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"شبكة عصبية للتعرف على الحروف العربية"

A Neural Network for Arabic Character Recognition

Dr. / A. T. ALAM ELDIN

Department of Electrical Engineering, University of Suez Canal, Port Said, Egypt

ملخص البحث

تلعب الشبكات العصبية دورا هاما في عمليات التعلم في أي نظام حاسب يمتلك امكانية الذكاء الاصطناعي وقد بدأ حديثا الاهتمام المتزايد با ستخدام الشبكات العصبية كوسيلة قوية وفعالة في عملية التعلم التي تمهد لاستخدام الحاسب في عمليات التعرف على الأشكال والأصوات والحروف ويرجع ذلك الى أن الشبكات العصبية تجرى عملية استخلاص السمات التي تكفي للتمييز بين الأشكال بدرجة أعلى من تلك التي تقدمها الطرق التقليدية.
هذا البحث يدرس امكانية تطبيق نماذج الشبكات العصبية للتعرف على الحروف العربية المكتوبة حيث تم دراسة قدرة الشبكات العصبية على التصنيف الصحيح للحروف المنفصلة . تم تصميم شبكة عصبية ذات ثلاث طبقات لتصنيف الحروف باستخدام طريقة الانتشار للخلف وهي أكثر طرق التعلم المستخدمة في الشبكات العصبية كما تم تدريب شبكات ذات أعداد مختلفة من النيورونات في الطبقة المتوسطة للوصول الى أقل عدد ممكن من النيورونات في تلك الطبقة . استخدمت مجموعتين من الحروف احداهما خالية من التشوهات والأخرى تحتوى على درجات مختلفة من التشوه لدراسة أثر التشوهات في أشكال الحروف على عملية التعلم . أظهرت النتائج التي تم التوصل اليها قدرة الشبكات العصبية على التعميم والتغاضى عن الفروق البسيطة في أشكال الحروف.

Abstract:

Neural network-based learning is an essential part of any intelligent system and is an inherent property in Artificial Neural Network (ANN) models. Recently, artificial neural network models have begun to emerge as powerful tools for learning.

Neural networks are designed and applied to the classification of isolated Arabic characters. We have studied the ability of networks to correctly classify both training and testing examples. Multilayered neural networks were trained to classify

the characters using the error backpropagation learning algorithm. Noisy characters could be efficiently recognized. In this paper we evaluate the performance of the backpropagation technique on recognition of Arabic characters. Results indicate a high percentage of correct recognition and fault tolerance capability. The most effective number of neural network layers and the number of units in the hidden layers are conducted through extensive experimental work on isolated Arabic characters. Further research for recognition of connected hand written characters is going on.

1. Introduction:

Artificial neural networks is a promising area of research in computer science and engineering and represent a fundamental shift in computer architecture and operation. The inspiration for neural network technology came from the study of the structure of brain tissue. The neural network computer systems posses some very useful properties:

- Massive parallelism
- High interconnectivity
- Simple processors
- Distributed representation
- Fault tolerance
- Collective computation
- Learning capability
- Self organization:
- Self calibration by automatic adjustment for nonlinearity or drift in system.
- Specialization in a specific task
- Generalization (Flexibility)
- Robustness (noise immunity)
- Applicability in poorly understood or experimental domains

The value of ANN technology includes its usefulness for pattern recognition, learning, classification, generalization and abstraction, and the interpretation of incomplete and noisy patterns. A natural overlap with traditional AI applications is thus in the area of pattern recognition for character, speech, and visual recognition [1-11].

Pattern recognition techniques have been successfully applied for Arabic character recognition. While these techniques can produce an accurate classifier, the process of selecting features is often uncertain, and the procedure is time consuming. Moreover the resulting classifier is often computationally complex to the point of prohibiting real-time processing for on-line applications [2].

