legal, banking or other high security environments. Signature verification problem pertains to determining where a particular signature is verily written by a person so that forgeries can be detected. Based on the hardware front-end, a signature verification system can be classified as either online or offline. On-line system employs an electronic pen and pad and a host of dynamic information like speed of writing, pressure applied, number of strokes, etc., can be extracted. In on-line signature verification system, signatures written on paper as has been done traditionally will suce. The signatures are converted to electronic form with the help of scanner or camera. Financial constraints dictate most of the applications requiring signature analysis not to be equipped with hardware necessary for on-line technique. So on-line technique appears to be more pragmatic. However, signature analysis using on-line technique is relatively more difficult as only static information is available[3].

The need to distinguish genuine from forged signatures is met in a variety of ways, not always successfully. Forensic scientists specialised in this field may be asked to determine the genuineness of otherwise of signatures for disputed claims and cheques, but only for large amounts. Currently, all signature verification for daily transactions is based on visual inspection by a teller or a store clerk with the result that large amounts of money are lost due to forgeries. In the business world, an automated signature verification system would be extremely useful for the reduction of forgery in monetary transactions[4].

Handwritten signature are the most wiedly employed form of secure personal identification, especially for cashing cheques and credit card transactions. However, for several reasons the task of verifying human signatures cannot be considered a trivial pattern recognition problem. Because signature samples from the same person are similar but not identical[5].

Figure 1 shows the diagram of a typical signature verification system. To enroll into the system, the user has to provide a set of training signatures. Typically, a feature vector is extracted from the data which describes certain characteristic of the signature and stored as a template. For verification, the same features are extracted from the test signature and compared to the template[6].

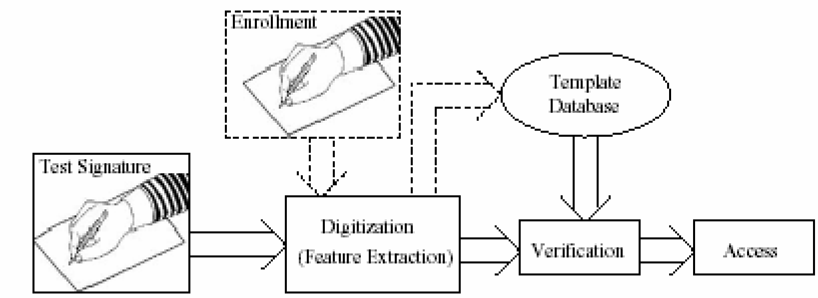

Figure 1. A typical signature verification system

1.3 THRESHOLDING

It is a technique used in image processing. Aim of thresholding of a numerical image provide easiness upon investigating features of the image. Image is explained with two colors via the process. A threshold value is established before thresholding process of an image. One(1) values are appointed to pixels which have higher grey values than threshold value, Zero(0) values are appointed to pixels which have lower grey values than threshold value. Figure 2 shows a thresholded signature image[7].

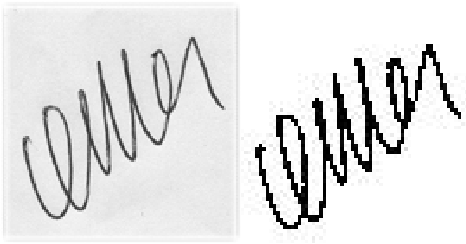

Figure 2. A thresholded signature image.

2. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network(ANN) methods seem appropriate for the task of signature verification for several reasons:

a) The learning and the generalisitions abilities of ANN' s should enable them to cope with the diversity and the variation of signatures.
b) Once the learning is achieved, the response of a ANN to an input is extremely fast, which is an important consideration if an automated system is to be developed for treating a flow of signatures.
c) With ANNs learning can continue with newly presented signatures to follow their evolution over time. Also, it is possible to retrain a ANN using new signatures.

For these reasons ANNs have performed well in other pattern recognition tasks such as character recognition and may be similary suitable for the task of signature verification. Hence, it is hence worthwhile examining the feasibility of a ANN-based signature verification system.

