Neural Network Classifiers for Off-line Optical Handwritten Amazighe Character Recognition

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Summary

Recognizing Amazighe characters is a difficult task in the area of optical character recognition (OCR). This paper describes a new hybrid Amazighe character recognition system based on an artificial neural network classifier using Legendre moments without any preprocessing. The features extraction stage uses a set of moment descriptors which are invariants under shift and scaling. The actual classification is done using a multilayer perceptron network; with learning algorithm to generate a near optimal feed forward neural networks dynamically for the task of object recognition. The proposed crossover operators aim to adapt the networks architectures and weights during the evolution process. To evaluate our proposed model a real-world database of Amazighe handwritten characters containing 7524 handwritten character images is used. This new database has been developed at the Communication an Electronics Laboratory of EMI (Ecole Mohamadia d'Ingenieurs). Experiments using our database demonstrate that combining features moments with neural network classifiers indeed are far more effective. Evaluating the proposed system with 924 test samples the recognition rate of 97.62% is achieved.

Keywords:
Character recognition, Amazighe characters, Legendre moments, neural networks

1-Introduction

In the past several decades, a large number of OCR systems have been developed for natural languages [1], [2], [3]. However, the problem of handwritten Amazighe character recognition has been rarely addressed [4], [5], [6]. The purpose of this paper is to develop an efficient system for recognizing Amazighe handwritten characters by combining Legendre moments as features and neural network classifier.

In this paper, the proposed contribution for Amazighe character recognition has two main steps: preprocessing and recognition. In the first one, we propose a novel method that extracts optimal character features based on Legendre moments. In fact, we should keep in mind that recognition of handwritten characters is a real challenging problem. Hence, it is required to develop more efficient feature extraction technique that can discover similarities among similar characters written under different conditions, and still distinguish them as unique class. As a matter of fact, the more successful the feature extraction stage, the easier classification process will be [7], [8]. For this, we introduce the Maximum Entropy Principle (MEP) as a selection criterion [9]. Our major goal is to reduce the input dimensionality of the classification problem by eliminating features with low information content or high redundancy with respect to other features [10].

In fact, orthogonal moments were first introduced by [11]. They have been used in face recognition [12], line fitting [9], signal noise removal [13], and ECG signal compression [14]. Like all other orthogonal moments, Legendre moments can be used to represent an image with near zero amounts of information redundancy [15], and invariance to scaling and translation could be achieved through image normalization, or directly by using the original Legendre polynomials [16]. Indeed, they possess better reconstruction power than geometrical moments [17], [18], [19]. Nevertheless, the presented results can be extended to other types of orthogonal moments [17], [18], [20], [21].

The second step (recognition) is achieved by using multilayer feed forward neural network as a classifier with the stochastic back propagation algorithm, where finite vectors obtained in the preprocessing phase are used as inputs. The method is tested using a new collected database of handwritten Amazighe characters. It is an attempt for generation of a complete database for the furtherance of handwritten recognition research on Amazighe scripts. This database recently developed at our laboratory has been developed to make it available freely to the fellow researchers. The database in its first version consists of 7524 characters and written by 57 different writers, subdivided into respective training and test sets.

Furthermore, Neural network is widely used as a classifier in many handwritten character recognition systems and other visual classification tasks [22], [23]. Also, due to their simplicity, generality, and good learning ability, these types of classifiers are found to be more efficient [24].

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The most important advantages of our method are (i) Avoid preprocessing techniques like skew correction, binarization, noise removal [5], which are time-consuming procedure, (ii) perform efficient features extraction algorithm using the Maximum Entropy Principle (MEP) as a selection criterion [9], in order to reduce the input dimensionality of the classification problem by eliminating features with low information content or high redundancy with respect to other features. In fact, the choice of features to represent the patterns is of capital importance due to the fact that they affect several aspects of the pattern recognition problem such as accuracy, required learning time and necessary number of samples [25].
Experimental results show that the proposed method reduces the computational burden of the recognition system in terms of the total number of layers and nodes, while showing improved performances in terms of recognition rate and generalization ability
The rest of this paper is organized as follows: In the coming section, we describe briefly the database used in our system. Section III points out the proposed method of moments features extraction. Section IV explains neural classifier. Section V is devoted to experimental results. Finally, Section VI draws conclusion and summarizes the paper.