In recent years, neural networks introduce a new computational paradigm for learning algorithms and pattern classification based on automated learning procedures for massively parallel networks of simple processing elements. New learning algorithms for neural networks have recently appeared [1-4] and have stimulated their application to new problem areas.

Neural networks are efficient for optical character recognition not only because of their high computational speed but because they are capable of automatically discovering features and patterns of interrelated features which serve to separate nearly similar classes. Further, as a consequence the learning procedure is capable of producing a classifier which is capable of generalizing to new character styles. Automatic feature discovery and generalization capabilities are essential for a classifier which must process variable font types and styles where the characters vary from one person to another.

This paper discovers the power of neural networks for solving the problems related to Arabic character recognition. Results show that a three layer network can perform as good as a human observer. Experiments show the effect of varying both the number of hidden layers and the number of units in a hidden layer on the performance of the recognition problem. The following section describes the neural network model, network design and the learning algorithm used in the study. The third section describes the classification experiments and present experimental results. The fourth section discusses strategies for learning and improving the network generalization. Section five describes the presentation of Arabic characters to the input layer. The sixth section introduces the neural network simulator and its user interface. Finally the paper concludes with a brief discussion of the results.

2. Neural network architecture:

The process of designing a neural network consists of three major parts: problem definition, architecture design, and implementation. These parts are sequential and iterative. The neural network used for classification of Arabic characters was composed of three layers of processing elements [Fig. 1] that performed nonlinear transformation on its summed inputs and produced outputs between 0.0 and 1.0. The output of the ith unit is computed by summing all of its weighted inputs y_j as follows:

$$x_i = \Sigma_j \, y_j \, w_{ji} \qquad \text{.........................(1)}$$

where w_{ji} is the weight from the jth to the ith unit. The sigmoid function is then applied to the result of this summation:

$$y_i = 1 \,/\, (1+e^{(-x_i)}) \qquad \text{.........................(2)}$$

The input layer (sensor neurons for data acquisition) of the network was made up of 56 units, each clamped to a single character bit of the character to be classified. The number of output units was arbitrarily set as one. The state of the output unit represents the class of the character presented to the input layer. An intermediate hidden layer allows the network to assign the input pattern to the appropriate output class.

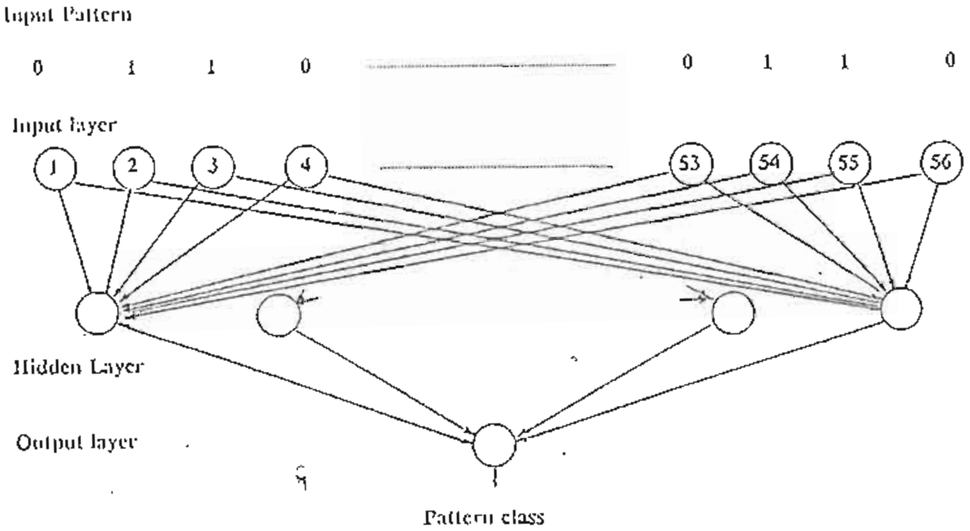

Fig. 1. Neural Network Architecture

The hidden layer represents domain knowledge in encoded form. The connections between the different neurons measure the degree of correlation between activity levels of neurons they connect. A schematic of the architecture is shown in Fig. 1. Since the network architecture must be adapted to the application, one has to optimize the weights for a given architecture and the number of layers and the number of units per layer.

