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# ENHANCED FEATURE EXTRACTION OF HANDWRITTEN CHARACTERS AND RECOGNITION USING ARTIFICIAL NEURAL NETWORKS

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## ABSTRACT

This paper presents an unconstrained system for off line handwritten Amazigh character recognition based upon Legendre moments and neural networks. Legendre moments are used in features extraction phase and optimized by maximum entropy principle. Neural networks methods are chosen due to their natural flexibility and the extent of parallel processing they allow. The performance rate of our proposed scheme is strongly influenced positively upon the feature extraction algorithm that has been applied in this work. The method is robust to different styles of writing, different levels of smoothing and insensitive to the nuances of characters. Also it is performing to the translation, scale invariance. The performance of the proposed method is examined in terms of Legendre moments order and neural networks size and architecture. Features like pixel density features and Euclidean distance features are extracted from the normalized characters. The two features are applied to two different neural networks. A comparison of these techniques and our method is made. Through comparison with cited methods, the proposed method has significantly advanced and the recognition rate reaches 97.46%.

**Keywords:** *Offline character recognition, Features extraction, Legendre Moments, Neural Networks, Multilayer Perceptron*

## 1. INTRODUCTION

In the past years, many approaches have been used to solve the problem of character recognition, first for printed characters and then extended to handwritten numbers and characters in many languages scripts [1-6]. In fact, until today, handwritten character recognition is still a challenging problem, because of different difficulties: wide variability of writing styles, accuracy of acquisition device, physical and mental state of the writer. For that, in recent years, there has been intense research works done on different languages script. However, less attention had been given to Amazigh script recognition and is quite a challenging task due to several reasons: Especially, the Amazigh script shows additional difficulties: the large category of alphabet sets, the shape of the characters is complex and they may have diacritic signs present above, similarity between different characters [7]. Indeed, this field of research is quite open and promising.

In this paper, a scheme, which aims to combine neural networks classifier with features extraction and selection method based on Legendre moments, is proposed to improve the recognition rate. Our proposed handwritten character recognition system is composed of four main stages: segmentation, normalization, features extraction and selection, and neural network classification. Segmentation produces isolated characters, after a preprocessing phase which is limited to the normalization, then, characters are fed to the features extraction and selection unit where pertinent Legendre moments features using the Maximum Entropy Principle (MEP) criterion are selected. Finally, characters are classified with Artificial Neural Networks (ANN) based on Multiple Layer Perceptron (MLP) [8], trained with back propagation algorithm [9]. The main purpose is to evaluate experimentally the behavior of the neural networks classifier in terms of Legendre moments order and ANN architecture and size.

It's important to mention that the used Amazigh alphabet database offer the following advantages:

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- Unconstrained: no restriction was imposed to the scripter;
- Variability of scripters with respect to sex, age, profession and cultural level,
- No preprocessing is needed.

Furthermore, the Multi-Layer Perceptron (MLP) trained with back-propagation algorithm is among the forms of neural networks classifiers that have shown a good power and performance [10-11] and have been successfully applied to character recognition systems with small error margins.

However, those classifiers are strongly affected by the quality of the pattern representation i.e. features. Consequently, in this work, we present an efficient feature extraction and selection method based on orthogonal Legendre moments which are nonlinear and invariant under translation, scaling, and image reversal. Indeed, we suggest the Maximum Entropy Principle (MEP) [12] as features selection criterion that produces finite optimal moments order, carrying out only moments containing sufficient and pertinent information needed for classification. Through experimental results, we will show that this method improve the recognition rate by the neural classifier.

The choice of Legendre moments is made due to the reduced computational complexity and their advantage against Zernike moments that employs the summation with square pixel over a circular region. This involves a geometric error in the digital version [13]. This is in contrast with the situation for Legendre moment descriptors employing rectangular integration regions.

The main contributions of our method can be summarized as follows:

- Discriminating between resembling characters which is inherent to the Amazigh writing,
- Avoiding the misclassification of some characters obtained by simple rotation of other characters,
- Solving the problem of the input layer of neural network using MEP,
- Proceeding without any preprocessing of characters samples.

The researchers have exposed many different algorithms. These algorithms have received a wide range of features and classifier types. Every algorithm has characteristics that are useful for specific applications, such as high accuracy, high speed, good thresholding performance, and generalization ability. This paper will outline the practical results of one of these classifiers: MLP, associated to our feature extraction method and a comparison of results between our method and pixel density features and Euclidean distance features methods has been reported on the same database.