2-History of Amazighe character

The Amazighe (Berber) language is spoken in Morocco, Algeria, Tunisia, Libya, and Siwa (an Egyptian Oasis); it is also spoken by many other communities in parts of Niger, Burkina Faso and Mali [26]. It is used by tens of millions of people in North Africa mainly for oral communication and has been integrated in mass media and in the educational system in collaboration with several ministries in Morocco [27].
In Morocco, the term Berber (Amazighe) encompasses the three main Moroccan varieties: Tarifite, Tamazighte and Tachelhite [28], more than 40% of the country's populations speak Berber. The establishment of The "Royal Institute of the Amazighe Culture" (IRCAM) carried out a major action to standardize the Amazighe language. In the same tread, and since 2003, the Amazighe language has been integrated in the Moroccan Educational System. It is taught in the classes of the primary education of the various Moroccan schools, in prospect for a gradual generalization at the school levels and extension to new schools [29].
As far as the alphabet is concerned, and because of historical and cultural reasons, Tifinaghe has become the official graphic system for writing Amazighe [30]. IRCAM kept only pertinent phonemes for Tamazighte, so the number of the alphabetical phonetic entities is 33, but Unicode codes only 31 letters plus a modifier letter to form the two phonetic units: ⴳⵯ (g^w) and ⴽⵯ (k^w).[27]. The whole range of Tifinaghe letters is subdivided into four subsets: the letters used by IRCAM, an extended set used also by IRCAM, other neo-Tifinaghe letters in use and some attested modern Touareg letters. The number reaches 55 characters [27], [31]. In order to rank strings and to create keyboard layouts for Amazighe in accordance with international standards, two other standards have been adapted [32]. The Figure 1 represents the repertoire of Tifinaghe which is recognized and used in Morocco with their correspondents in Latin characters.

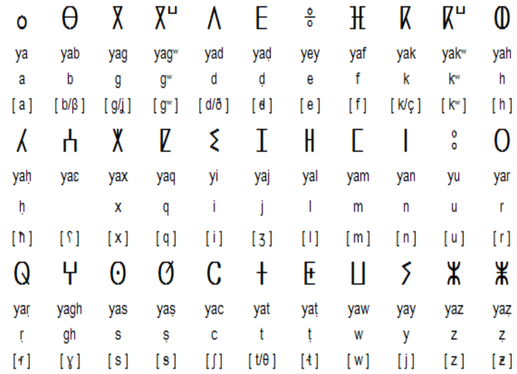

Figure 1: Neo-Tifinaghe alphabet as used in Morocco with their Correspondents in Latin Characters.

The Amazighe script is written from left to right; it uses conventional punctuation marks accepted in Latin alphabet. Capital letters, nonetheless, do not occur neither at the beginning of sentences nor at the initial of proper names. So there is no concept of upper and lowercase characters in Amazighe language. Regarding the figures, it uses the Arabic Western numerals. The majority of graphic models of the characters are composed by segments. Moreover, all segments are vertical, horizontal, or diagonal. (Figure 1)

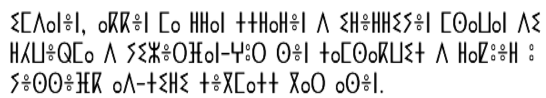

Figure 2: Sample text in Tamazighte

Translation

All human beings are born free and equal in dignity and rights. They are endowed with reason and conscience and should act towards one another in a spirit of brotherhood.
(Article 1 of the Universal Declaration of Human Rights)

3-Data collection

Effective research work on handwritten recognition for Amazighe scripts is seriously hampered because of the unavailability of standard databases those may be used for testing of algorithms and for comparison of results. For the above reason, this paper describes an attempt for generation database for handwritten Amazighe characters. This database will facilitate fruitful research on handwritten recognition of Amazighe through free access to the researchers. Descriptions of these components of the present database are given below.
The database contains forms (Figure 3) of unconstrained handwritten characters including 7524 isolated characters, gathered from 57 different and independent writers, referring to Tifinaghe alphabet adopted by IRCAM [32], [33]. Figure 2 shows a sample of Tifinaghe alphabet. The whole set of available isolated characters datas have been split into a training set consisting of 6600 samples and a test set consisting of 924 samples. This database will be upgraded in an incoming work.
Before collection of datas, the following points were decided to make the database as much representative as possible. Common factors responsible for variations in handwriting styles include age, sex, education, profession, writing instrument, writing surface, (Figure 4). No restriction was imposed on the writers except for specifying rectangular regions for writing isolated characters of different sizes. Since such rectangular regions are large enough, the restriction may not be considered as a serious one.

