Global Journals Inc.
Global Journal of Computer Science and Technology
Volume 11 Issue 15 Version 1.0 September 2011
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 0975-4172 & Print ISSN: 0975-4350

Recognition of Handwritten Tifinagh Characters Using a Multilayer Neural Networks and Hidden Markov Model

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GJCST Classification : *G.3, F.1.1*

RECOGNITION OF HANDWRITTEN TIFINAGH CHARACTERS USING A MULTILAYER NEURAL NETWORKS AND HIDDEN MARKOV MODEL

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Abstract - In this paper, we propose a system for recognition handwritten characters Tifinagh, with the use of neural networks (the multi layer perceptron MLP), the hidden Markov model (HMM), the hybrid Model MLP/HMM and a feature extraction method based on mathematical morphology, this method is tested on the database of handwritten isolated characters Tifinagh size consistent (1800 images in learning and 5400 test examples). The recognition rate found is 92.33%. The MLP, HMM and MLP+HMM classifiers show good enough results.

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I. Introduction

Automatic recognition of handwritten characters is the subject of several research for several years. This has several applications: In the field of multimedia and the compression of image etc... Automatic recognition of a Tifinagh character is done in three steps: the first phase is that of pretreatment to reduce noise, the second for extraction of characteristics and the third to make the classification (Neural Networks, Hidden Markov Model, Hybrid Model MLP/HMM). Neural networks are a system of calculate widely used for the recognition of images [1, 2, 3, 4]. In learning we use the gradient descent algorithm, in Hidden Markov Model we use a vector of extraction as a suite of observation and we seeks to maximize the model with the best probability. The Baum-Welch algorithm is used to learning. And for the Hybrid model MLP/HMM we considered the output of the neural networks as a probability of emission for the hidden markov model. We propose a system of recognition implemented on a base of Tifinagh characters manuscripts. This paper is organized as follows: Section 2 is devoted to the test database. In section 3, we describe the method of characteristics extraction based on mathematical morphology. In section 4, we present an overview on the neural networks MLP. Experimental results of neural networks are presented in section 5. The hidden Markov model HMM is presented in section 6. Experimental results on the hidden Markov model will be presented in section 7. In section 8, we present the hybrid model MLP/HMM. Recognition system is illustrated in the following figure (Figure 1).

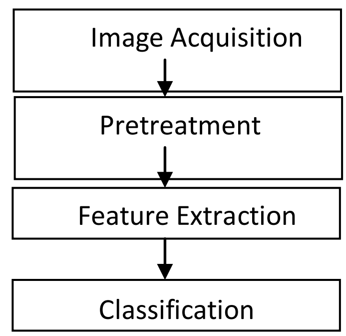

Figure 1: The recognition process

II. Tifinagh Database

The database used is Tifinagh, it is composed of 7200 characters Tifinagh (manuscripts + Imprimed) (1800 in learning and 5400 in test). The number of characters according to IRCAM Tifinagh is 33 characters. Example of IRCAM Tifinagh characters:

Figure 2 : Tifinagh characters

III. P Reprocessing

In the preprocessing phase, the images of handwritten characters are rendered digital with a scanner, then it make the binary image with thresholding. After standardization for image extracted in a square the size standard is: 150 x 150.

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IV. Extraction

The method used for extraction is based on mathematical morphology [5, 6, 7]. We seek to detect five zones characteristics for each image: West zone, East zone, North zone, South zone and central zone. These characteristic areas are detected by the dilatation of the processed image in the four directions.

a) The dilation of the image:

The dilation is a transformation based on the intersection between the object of the image A (white pixels) with a structuring element B. It is defined by the following formule

$$\text{Dilatation } (A, B) = \{x \in \text{Image} \,/\, B_x \cap A \neq \varnothing\}$$

Where A is the object of the image (the white pixels), B the structuring element which is a particular set of Center x, known size and geometry (in this work is a right half).

Example of the dilatation characters to the East.

Figure 3 : The dilatation characters to the East

And the same thing for other directions West, North and South.

Figure 4 : The dilations of the character to the West, North and South

b) Detection the characteristic zones of the image:

Is determined for each character the discriminating parameters (zones). The characteristic zones can be detected by the intersections of dilations found to the East, West, North and South. We define for each image five types of characteristic zones: East, West, North, South, and Central zone.

i. *Extraction of East characteristic zone :*

A point of the image (Figure 5) belongs to the East characteristic zone (Figure 6) if and only if:

- This point does not belong to the object (the white pixels in image).
- From this point, moving in a straight line to the East, we do not cross the object.
- From this point, moving in a straight line to the south, north and west one crosses the object (Figure.5). The result of the extraction is illustrated in (Figure.6).