The organization of the paper is as follows: In the coming section, we describe the proposed Amazigh database and characteristics of Amazigh script used in our system. Section 3 points out the proposed method of moment features extraction. Section 4 explains the neural classifier used. Section 5 is devoted to experimental results. Finally, Section 6 draws conclusion and summarizes the paper.

## 2. OVERVIEW OF DATABASE AND CHARACTERISTICS OF AMAZIGH SCRIPT

### 2.1. Characteristics of Amazigh Script

The Amazigh script contains a large category of alphabet sets. The most important are: oriental and occidental Libyan berber, Saharian tifinagh and neo-tifinagh like tifinagh-IRCAM (Figure 1). In this paper we have chosen tifinagh-IRCAM adopted by the Royal Institute of the Amazigh culture, because it's officially recognized by the international organization of standardization (ISO) as the basic multilingual plan [14].

Tifinagh alphabet compared to Libyan or Saharian alphabet (Figure 1), contains 33 characters, but Unicode codes only 31 letters plus a modifier letter to form the two phonetic units [14], written horizontally from left to right, and letters within a word are not joined. There is no connection between separate words, so word boundaries are always represented by a space. Characters are consisted by loops, curves and lines. As shown in table 1 some characters have the same shape and differ only by rotation or by the addition of secondary parts, this, increases the complexity of recognizing those characters.

So, the features and the classifier chosen must be enough discriminate to separate resembling characters. Our purpose is to point out this problem and to propose a discriminate recognition system to resolve it.

*Figure 1: Amazigh Alphabet.*

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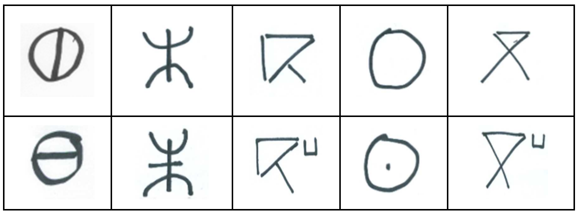
*Table 1. Resembling Characters in Tifinagh Alphabet.*



### 2.2 Database Collection

Few works of Amazigh recognition systems have been published, using specific, more or less small dataset of their own, or they use large databases that are not available to the public, furthermore, existing databases are constructed with much restrictions imposed to writers.

In order to evaluate our recognition system we use a local database constructed in our laboratory and collected from separated sets of writers.

Our database has the following characteristics:

- Unconstrained;
- No pre-processing: no skew correction;
- Large variability of scripters: sex, age, profession.

In this section we give a description of all steps we undertook to build our database.

#### 2.2.1 The form

Our goal was to collect images of handwritten characters, with the following conditions:

- write without strong constraints;
- Provide sufficient information about the writer: age, profession, and identity.

Each writer was asked to fill four forms of alphabet, so one had to write 132 characters.

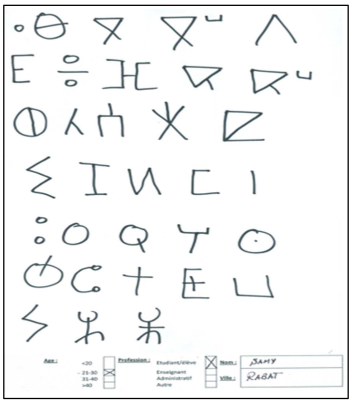


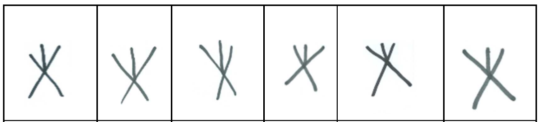
*Figure 2: Sample of a Filled Form*

#### 2.2.2 Form processing

Before analyzing the different processing steps, we should mention that we are especially interested at the offline processing. For our case, the acquisition is made with a numeric scanner of resolution 300 dpi, images are stored as grayscale BMP images of 100 × 100 size, with 8 bits/pixels, the used samples are all possible classes of the handwritten Amazigh alphabet with free writing sizes and variable thickness (all the subjects used different felt tip pens). Figure 2 shows a sample of the used forms.

The handwritten characters samples were acquired from various persons both male and female of different age groups. The group writers is of 57 one, with 20 of female persons. Their handwriting was sampled on A4 size paper. As we can see in table 2, the resulting characters exhibit variations in slant, stretch, scale, and translation.

*Table 2. Handwritten Forms (b, c, d, e, f, g) of The Character "YAZ" of Different Transformations.*



| | | | | | |
|---|---|---|---|---|---|
| (A) Regular | (B) usual | (C) stretch | (D) slant | (E) translate | (F) scale |

No restriction was imposed on the writers. After segmentation and labeling of the character images, Normalization is applied to all images in order to regulate the size, position, and shape of character images, to reduce the shape variation between the images of same class.