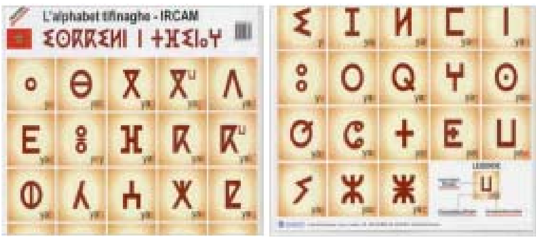

Figure 3: the Amazighe alphabet adopted by IRCAM

The forms are scanned at 300 d.p.i. and stored as grayscale BMP images of 100 × 100 size. Samples of isolated characters from the present database are shown in Figure 4.In some cases a character may touches or crosses the horizontal or vertical lines of the bounding box. Therefore two types of errors may happen, In the major error case, some character's dots or some complementary strokes of it were omitted and the result was not distinguishable, but in the minor error case, usually the last part of the character was missed.

Figure 4: a sample of the characters set representing the Amazighe alphabet written by writers

Here, it may be noted that the character data arising from scanning operation have wide variety of background arising from different paper quality and variations in color or gray shades. However, we did not maintain any color information in our database.

4- Features extraction

For extracting the feature, the moment based approach is proposed. The most important aspect of handwritten recognition scheme is the selection of good feature set, which is reasonably invariant with respect to shape variations caused by various writing styles. The major advantage of this approach stems from its robustness to small variation, ease of implementation and provides good recognition rate. Moments based feature extraction method provides good result even when certain preprocessing steps like filtering, smoothing and slant removing are not considered. Especially, the advantages of considering orthogonal moments are that they are shift, and scale invariants and are very robust in the presence of noise [34], [35]. The invariant properties of moments are utilized as pattern sensitive features in classification and recognition applications [15], [36].
In this section, we explain the concept of feature extraction method used for extracting features for efficient

classification and recognition. The following paragraph explains in detail about the feature extraction methodology. Statistical moments represent average values of processes (powered to order n) when a random variable is involved. Here, the original images were considered as two dimensional arrays of a random variable of dimension $N \times N$. The random variables took values from level 0 to 255, as the images were considered in gray levels quantized in 8 bytes
(Gray levels were obtained from BMP format). Moments were calculated for the random variable X, which was identified with the image block. In addition, X is a matrix of two coordinates (x, y) obtained from the image matrix $f(x, y)$. The definition of $(p+q)$ order invariant moment around the origin is given by:

The Legendre moments of order $(p + q)$ are defined for a given real image intensity function $f(x, y)$ as

$$\lambda_{p,q} = \frac{(2p+1)(2q+1)}{4} \int_R \int_R P_p(x) P_q(y) f(x,y)\, dx\, dy \quad (1)$$

Where $f(x,y)$ is assumed to have bounded support

The Legendre polynomials $P_p(x)$ are a complete orthogonal basis set on the interval $[-1,1]$ for an order p they are defined as

$$p_p(x) = \frac{1}{2^p p!} \frac{d^p}{dx^p} (x^2 - 1)^p \quad (2)$$

The orthogonality property is guaranteed by the equality

$$\int_{-1}^{1} p_p(x) p_q(x) dx = \frac{2}{(2p+1)} \delta_{p,q} \quad (3)$$

Where $\delta_{p,q}$ is the Kronecker function, that is,

$$\delta_{p,q} = \begin{cases} 1 & if\ \ p = q \\ 0 & otherwise \end{cases} \quad (4)$$

4-1-Image reconstruction by Legendre moments

By taking the orthogonality principle into consideration, the image function $f(x,y)$ can be written as an infinite series expansion in terms of Legendre polynomials over the square $[-1,1] \times [-1,1]$:

$$f(x,y) = \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} \lambda_{p,q} P_p(x) P_q(y), \quad (5)$$

Where the Legendre moments are computed over the same square
If only Legendre moments of order smaller than or equal to θ are given, then the function $f(x,y)$ can be approximated by a continuous function which is a truncated series:

$$f_\theta(x,y) = \sum_{p=0}^{\theta} \sum_{q=0}^{p} \lambda_{p-q,q} P_{p-q}(x) P_q(y), \quad (6)$$