3. Pattern classification capability of ANNs:

The input patterns could be classified by partitioning the input space with hyperplanes [4]. A single hidden layer permits AND operations of the half spaces formed by the hyperplanes of the first layer of weights. A second hidden layer can OR the convex regions to produce arbitrarily shaped regions with concavities and holes. Therefore, two hidden layers are sufficient to form regions or clusters of any shape [4] but not necessary. A single hidden layer is proven sufficient for the purpose of Arabic character recognition.

4. Back propagation learning algorithm:

A practical neural-network-based learning character recognition system is described, which is applicable to different standard character styles and font types.

Backpropagation is an iterative learning technique whose convergence is highly problem dependent. For each learning cycle, the input layer was clamped to the lexicographical bit pattern of a character from the training set. The activity of each unit was propagated forward through each layer of the network using (1) and (2). The activity at the output layer was compared to the desired output, and an error for each output unit was calculated as follows:

$$E = 0.5 \, \Sigma_c \, \Sigma_i \, (y_{i,c} - d_{i,c})^2 \quad \ldots\ldots (3)$$

where c is an index over cases (input-output pairs), i is an index over output units, y is the actual state of an output unit, and d is the desired state. The learning procedure minimizes E by performing gradient descent in the weight space [1].

The error term of equation 3 is used for updating weights according to the layer dealt with. The weight update equation for the output layer is defined by [4]

$$w^o_{kj}(t+1)=w^o_{kj}(t)+\alpha\delta^o_{pk}\, i_{pj} \quad \ldots\ldots (4)$$

The hidden layer weights are updated according to the following equation [4]

$$w^h_{ji}(t+1)=w^h_{ji}(t)+\alpha\delta^h_{pj}\, x_i \quad \ldots\ldots (5)$$

There are many different variables that affect the learning time:
(1) the number of units in both input and output layers
(2) the number of hidden layers
(3) the number of units in each hidden layer
(4) the fan-in and fan-out of hidden units
(5) the number of patterns in the training set
(6) the learning rate (see Fig. 2)

The effect of the number of units in the hidden layer on the number of learning cycles and consequently on the learning time is shown in table 1.

Table 1.

No. of units	No. of learn cycles
2	257900
4	264000
8	326800
16	282800
32	108700
56	100400
64	093100

Experiments showed that increasing the number of hidden units decreases the learning time monotonically after reaching a certain peek value (8 units in this case).

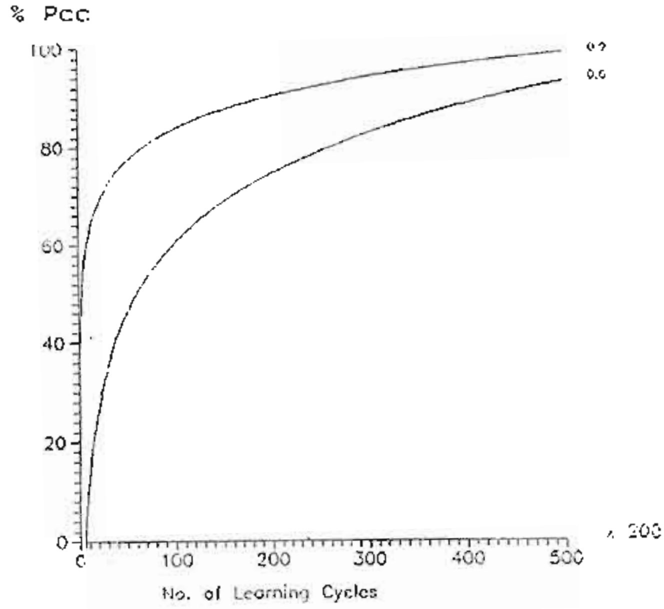

Fig. 2 Relation between no. of learn cycles and percentage of correct classification (Pcc) for different learning rates

5. Character presentation to the input layer:

Characters are input to the system in a lexicographical ordering of the binary bit array representing the character. Different sets of alphabetic characters were introduced to the network. A single hidden layer network is found to be sufficient .