In the ANN based signature verification applications, the pixel values of signature image is used as inputs to ANN for recognizing the signature. In a signature field of 160*35 pixels, there exist an input number of 5600 neurons[1].

Using inputs that have too many neurons cause the learning to delay in such studies. In these cases calculations will increase and the sources will be used more. So all the process will slow down.

In this study in order to eliminate above difficulties, some specialities of the signature are used to realize the signal verification process instead of using all the pixels as inputs.

3. THE SYSTEM DEVELOPED USING ARTIFICIAL NEURAL NETWORKS FOR SIGNATURE VERIFICATION SYSTEMS AND APPLICATIONS

This chapter covers design experiments using the adaptive backpropagation neural networks for off-line signature verification. Stages of the experiments explained in the following.

1. Obtaining the signatures
2. Thresholding and preparing signatues to give ANN
3. Designing the structure of the network

3.1 Obtaining the Signatures

In this study, 30 genuine signatures into 64x64 pixel square box obtained from total 13 people. Signatures are expressed by AE, BG, EO, FB, HZ, İSA, NE, OT, SB SC, SS, UE, VB. Obtaining signatures were performed two stages. 15 signatures were obtained each stage. All of the signatures are always used daily life and genuine. In the study, a signature database was composed. It consists of 390 signatures. Figure 3 shows samples that belogs to H.Z. person.

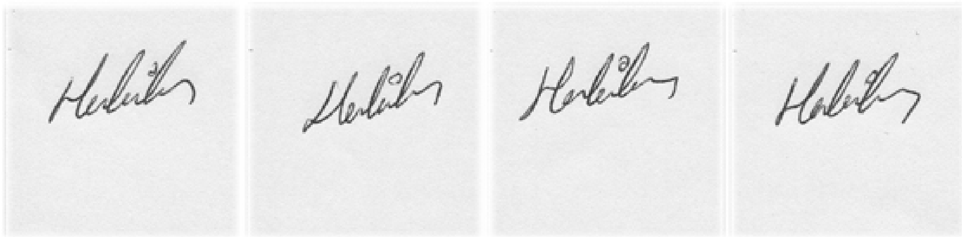

Figure 3. Sample signatures belong to H.Z.

3.2. Thresholding and Preparing Signatues to Give ANN

Before being used as data at ANN, The images of the scanned signatures should be pre-processed and converted to the appropriate format. As for the threshold level, various values have been tried according to the histogram values and these three values have been selected to be used as threshold: 185, 170, 155.

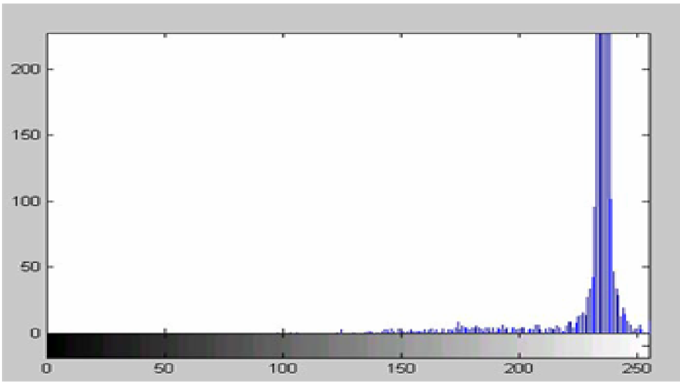

Figure 4. Histogram graphic belongs to H.Z.

Figure 5, 6 and 7 shows the signatures thresholded with 185, 170, 155 thresholding value that belogs to hz.