The database contains a total 7524 isolated characters, gathered from 57 different and independent writers, The whole set of available isolated characters data have been split into a training dataset consisting of 6600 characters taken randomly for training the classifiers, and a testing set consisting of 924 characters.

## 3. FEATURES EXTRACTION AND SELECTION

Features extraction stage plays a major role in improving recognition accuracy [15] in any character recognition system. Hence, selection of a feature extraction method is probably the single most important factor in achieving high recognition performance [16].

For this purpose, it is important to characterize the good features, which should satisfy the following conditions:

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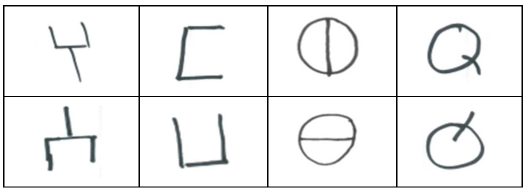
- Invariance to transformations: the image features should be as invariant as possible to image transformations including translation, rotation, and scaling, etc [15].
- Discrimination power: in the sense of minimizing the within-class pattern variability while enhancing the between–class pattern variability [17].
- Robustness to noise: the image features should be robust to noises and various degraded situations [12].
- Computational cost: the extraction algorithm should require a reasonable computational time [18].

Moments as features satisfy the invariance property [18], robustness to noise [12], computational cost [17, 18]. Furthermore, moments satisfy the reconstructability property [17], which ensures that complete information about character shape is present in the extracted features. So the characters can be reconstructed from the extracted features.

In this paper, we choose to use Legendre moments due to their invariance to the basic geometric transformations such as translation and scaling [19], and their robustness in the presence of noise [12]. In the case of Amazigh alphabet, rotation image invariance is not desirable, so using Zernike moments which are rotation invariant may involve confusion between some characters (Table 3), which can lead to 12% of misclassified characters over the alphabet set.

*Table 3. Different Characters Obtained By Rotating Others*



Furthermore, Moments based feature extraction method provides good result even when certain preprocessing steps like filtering, smoothing and slant removing are not considered. In the next section we will describe Legendre moments and their properties.

### 3.1 Pixel Density Features

Many characters are almost similar in shape and show a difference in only some part or portion of the character. Some character pairs show the difference in their shape in a smaller region. To explore the regions of dissimilarity between the characters, The characters are partitioned into 100 non-overlapping zones of size 10x10 and the number of pixels in each zone is calculated. These 100 features are applied as inputs to the neural network.

Features based on pixel density are calculated directly from the size-normalized image I as follows [20]: The total number of features based on pixel density is $N*M$ while the total number of features based on zone characteristics is $2*N*M$. All features range from 0 to 1.

$$d = \frac{1}{N*M} \sum_{x=1}^{M} \sum_{y=1}^{N} I(x,y) \qquad (1)$$

These features capture the general groupings of pixels in the image. A sampling grid of the size of 10x10 is placed on the image, and the density is computed for each grid zone by counting the number of image pixels that fall into each grid.

Thresholding converts these area counts into a single bit for each region. The feature vector of the experiments is designed to contain the densities of 10x10=100 zones for each image.

### 3.2 Euclidean Distance Features

The second method of feature extraction calculates the Euclidean distance in a character. The Euclidean distance computes the distance of the features within the character. It is calculated in both horizontal and vertical direction yielding 200 features. The distance between pixels can be measured using Euclidean distance in which the value at a pixel is linearly proportional to the Euclidean distance between that pixel and the object pixel closest to it [21]. The Euclidean distance d between two pixels $(i, j)$ and $(k, l)$ is:

$$d[(i,j),(k,l)] = \sqrt{(i-k)^2 + (j-l)^2} \qquad (2)$$

Thus the Euclidean distance between a pixel and the nearest nonzero pixel of the binary character is found in a 100 × 100 character image and the 200 features obtained are applied to neural network.

### 3.3 Legendre Moments

Statistical moments represent average values of processes (powered to order n) when a random

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variable is involved. Here, the original images were considered as two dimensional arrays of a random variable of dimension N×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 obtained from the image matrix.