One characteristic that is often desired in pattern recognition problems is invariance of the network output to changes is the position and size of the input pattern. Various techniques have been used to achieve translation, rotation, scale and time invariance [1]. Our method involves including in the training set several examples of each exemplar transformed in size, angle, and position, but with a desired response that depends only on the original exemplar.

6. A Neural Network Simulator:

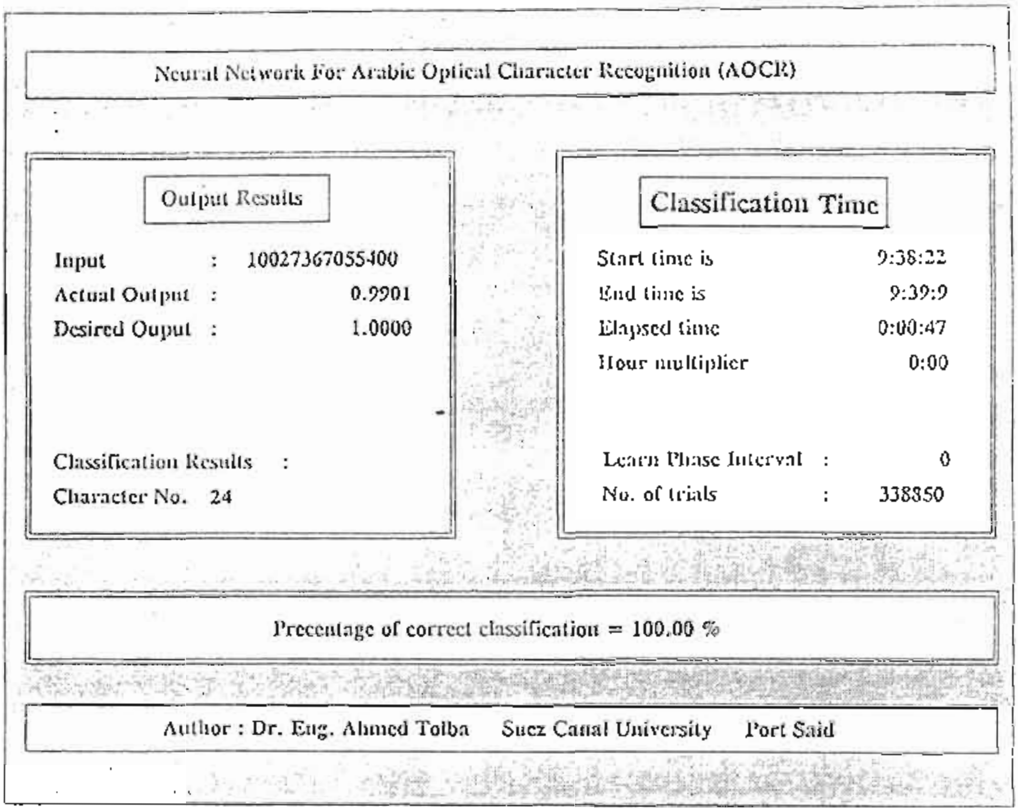

Figure 3. User interface to the neural network Simulator (NACR).