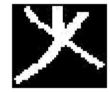


Figure 5 : Image of the character

Figure 6 : The East characteristic zone (EZ)

ii. *Extraction of West characteristic zone:*

A point of the image (Figure 7) belongs to the West characteristic zone (Figure 8) if and only if:

- This point does not belong to the object (the white pixels in image).
- From this point, moving in a straight line to the West, we do not cross the object.
- From this point, moving in a straight line to the south, north and East one crosses the object (Figure.7). The result of the extraction is illustrated in (Figure.8).

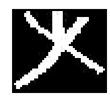


Figure 7: Image of the character

Figure 8 : The West characteristic zone (WZ)

iii. *Extraction of South characteristic zone:*

o A point of the image (Figure 9) belongs to the South characteristic zone (Figure 10) if and only if:

- This point does not belong to the object (the white pixels in image).
- From this point, moving in a straight line to the South, we do not cross the object.
- From this point, moving in a straight line to the north, East and West one crosses the object (Figure.9). The result of the extraction is illustrated in (Figure.10).

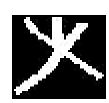


Figure 9 : Image of the character

Figure 10 : The South characteristic zone (SZ)

iv. *Extraction of North characteristic zone :*

A point of the image (Figure 11) belongs to the North characteristic zone (Figure 12) if and only if:

- This point does not belong to the object (the white pixels in image).
- From this point, moving in a straight line to the

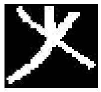


Figure 11 : Image of the character

Figure 12 : The North characteristic zone (NZ)

v. *Extraction of Central characteristic zone :*

A point of the image (Figure 13) belongs to the Central characteristic zone if and only if:

- This point does not belong to the limit of the object.
- From this point, moving in a straight line to the south, north, east and west we cross the object. The result of the extraction is illustrated in the (FIG.13).

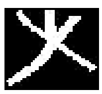


Figure 13 : Image of character

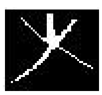


Figure 14 : The central characteristic zone (CZ)

Each character is characterized by five components: NWZ, NEZ, NNZ, NSZ and NCZ. with these latter parameters are the numbers of pixels of value 1 respectively in the characteristic zones West, East, North, South and Central. The vector of extraction will be defined as follows:

Vext = [WZ, EZ, NZ, SZ, CZ]

With Npixels is a Number of pixels in the image size 150 x 150

WZ = NWZ / (Npixels).
EZ = NEZ / (Npixels).
NZ = NNZ / (Npixels).
SZ = NSZ / (Npixels).
CZ = NCZ / (Npixels).

V. Neural Networks

The neural networks [8, 9, 10, 11, 12] based on properties of the brain to build systems of calculation best able to resolve the type of problems as human beings live know resolve. They have several models, one of these models is the perceptron.

a) Multi-layer perceptron (MLP)

[13, 14, 15] The classification phase is as follows:

The number of neurons in the network is:

- Five neurons in the input layer (the number five corresponds to the values found in the vector of extraction).
- Eighteen neurons in the output layer (the number eighteen corresponds to the number of characters used).
- The number of neurons in the hidden layer is selected according to these three conditions:
- Equal number of neurons in the input layer.
- Equal to 75% of number of neurons in the input layer. Equal to the square root of the product of two layers of exit and entry.

According to these three conditions are varied the number of neurons of layer hidden between five and ten neurons. The method used for learning is the descent of the gradient (gradient back-propagation algorithm) [16, 17, 18, 19, 20].

Layers	Neurons		Constant of learning
Input	5		$\alpha = 0.9$
Hidden	9		
Output	18		
Squared error			Activation function
$E = \frac{1}{2}(t-o)^2$ t : the theoretical output. o : the desired output.			Sigmoid function $F(x) = \frac{1}{1+e^{-x}}$

Figure 15 : Details of the neural networks

VI. Classification

After extracting the characteristic data of the input image, we will classify its data with neural networks (Multilayer perceptron). We must compute the coefficients of weight and desired outputs.

a) Experimental Results

The values of characteristic vectors obtained in the extraction phase are introduced at the input of the neural network, and we know the desired output and the network is forced to converge to a specific final state (supervised learning). Each character is characterized by a vector of five components. For the formation of the network (multi-layer perceptron MLP), we started by a set of eighteen images, and we finished with 50 sets of 900 images, to find the best parameters that maximizes network (Figure.20).