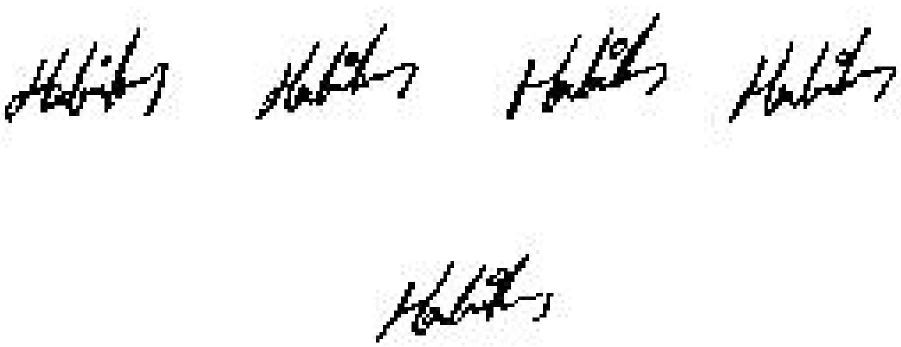

Figure 5. Signatures which belong to hz composed with 185 thresholding value after thresholding.

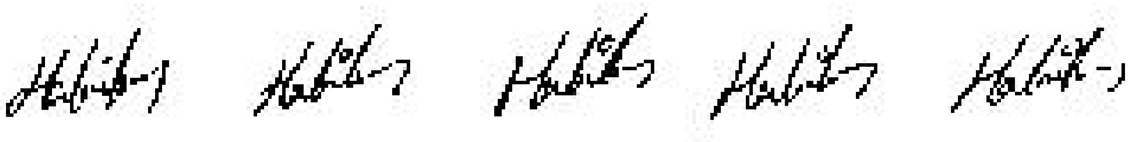

Figure 6. Signatures which belong to hz composed with 170 thresholding value after thresholding.

Figure 7. Signatures which belong to hz composed with 155 thresholding value after thresholding.

As can be seen in figure 5,6,7, signatures thresholded with 155 thresholding value have more blurred pixels. This blurred pixels decreased with 170 and 185 thresholding value. Eventually, bold pixels increased with higher thresholding value. Further, blurred pixels decreased. In this way, thresholding value is a characteristic factor for signatures.

In this study, signatures are distinguished each others using five features included; signature's density, relative horizontal difference between centers, relative vertical difference between centers, signature's width, signature's high.

Input 1 {signature's density};

$$\mathrm{Input}(1) = a / (x1 * y1)$$

a = signature's weight (total number of squares) ;
x1 = signature's horizontal size ;
y1 = signature's vertical size ;

Input 2 { relative horizontal difference between centers};

$$\mathrm{Input}(2) = \mathrm{abs}(x2 - x3) / \ x1$$

x2 = signature's size center to x axis;
x3 = the centre of gravity of the signature to x axis;

Input 3 {relative vertical difference between centers};

$$\mathrm{Input}(3) = \mathrm{abs}(y2 - y3) / y1$$

y2 = signature's size center to y axis;
y3 = the centre of gravity of the signature to y axis;

Input 4 {Width} (normalized);

$$\mathrm{Input}(4) = x1 / 64$$

Input 5 {High}(normalized);

$$\mathrm{Input}(5) = \ y1 / 64$$

This formulas can be seen in the following scheme.

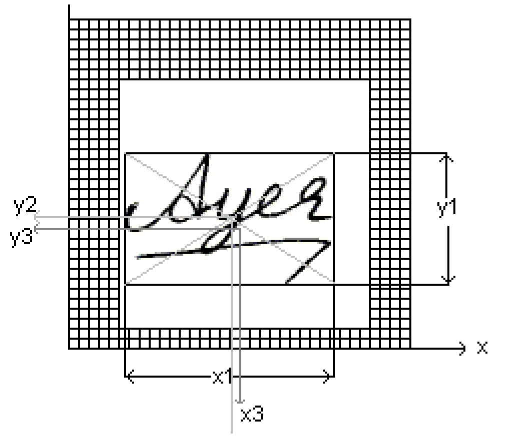

Figure 8. Schematic demonstration of the inputs

Total Inputs are 15 pieces to ANN. Some of them included G1, G2, G3, G4, G5 inputs obtained with 185 thresholding value. Some of them included G6, G7, G8, G9, G10 inputs obtained with 170 thresholding value.The others included G11, G12, G13, G14, G15 inputs obtained with 155 thresholding value.