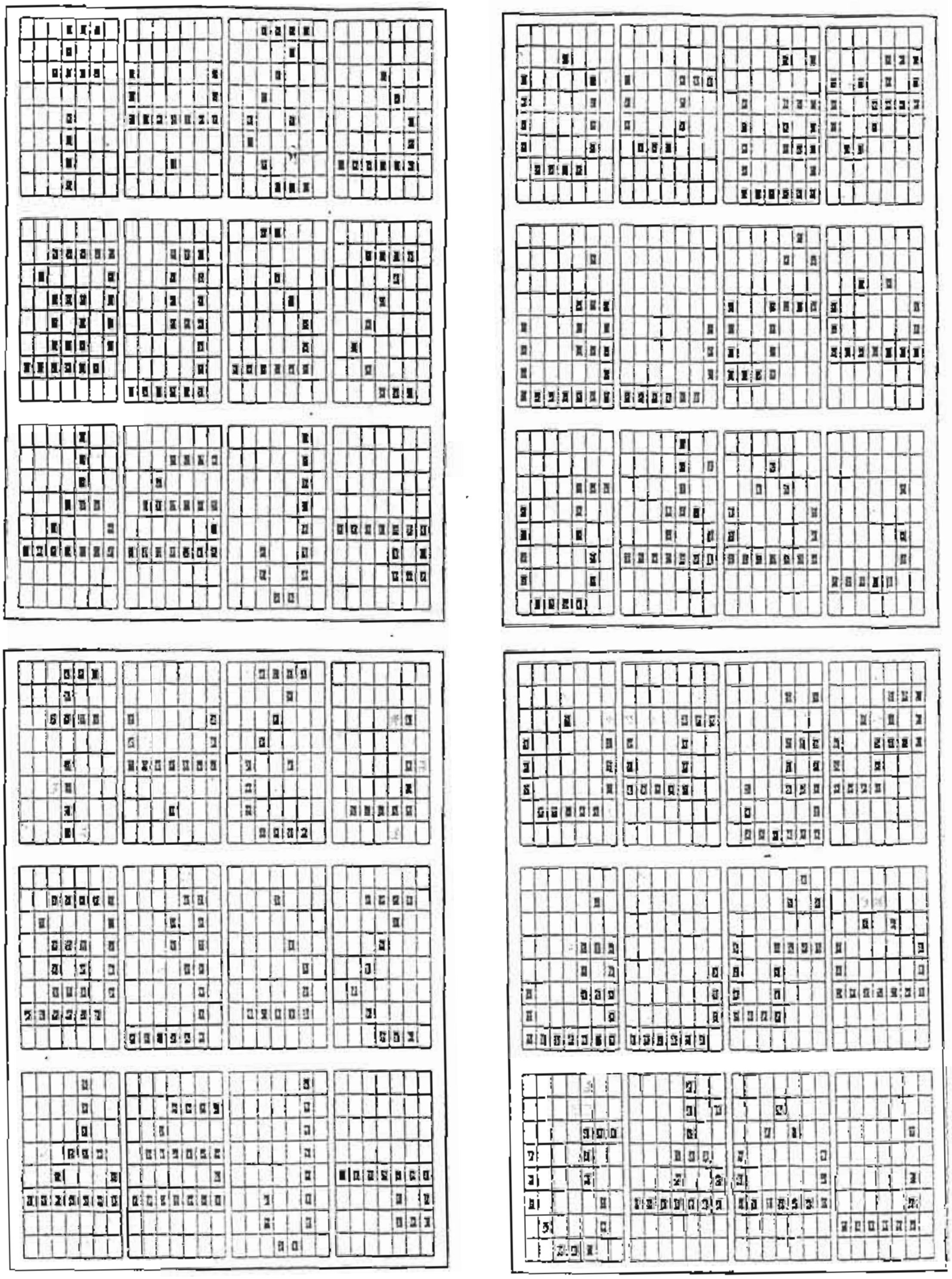

Figure 4. Patterns that MACR ccessfully identified.

