IDENTIFICATION DES MODELES MANUSCRITS ARABES EN UTILISANT LES RESEAUX NEUROLOGIQUES

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Résumé :

Dans cet article, nous présentons un algorithme de réseau neurologique qui apprend et identifie les modèles manuscrits arabes écrits ou dessinés et comprenant des caractères ou des mots simples. Il démontre également la différence entre les modes d'apprentissage supervisés et non supervisés.

L'algorithme utilise un réseau neurologique de deux-couche simple et aucune couche cachée pour apprendre et identifier des modèles. Le caractère dessiné par main ou par souris est digitalisé sur une grille des neurones d'entrée. La réponse est représentée par un neurone simple de rendement.

Des rapports assez bons d'identification sont obtenus avec cet algorithme pour la plupart des modèles utilisés.

Mot-clé : *Réseaux neurologiques, reconnaissance de caractères, modèles arabes*

Abstract:

In this paper, we present a neural networks algorithm that learns and recognises hand written Arabic or mouse-drawn patterns including characters and simple words. It also demonstrates the difference between the supervised and unsupervised learning modes.

The algorithm uses a simple two-layer neural network and no hidden layers to learn and recognise patterns. The hand-drawn or mouse drawn character is digitised onto a grid of input neurons. The answer is represented by a single output neuron.

Fairly good recognition ratios are obtained with this algorithm for most used patterns.

Keyword: *Neural networks, Character recognition, Arabic patterns*

INTRODUCTION

The algorithm could learn and recognise both characters and symbols. It is based on neural networks [1] to identify mouse-drawn characters or symbols. We can either teach it to recognise new characters, or it can learn on its own. The recognition ratio progressively improves as it learns hand-writing (or mouse-drawing).

The neuron will get active and send inputs to all the neurons [2] that are connected to it. The neural network's suppleness comes from the configuration of the links, which can reinforce, nullify or even cancel out the input signals [3].

The algorithm [5] uses a large two-layer neural network to learn and recognise patterns. The hand-drawn image is digitised onto a grid of input neurons (Figures 2 and 3). Each possible solution [4] is represented by a single output neuron as there are no hidden layers; every input neuron is connected directly to every output neuron. The data is determined in the links between neurons. If a link between an input neuron and an output neuron is positive, that means that if the input is *on* then the total score for that output neuron is increased by a small amount. If the link is negative, then it results that if that input is on, the corresponding output has its total reduced by an amount. The output neuron with the highest score (best match) [6] is considered the winner. This is known as a competitive network.

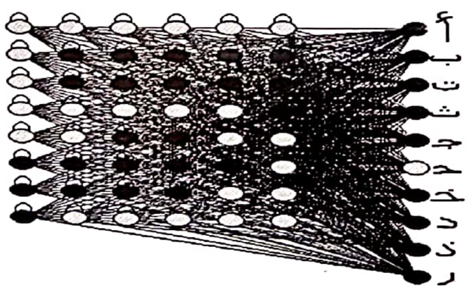

Figure 1: Grid of input neurons

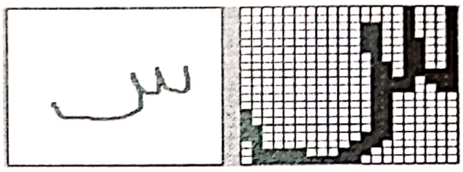

Figure 2: Example of Inputting and Digitising Pattern

The algorithm learning method is extremely simple. There is no back-propagation, delta-rule. All is about is a simple arithmetic. The links [7] between active input neurons and the selected output neuron have their weights increased by one and those between inactive inputs neurons and the selected output neuron have their weights decreased by one.

The algorithm recognises individually printed characters and progressively adapts to the style of writing that the owner uses.

First of all, we define two parameters which play a major role in neural networks applications: the *recognition ratio* and the *confusion ratio*:

- The recognition ratio, or the recognition probability is defined as the percentage of recognising a given character or pattern.
- The confusion ratio however is defined as the uncertainty ratio that is the probability that a character/pattern is confused with a given (input) one.

RESULTS and DISCUSSION

1. Character or pattern recognition

Some examples of hand written characters recognition are shown below. In figure 4 depicts the written character, the digitised pattern and the probability ratios. Table 1 shows the recognition ratios for different Arabic characters. The latter seem to depend on the shape of the character.

The more complex the character is, the less it is recognised.