3.3. Desıgnıng Of The Structure Of The Network

Structure of the network is feedforward neural networks for this experiment. It performed in this style so that used 5 inputs to the network. Numbers of the neuron for hidden layer are set 25, 30, 35 pieces neuron. Numbers of the neuron for output layer are 13 pieces. Reliability rank were showed with one(1) or zero(0). Signatures are forged for 0 value or genuine for 1 value. Figure 8 shows the architecture of the network.

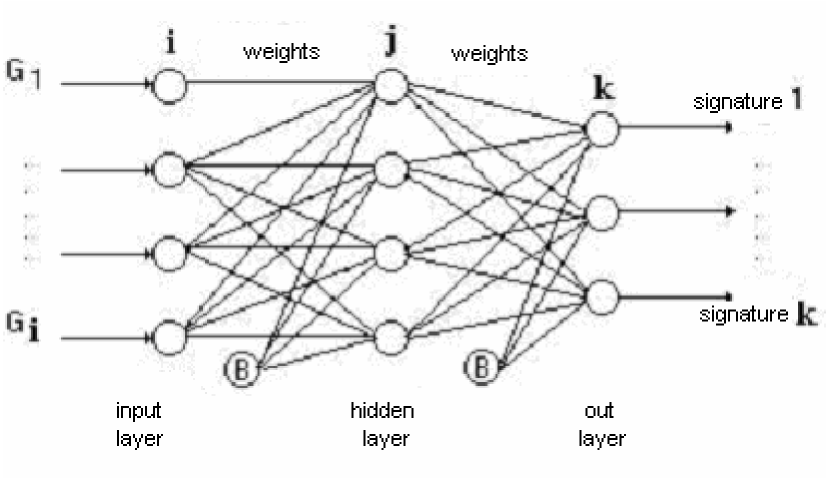

Figure 9. The architecture of the network

Inputs are G1, G2, G3, G4, G5 for 5-input network. Numbers of the neurons in hidden layer are 25, 30, 35. Number of the neuros in output layer are 13. Epochs of the network are between 0-1000, 1000-5000, 5000-10000, 10000-50000, 50000-100000.

Calculation of ANN1: 5 inputs, 25 neurons in hidden layer, 13 neurons in output layer. The network was trained between the epoch ranges using 260 signatures. Then the network was tested. Test was implemented using 390-signature database.

Calculation of ANN2: only increased number of the neurons in hidden layer from 25 to 30. Number of the neurons in hidden layer for ANN3 was increased from 30 to 35.

Briefly, ANN1 was modified to calculate ANN2 and ANN3.

Number of the inputs for the second structure are 10. Inputs are G1, G2, G3, G4, G5, G6, G7, G8, G9, G10 . Half of them(G1, G2 ,G3, G4, G5) were thresholded with 185 thresholding value, the others with 170.

Calculations are the same to ANN1 and increased only input numbers for ANN3 . Number of the neurons in hidden layer are 25 to ANN4, 30 to ANN5, 35 to ANN6 and 13 in output layer.

15 inputs were used to the third structure. Inputs are G1, G2, G3, G4, G5, G6, G7, G8, G9, G10, G11, G12, G13, G14, G15. Five of them were thresholded with 185 thresholding value. Other five inputs were thresholded with 170 thresholding value and the others with 155 thresholding value.

4. RESULTS AND DISCUSSION

The performance of the network was compared depending on epoch numbers and showed in the following figures and tables.