An Artificial Neural Network Simulator for Arabic Character Recognition (NACR) was developed and is used in research into classification of image data, speech data and gas data. The ANNS was implemented on a 50 MHz 486 EISA machine. The ANNS provides a flexible tool for designing of different network architectures and facilitates the interfacing of sensory data of any source with the input layer. A user-friendly interface makes it possible to design a neural network by inputting the number of neurons in the input layer, the number of neurons in the hidden layer and the number of learn cycles. An important topic which is considered is the capability of saving the weighting and bias matrices after a user-specified number of learn cycles to accumulate the learning results along the learn period. The percentage of correct classification for different numbers of learn cycles is stored in a disk file to reflect the behavior of the network. The learning rate could also be adjusted adaptively with the percentage of correct classification approaching hundred percentage. It is possible also to estimate the elapsed time in both the learning and classification stages. The ANNS consists of independent modules equivalent to the learning phase and the classification phase. Options are given to select one of two possible learning states: learning for the first time or continuation of a previous learning epoch. The first state involves initializing both the weighting and bias matrices with random values. The second state involves uploading the previously stored weighting coefficients and biasing values for further learning. Figure 3. shows the user interface screen to the ANNS.

7. Experimental results:

The presented neural network for Arabic character recognition (NACR) was trained to recognize isolated Arabic characters. Figure 4 shows a number of patterns that were correctly identified by the system. Notice that identification occurs even when the patterns are distorted or degraded with noise.

An important property of a given neural network is that it always converges to a stable state. Table 2 shows the number of learning cycles, desired outputs and actual outputs for different numbers of hidden units. These results indicate the convergence of the network behavior at different numbers of learn cycles.

8. Conclusions:

The experiments presented involved learning the neural network to recognize isolated Arabic characters. Digitization noise and difference of character style have no effect on the system performance. As a result of this feature (generalization), Arabic character network-based learning recognizer is easy to design to accommodate writer changes.

The neural network based character recognizer being developed is trained to represent the system characteristics, making it applicable to noisy characters of different styles. The experiments presented in this paper demonstrate that practical real-time Arabic character recognition using neural network learning techniques to develop nonlinear mappings and sensor data processing can be implemented using low-cost microprocessors and practical amounts of memory. The required computations increase linearly with the number of input variables.

Table 2.

Desired o/p	Actual Output				
	2	4	8	16	32
0.0417	0.0403	0.0417	0.0422	0.0416	0.0412
0.0833	0.0811	0.0833	0.0833	0.0833	0.0832
0.1250	0.1277	0.1251	0.1251	0.1251	0.1251
0.1667	0.1589	0.1667	0.1666	0.1666	0.1668
0.2083	0.2124	0.2083	0.2083	0.2083	0.2084
0.2500	0.2594	0.2500	0.2499	0.2500	0.2501
0.2917	0.2953	0.2917	0.2917	0.2918	0.2919
0.3333	0.3337	0.3334	0.3333	0.3333	0.3336
0.3750	0.3752	0.3750	0.3750	0.3750	0.3753
0.4167	0.4176	0.4167	0.4167	0.4166	0.4167
0.4583	0.4583	0.4584	0.4583	0.4583	0.4585
0.5000	0.5014	0.5001	0.5000	0.5001	0.5003
0.5417	0.5417	0.5417	0.5416	0.5416	0.5418
0.5833	0.5830	0.5834	0.5834	0.5634	0.5836
0.6250	0.6283	0.6250	0.6250	0.6250	0.6250
0.6667	0.6669	0.6666	0.6667	0.6666	0.6668
0.7083	0.7078	0.7084	0.7086	0.7083	0.7084
0.7500	0.7503	0.7500	0.7500	0.7500	0.7502
0.7917	0.7926	0.7917	0.7917	0.7917	0.7920
0.8333	0.8355	0.8338	0.8337	0.8338	0.8340
0.8750	0.8750	0.8750	0.8750	0.8750	0.8752
0.9167	0.9172	0.9166	0.9167	0.9167	0.9168
0.9583	0.9406	0.9588	0.9583	0.9581	0.9575
1.0000	0.9904	0.9908	0.9909	0.9910	0.9903

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