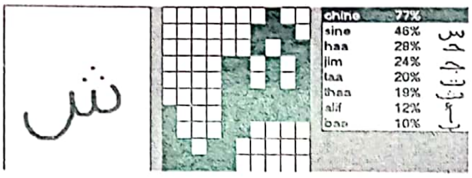

Figure 3: Hand written character recognition

Character	أ	ب	ت	ث	ج	ع	س	ش	و
Recognition Ratio (%)	82	83	75	74	70	70	71	63	75

Table 1: Recognition ratios for some Arabic characters

Table 2 below shows the confusion ratios of the Arabic letter "Alif" with other characters. It is clearly seen that the confusion increases with increasing similarity of the character with letter "Alif"

Character	أ	ز	ع	غ	م	د	ح	ج
Recognition Ratio (%)	82	52	51	50	50	50	51	53

Table 2: Confusion ratio for letter "Alif"

We now attempt to reveal the influence of grid dimensions, pen widths, background noise, and learning on the recognition ratios.

1.1 Influence of the grid dimensions on the recognition ratio

Grid Dimensions	Recognition ratio (%)
5x5	91
10x10	92
20x20	85
30x30	84

Table 3: Recognition ratio, Grid dimensions

As is shown in table 3, the recognition ratio improves gradually as the grid decreases. This is, however accompanied by a corresponding increase in the confusion ratio.

1.2 Influence of the pen width on the recognition ratio

Pen width	Recognition ratio (%)
2	73
5	84
7	95
9	98

Table 4: Recognition ratio, Pen width

As is depicted in table 4 above, the recognition ratio increases drastically as the pen width increases, e.g. it proceeds from 73% for a pen width of 2 to 98% for pen width equal to 9. But this increase in the recognition ratio is associated with a corresponding increase in uncertainty that is the net confusion in identifying patterns increases.

1.3 Influence of learning depth on the recognition ratio

Character	ع	غ	أ
Recognition Ratio (%)	67	59	50

Table 5: Confusion ratio after 10 input patterns

Character	ع	غ	أ
Recognition Ratio (%)	83	62	59

Table 6: Confusion ratios after 20 input patterns

Table 5 and 6 clearly exhibit the influence of the learning depth of the net on the recognition ratios, which progressively improves as the net learns more and more patterns.

1.4 Influence of background noise

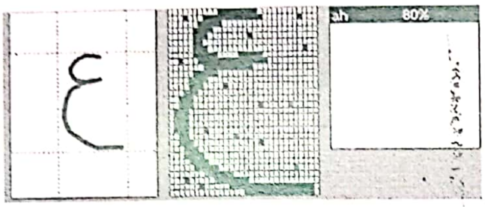

Figure 4. Character recognition in background noise

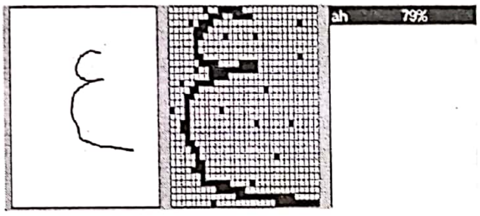

Figure 5: Character recognition in noisy background

Using different pen thickness

Figures 4 and 5 reveal the influence of background noise on the recognition ratio. Weak background noise (tiny dots) seems to have no effect on the recognition ratios. It should be noted, however that the dimension of the dots that compose the noise have a significant influence on the results.

2. Words or complex patterns Recognition

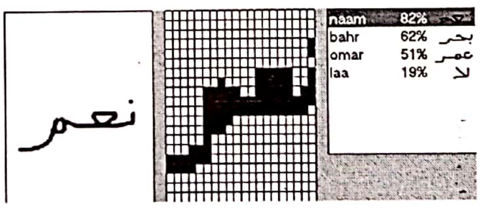

Figure 6: Hand written word recognition

Words	المدرسة	المدينة	البحر	نعم	ماء
Recognition ratio (%)	70	67	67	60	53

Table 7: Confusion ratios for words

The algorithm could also recognise some simple words as shown in figure 6. However, the net could hardly distinguish between similar words and/or long words as is shown in table 7. But the pattern recognition confusion [8] could be considerably reduced with more learning.

CONCLUSION

The simple algorithm that we used in this work has given good results for simple patterns (characters or simple words). We showed that the solutions could be improved by increasing the learning depth, i.e. presenting more input patterns to the net.

The pen depth has a strong influence on the pattern recognition at the expense of a significant confusion ratio.

Weak background noise seems to have no apparent influence on the solution. But strong background noise (streaks, blobs, etc...) could make the pattern virtually unrecognisable.

As a conclusion, this simple algorithm pattern appears to work fairly well with simple patterns. The learning procedure is very fast for the net has no hidden layers then no back propagation error procedure. It is most suited for simple pattern recognition or for other language characters recognition, such as Japanese or Chinese letters.

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