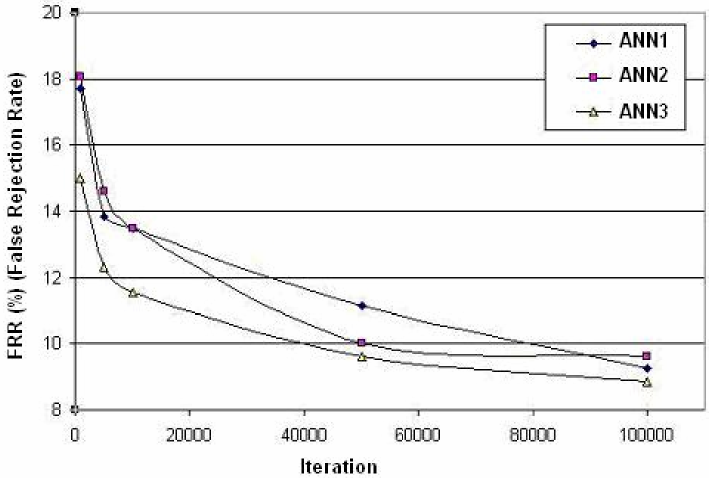

Figure 10. Comparing performances of the ANN1, ANN2 and ANN3

Table 1. Epoch numbers of the ANN1, ANN2, ANN3 and FRR(False Rejection Rate) values

Iteration (Epoch)	FRR (%)		
	ANN1	ANN2	ANN3
1000	17,692	18,077	15
5000	13,846	14,615	12,308
10000	13,462	13,462	11,538
50000	11,154	10	9,6154
100000	9,2308	9,6154	8,8462
Test	16,154	16,667	15,641

As can be seen from figures and tables, learning rate is increased depending on epoch numbers. In other words, learning rate for ANN1, ANN2, and ANN3 is higher with higher epoch numbers. FRR also decreased depending on learning rate. While learning rate for ANN1, ANN2 and ANN3 is 17.692, 18.077 and 15 with 1000 epoch numbers, learning rate decreased with 100.000 epoch numbers. The best results were obtained from ANN3.

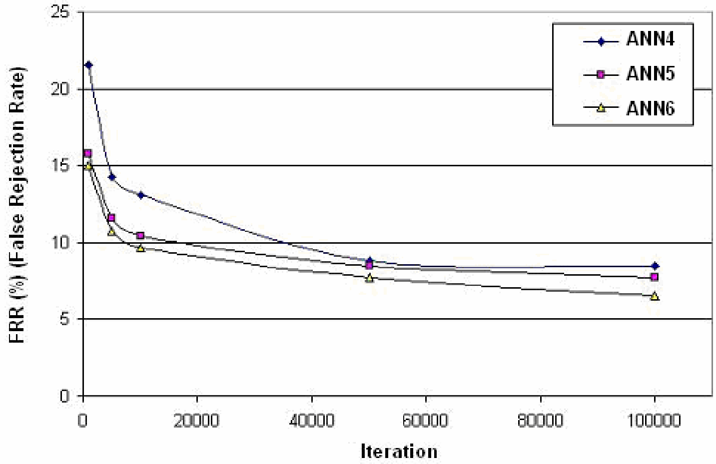

Figure 11. The performances of the networks used signature verification

Table 2. Epoch numbers of the ANN4, ANN5, ANN6 and FRR(False Rejection Rate) values

Iteration (Epoch)	FRR (%) ANN4	ANN5	ANN6
1000	21,538	15,769	15
5000	14,231	11,538	10,769
10000	13,077	10,385	9,6154
50000	8,8462	8,4615	7,6923
100000	8,4615	7,6923	6,5385
Test	13,333	13,59	13,077

As can be seen from figures and tables, learning rate increased depending on epoch numbers. In other words, learning rate for ANN4, ANN5, and ANN6 is higher with higher epoch numbers. FRR also decreased depending on learning rate. While learning rate for ANN4, ANN5 and ANN6 is 21.538, 15.769 and 15 with 1000 epoch numbers, learning rate decreased with 100.000 epoch numbers. The best results were obtained from the network which has higher number of the neurons in hidden layer.