Handwritten character sets	Numbers of characters	Manuscripts Test database	Printed Test database
1 set	18	62.43	60.20
10 sets	180	78.88	60.36
20 sets	360	81.57	61.86
30 sets	540	81.75	62.46
40 sets	720	84.23	63.83
50 sets	900	84.91	63.88
Numbers of images for test		2340 Images	3060 Images

Figure 16 : Experimental results for MLP

VII. Hidden Markov Models

Hidden Markov models (HMMs), (Choisy C., et al 2002), (Choisy C., et al 2002), (Choisy C., 2002) are statistical models parametric signal production, widely used in speech recognition and recognition of the writing later.

a) Markov Chain

A chain of discrete Markov of order n is a discrete stochastic process X = {X_t | t = 1, …, T} with discrete random variables, checking the Markov property:

$$P(X_t=q_{it}|X_{t-1}= qi_{t-1},\ldots,X_1= qi_1)=P(X_t=qi_t|X_{t-1}= q_{it-1},\ldots,X_{t-n} = qi_{t-n})$$

Ou Q={q_1,….,q_n} represents all the States.

b) Stationary chain

A Markov chain of order 1 is stationary if for any t and k there is:

$$P(X_t=q_i|X_{t-1}= q_j)= P(X_{t+k}=q_i|X_{t+k-1}= q_j)$$

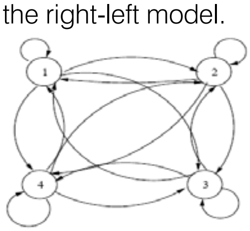
In this case, it defines a transition probability matrix A = (a_{ij}) such as:

$$a_{ij} =P(X_t=q_j|X_{t-1}= q_i)$$

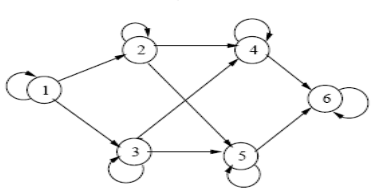
At a time given a any process.

c) Types of HMMs

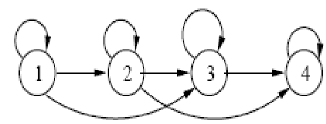
The main types of Markov models hidden are the ergodic and the right-left model.



Ergodic



left-right : parallel



left-right : sequential

d) Evaluation of the probability for observation:

Are O=o1o2…oT a suite of observations and Q = q1q2…qT suite of associated states. The probability for the observation of O, as the model β (or class) is equal to the sum on all possible States Q the joint probabilities of O and Q.

$$P(O|\gamma) = \sum P(O,Q|\gamma)$$

e) Calculation of $P(O|\gamma)$ using Forward-Backword function :

Observation can be done in two times:

- Emission of early observation O (1: t).
- Emission of the end of the observation O (t+1: t).

The evaluation of the observation is given by:

$$P(O|\gamma) = \sum \alpha(t,qi) * \beta(t,qi)$$

f) Recognition:

Knowing the class to which belongs the character it is compared to models λ_k, k = 1, ……, L of its class. The selected model will be the one to provide the best probability corresponding to the evaluation of its suite of primitive i.e: max (P(O/ λ_k))

With O: The suite of observation in this work is the vector of extraction.

λ_k: is the Markov model consisting of the transition matrix A, the observation matrix B and boot matrix Πi.

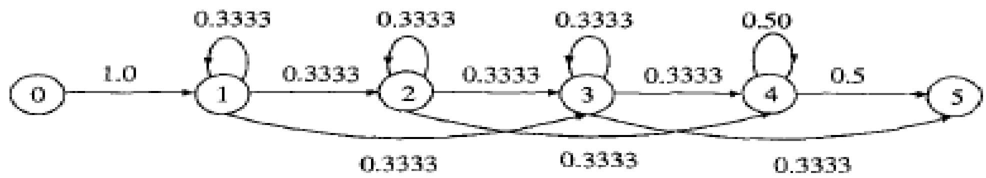


Figure 17 : Initial transitions

g) *Chain of treatment*

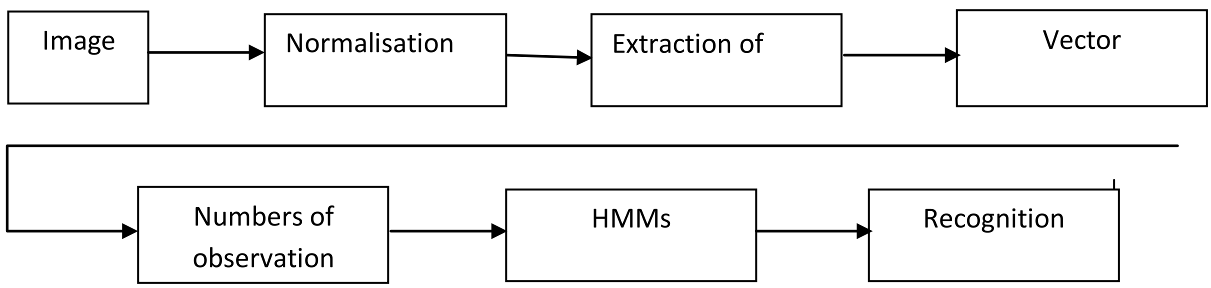


Figure 18 : The process for the HMM

h) *Experimental results*

For the classification with hidden Markov model, considering the values of the characteristic vectors obtained in recognition of the characters as a sequence of observations, it initializes the model and is sought with the Baum-Welch algorithm (learning) to find the best probability that maximizes the parameters of the model (A: the transition matrix, B: the observation matrix, Πi: the boot matrix). Each character is characterized by a vector of five components extraction. The experimental results are illustrated in the following figure (Figure 19).