Furthermore, $\lambda'_{p,q}s$ must be replaced by their numerical approximation which will be pointed out on the following section. The number of moments used in the reconstruction of image for a given θ is defined by

$$N_{total} = \frac{(\theta+1)(\theta+2)}{2} \quad (7)$$

4-2-Approximation of the Legendre moments

In practice the Legendre moments have to be computed from sampled data, that is, the rectangular sampling of the original image function $f(x,y)$, producing the set of samples $f(x_i, y_j)$ with an (M, N) array of pixels, thus we define the discrete version of $\lambda_{p,q}$ in terms of summation by the traditional commonly used formula [14]:

$$\tilde{\lambda}_{p,q} = \frac{(2p+1)(2q+1)}{4} \sum_{i=1}^{M} \sum_{j=1}^{N} P_p(x_i) P_q(y_j) f(x_i, y_j) \Delta x \quad (8)$$

Where $\Delta x = (x_i - x_{i-1})$ and $\Delta y = (y_j - y_{j-1})$ are sampling intervals in the x and y directions.
It is clear, however, that $\tilde{\lambda}_{p,q}$ is not a very accurate approximation of $\lambda_{p,q}$, in particular, when the moment order $(p+q)$ increases
The piecewise constant approximation of $f(x,y)$ proposed recently by Liao and Pawlak [21, 37], yields the following approximation of $\lambda_{p,q}$:

$$\tilde{\lambda}_{p,q} = \sum_{i=1}^{M} \sum_{j=1}^{N} H_{p,q}(x_i, y_j) f(x_i, y_j), \quad (9)$$

With the supposition that $f(x,y)$ is piecewise constant over the interval

$$\left[x_i - \frac{\Delta x}{2}, x_i + \frac{\Delta x}{2}\right] \times \left[y_j - \frac{\Delta y}{2}, y_j + \frac{\Delta y}{2}\right] \quad (10)$$

And where

$$H_{p,q}(x_i, y_j) = \frac{(2p+1)(2q+1)}{4} \int_{x_i-\Delta x/2}^{x_i+\Delta x/2} \int_{y_j-\Delta y/2}^{y_j+\Delta y/2} P_p(x)P_q(y)dxdy \quad (11)$$

represents the integration of the polynomial $P_p(x)P_q(y)$around the (x_i, y_j) pixel.
This approximation allows a good quality of reconstructed images by reducing the reconstruction error.
In this paper, we determine the order of the truncated expansion of $f_\theta(x, y)$ which provides a good quality of the reconstructed object. The moments used in this reconstruction process will constitute the optimal subset for representing this object. Then, we introduce the Maximum Entropy Principle (MEP) to extract relevant moments that uniquely represent the patterns [9], [38], [39]. By applying the Maximum Entropy Principle the entropy function monotonically increases up to a certain optimal order where sufficient image information is recreated and then become relatively constant [9].

5-Classification and recognition

Neural network is widely used as a classifier in many handwritten character recognition systems [15], [40]. Also, due to the simplicity, generality, and good learning ability of neural networks, these types of classifiers are found to be more efficient [15]. In this paper, multilayer feed forward neural network (MFNN) is used to classify the patterns. In our algorithm, the stochastic gradient algorithm as a minimization procedure is used during the learning phase. The weights are updated on the basis of a single sample.
The inputs of the MFNN are feature vectors derived from the proposed feature extraction method described in the previous section. The number of nodes in the output layer is set to the number of Amazighe characters classes.
Experiments were conducted using the initial weight vectors that have been randomly chosen from a uniform distribution in (-1, 1), this weight range has been used in [41], [42].
Structure of MLP network for English character recognition is shown in Figure 5.
In this paper, a neural network is used as a classifier in character recognition where the inputs to the neural network are feature vectors derived from the proposed feature extraction technique described in the previous section [43].

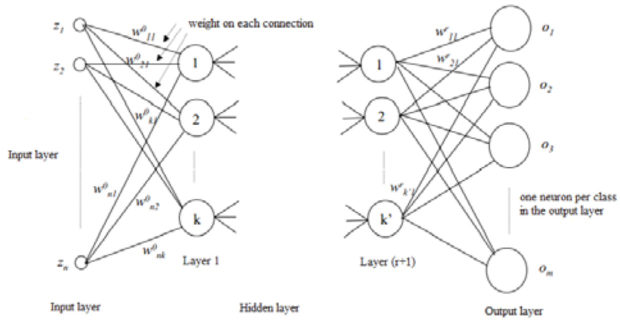

Figure 5: Multi-layer-Perceptron neuronal network

The output of each node is a pondered sum of its inputs:

$$o_i = \varphi(a_i) = \varphi(\textstyle\sum_{k=1}^{N}(w_{ik}z_k)) \quad (12)$$

With $Z_k$the k^{th} composant of sample vector.
W_{ik} is the weight of the connection which rely unit k and unit i.
a_i is the activation of the unit i.
φ is the activation function of the units which is a threshold function with the following expression :

$$\varphi(x) = \begin{cases} -1, & x < \theta \\ +1, & x \geq \theta \end{cases} \quad (13)$$

Our procedure of handwritten Amazighe character recognition is given below

- Capture the scanned characters into 100x100 pixels
- Apply our proposed Feature Extraction method without any image preprocessing
- Implement the Neural Network Classifier with the subset already extracted
- Get the recognized character.