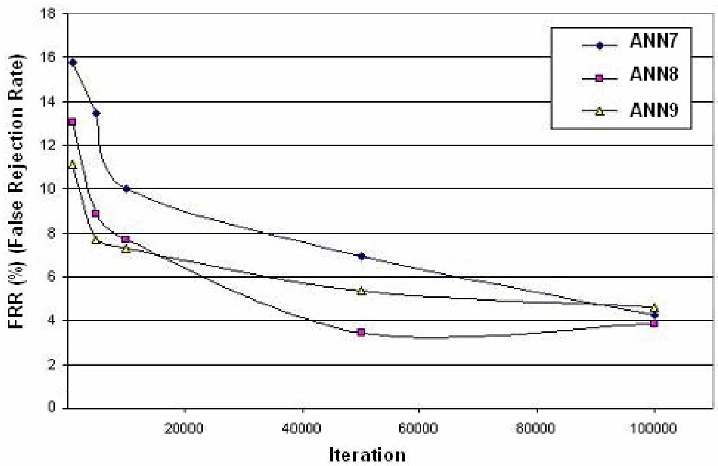

Figure 12. The performances of the networks used signature verification

Table 3. Epoch numbers of the ANN7, ANN8, ANN9 and FRR(False Rejection Rate) values

Iteration (Epoch)	FRR (%) ANN7	ANN8	ANN9
1000	15,769	13,077	11,154
5000	13,462	8,8462	7,6923
10000	10	7,6923	7,3077
50000	6,9321	3,4615	5,3846
100000	4,2308	3,8462	4,6154
Test	9,4872	10,769	11,538

As can be seen from figures and tables, learning rate increased depending on epoch numbers. In other words, learning rate for ANN7, ANN8 and ANN9 is higher with higher epoch numbers. FRR also decreased depending on learning rate. While learning rate for ANN7, ANN8 and ANN9 is 15.769, 13.077 and 11.154 with 1000 epoch numbers, learning rate decreased with 100.000 epoch numbers. The best results were obtained from the network which has higher number of the neurons in hidden layer.

Figure 13 shows the performances of the learning rate of the network depending on number of the neurons in hidden layer.

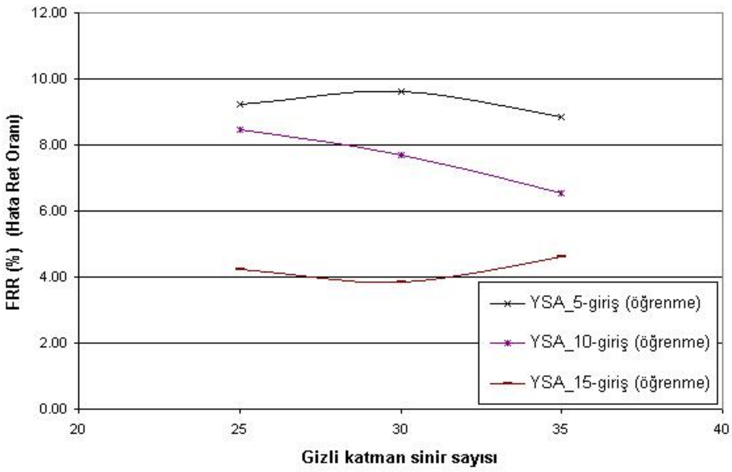

Figure 13. FRR Values depending on number of the neurons in hidden layer.

Table 4. FRR values depending on input numbers and number of the neurons in hidden layer

İnput numbers of the network	Number of the neurons in hidden layer	FRR (%) Learning
5	25	9,23
	30	9,62
	35	8,85
10	25	8,46
	30	7,69
	35	6,54
15	25	4,23
	30	3,85
	35	4,62

As can be seen in figure 13 and table 4, the best results for learning were obtained from ANN9 which has 15 input numbers and 35 neurons in hidden layer.

According to the results, learning rate increased depending on input numbers and neurons in hidden layer. In this study, signatures were distinguished with 5 features to evaluate suitabilities of adaptive neural networks for off-line signature verification. This 5 features are signature's density, horizontal relative difference between signature's centers, vertical relative difference between signature's centers, signature's width and signature's high. For the best results, three thresholdings were performed to inputs. Number of the neurons in hidden layer were increased to maximize learning rate. Eventually, It is investigated that ANN is applicable for signature verification problems..

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