Number of characters in the base	Type of characters used	Manuscripts Test database	Printed Test database
5400	18	92.22	77

Figure 19 : Experimental results for the HMM

VIII. Hybrid Model MLP/HMM

Under certain conditions, neural networks can be considered statistical classifiers by supplying output of a posteriori probabilities. Also, it is interesting to combine the respective capacities of the HMM and MLP for new efficient designs inspired by the two formalisms

a) *The hybrid system*

A perceptron can provide the probabilities of belonging P(ci/x(t)) a vector model x (t) to a class ci. Several systems have been developed on this principle [22]. These systems have many advantages over approaches purely Markov. However, they are not simple to implement because of the number of parameters to adjust and the large amount of training data necessary to ensure the global model. In this section, we show how our hybrid system is designed. The architecture of the system consists of a multilayer perceptron upstream to a type HMM Bakis left-right. The hybrid system, including the figure 20 shows the overall design scheme to provide probabilities of belonging to different classes. The system is composed of two modules: a neural module and a hidden Markov module.

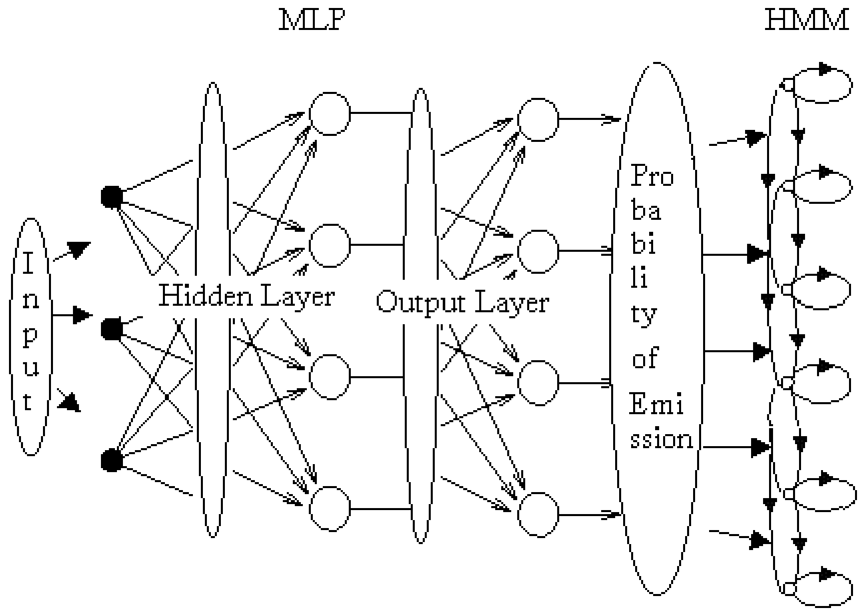


Figure 20 : Global schema design of the hybrid mode

The observations being the various classes, we associate with each State an observation. Also our goal is to find the best way of maximizing the probability of a sequence of observations, the method used for recognition with the hybrid model is the method used in (section 7.6) for the hidden markov model. The HMM has in input two matrices and a vector: a matrix of transition probabilities, a matrix of emission probabilities which is the output of the MLP (posterior probabilities), and a vector representing the initial probability of States.

b) Results of the hybrid system

Number of characters in the base	Type of characters used	Manuscripts Test database	Printed Test database
5400	18	92.22	77

Figure 21: Experimental results for the HMM

Type of characters	MLP	HMM	MLP+HMM
Manuscripts	84.91	92.22	92.30
Printed	63.83	70	87.77

Figure 22 : Comparison between three methods of classification

IX. Conclusion

In this work, we use a method based on neural networks (multi-layer perceptron and back-propagation), the hidden Markov model and hybrid model MLP + HMM for the classification of manuscripts Tifinagh characters. A technique of extraction based on mathematical morphology is used in the phase of extraction of characteristics before the implementation in classification of characters. We prove that the HMM and MLP approaches can be a reliable method for the classification. We introduced the hybrid system to make more intelligent classification process by modeling the output of the neural network as probabilities of emission When to initialize the settings of the hidden markov model. As perspectives we can increase the database and type characters used in recognition for the generalization of this method of extraction for the recognition of all Tifinagh characters (33 characters according to IRCAM).

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