A complete flowchart of handwritten English character recognition is given below in Figure 6

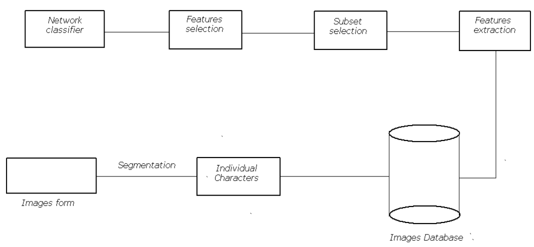

Figure 6: System for Amazighe character recognition

6-Experimental results

In this experiment, we are interested in determining how well the pre-trained recognizer works for a new user under classification methods. Each time, a different individual's data set is held out for a test set, and the neuronal classifier is trained with all other users' data and then tested on the holdout set. For each round, there are 6600 characters for training, and 924 characters for testing.

The training and testing data were different; even more the data used for testing were outside training set. The Training dataset consists of 200 samples for character, and the testing dataset consists of 28 samples for each character of different handwritten, some data samples are shown in figure 7. Back propagation algorithm is used for the training of the Neural Network. At the training time, weight and bias will be updated in each iteration if there is a difference between the computed output and the target.Table 1 shows the recognition rate of multiples orders of moments,the classifier recognition rate (%) is considered as the number of recognized characters in the training (test) phase over the total number of characters.

Table 1: rate of recognition of different moments order

order	10	15	20	25	30	35
Recognition Rate (%)	97,2	97,3	97,8	97,7	96,8	96,5

Figure 7: the classes' prototypes chosen for our recognition problem

Table 2: moments order of recognition of different samples

Optimal order of recognition	Char 1	Char 2	Char 3	Char 4	Char 5	Char 6
Sample 1	15	20	22	20	25	20
Sample 2	18	20	18	20	22	16
Sample 3	25	22	23	20	17	21
Sample 4	24	18	20	19	18	23
Sample 5	20	26	17	21	21	20
Mean order	21,4	21,2	20	20	20,6	20

Table 2 shows optimal orders obtained by our moment extraction algorithm, for a sample of handwritten characters

Table 3: different test error rates obtained with different MFNN architectures (one hidden layer), where the feature subset size is 231 corresponding to order 20

Architecture	τ(%) On the test set
231-100-33	3,92
231-200-33	3,78
231-300-33	2,92
231-400-33	2,59
231-500-33	2,40
231-600-33	2,38
231-700-33	2,80

The classifier error rate τ (%) is considered as the number of misclassifications in the training (test) phase over the total number of training (test) images.

First, the comparison of many different architecture is considered, using the same dataset test without any pre-processing. The results obtained are provided in Table 3.

The results show that increasing the number of hidden nodes, improves performance considerably, but over a number of nodes we have overtraining which decrease considerably performances.

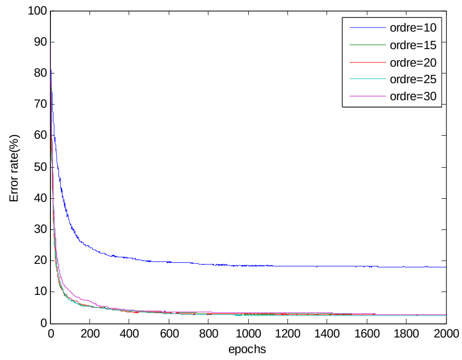

Figure 9: Error recognition rate by number of iterations, of different moments order for the same neural architecture (one hidden layer)

Through figure 9, we see that while augmenting the moment order we have a better rate of error, the best results are obtained with the order of 20.

Table 4: Error rate by number of hidden layers

Number of hidden layers	1	2	3
Error rates	2,38%	5,5%	8,7%

A close inspection of Table 4, shows that the recognition rate using one hidden layer is higher than those obtained by two and three hidden layers, but error rates and computing time using two hidden are less than those obtained by one hidden layer.

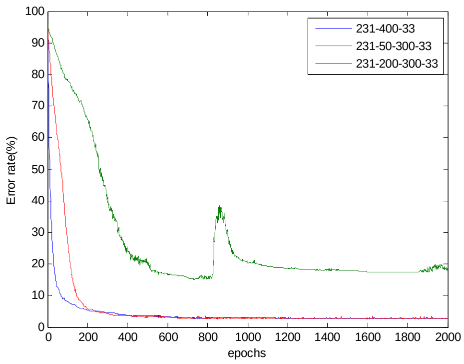

Figure 10: Error rate of different architectures for moment order set to 20

We see that the number of hidden nodes influences heavily the network performance. Insufficient hidden nodes will cause under fitting where the network cannot recognize the characters because there are not sufficient adjustable parameters to model the input-output relationship.
Excessive hidden nodes will cause over fitting where the network fails to generalize. There is no theoretical development based on which, the optimal number of neurons in the hidden layer can be determined.

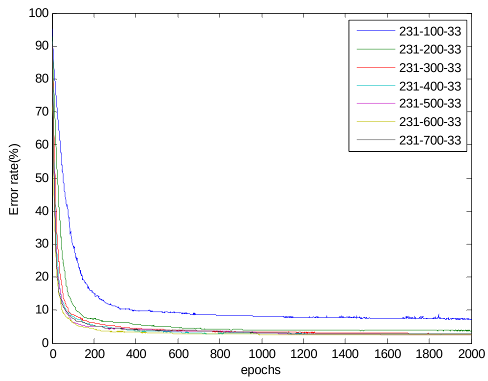

Figure 11: Error rate of the same architecture (one hidden layer) and different number of nodes

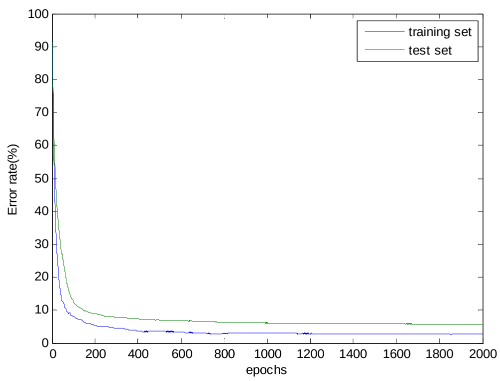

Figure 12: Training and test rates of the ANN versus 2000 iterations

Figure 11shows the behaviour of the error rates on the test set, with fixed neural network architecture and different nodes, this shows that better classification results are obtained with more nodes
Error rates on both sets usually go up and down simultaneously. However, if the neural network is trained again and again and more than the needed information is provided, the error rate on the training set continues to decrease but it will revert on the testing set. This situation is called over-training. The relationship between error rate on training and testing sets is shown in Figure 12.
From Table 4 we can see that neural network method with, hidden layers (only one hidden layer) and hidden nodes can easily provide excellent results in terms of test error.
The recognition converges faster when a number of iterations is great, due to the very small number of training examples.
We believe, it is because there is a great level of consistency in how a user draws shape (character). Of course, the more examples, the better is to train the recognizer and two different samples.
The designing of a feed forward structure that would lead to the minimizing of the generalization error, of the learning time and of the network dimension implies the establishment of the layer number, neuron number in each layer and interconnections between neurons. At the time being, there are no formal methods for optimal choice of the neural network's dimensions.
The choice of the number of layers is made knowing that a two layer network (one hidden layer) is able to approximate most of the non linear functions demanded by practice and that a three layer network (two hidden layers) can approximate any non linear function. Therefore it would result that a three layer network would be sufficient for any problem. In reality the use of a large number of hidden layers can be useful if the number of neurons on each layer is too big in the three layer approach.

7-Conclusion

An improved method of construction for handwritten character recognition has been presented. The Legendre moments features used for character recognition are shown to be effective for developing training and test sets which have improved generalization capability.
Further improvements can be made by using more realistic training data and by modifying the hidden layers of the ANN to be sensitive to shifts of characters. The system showed good performance (97%) on a database of 7524 handwritten Amazighe characters.

The results of structure analysis show that if the number of hidden nodes increases the number of epochs (iterations) taken to recognize the handwritten character is also increases. A lot of efforts have been made to get higher accuracy but still there are tremendous scopes of improving recognition accuracy by developing new feature extraction techniques or modifying the existing feature extraction technique

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