Legendre moments of order (p + q) [22], are defined for a given real image intensity function as

$$L_{p,q} = \frac{(2p+1)(2q+1)}{4}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} P_p(x)P_q(y)dxdy \qquad (3)$$

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

$p, q = 0,1, \ldots, \infty$

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:

$$P_p(x) = \frac{1}{2^p p!}\frac{d^p}{dx^p}(x^2-1)^p \qquad (4)$$

### 3.4 Features Subset Selection Using MEP

In this paper, the recognition of characters will be considered in a straight link with the reconstruction process. So a features subset used in recognition process is exactly the same which is needed in reconstruction until an order. The function can be approximated by a truncated series [22], having only Legendre moments of order smaller than or equal to:

$$f_\theta(x, y) = \sum_{p=0}^{\theta}\sum_{q=0}^{\theta} L_{p-q,q}P_{p-q}(x)P_q(y) \qquad (5)$$

Where $L_{p-q,q}$ is Legendre moment of order p calculated refer to equation (3).

The number of moments used in the recognition for a given θ is defined by:

$$N_{total} = \frac{(\theta+1)(\theta+2)}{2} \qquad (6)$$

To ensure good reconstructed characters from the extracted features, the complete information about the character shape should be present in the extracted features. Indeed, exact reconstruction may require an arbitrarily large number of features, reasonable approximations of the original character shape can usually be obtained by using a small number of features with the highest information content [22].

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 and recognizing this object. Then, we introduce the Maximum Entropy Principle (MEP) to extract relevant moments that uniquely represent the patterns [12, 22].

Here, we introduce The MEP which permit to estimate the optimal number of moments directly from the available datas and does not require any a priori image information

Let $F_w$ be a set of estimated underlying probability density function for various Legendre moment orders θ:

$$F_w = \{\hat{p}_\theta / \ \theta = 1, \ldots\ldots, w\} \qquad (7)$$

Probability density function denoted $\hat{p}_\theta^*(x_i, y_j)$, which represent the optimal probability density function, gives the optimal order of moments [12].

The Shannon entropy of $\hat{p}_\theta^*(x_i, y_j)$ is defined as:

$$S(\hat{p}_\theta^*) = -\sum_{x_i, y_j \in \Omega} \hat{p}_\theta(x_i, y_j)\log(\hat{p}_\theta(x_i, y_j)) \qquad (8)$$

And the optimal $\hat{p}_\theta^*$ is such that

$$S(\hat{p}_\theta^*) = \max\{s(\hat{p}_\theta) / \ \hat{p}_\theta \in F_w\} \qquad (9)$$

The process of determining the optimal order θ, consists in estimating the the probability density function. For different orders and selecting the one and only one for which the entropy reaches maximum. The entropy function monotonically increases until a certain optimal order which

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correspond to the maximum image information, and then still relatively constant.

The following is the basic algorithm which consists in an exhaustive search to determine the optimal order which maximizes $S(\hat{p}_\theta^*)$:

1-Initialize $\theta$;
2-Compute the p.d.f. $\hat{p}_\theta$;
3-If $\hat{p}_\theta$ is maximum, then $\theta$ is optimal and $\hat{p}_\theta = \hat{p}_\theta$; else $\theta = \theta + 1$ and go to 2.

The optimal order is the mean of different optimal orders obtained from different characters samples. This will be used to select an informative subset as input for neural network classifier. This latter will be detailed in the coming section

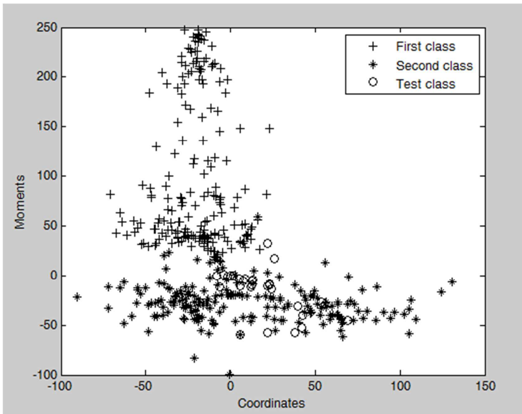


*Figure 3: Decision Regions of Legendre Moments*

Figure 3 shows the decision regions of a two class problem with 231 samples of two classes (two character), and the test class which will be affected to the class using Euclidean distance.

It's clear from the figure that Legendre moments have extreme discrimination power. The two classes are well separated in the space and the test set that is belonging to class 2 is clearly separated from class 1 and belong to the same region as class 2.

## 4. CLASSIFICATION AND RECOGNITION

Many classification techniques have been applied to handwritten character recognition. The most used are statistical methods based on Bayes decision rule [23], Support Vector Machines (SVMs) [24], artificial neural networks, especially, multilayer perceptron (MLP) [25], and Hidden Markov Models (HMM) [26].

In this paper we choose using artificial neural network for the following properties: [10, 11]

- The capability of neural network to generalize;
- The insensitivity to the missing data which is very beneficial in recognizing handwritten characters;
- Fast, parallel and compact approach for processing the extracted features of the isolated characters.

The proposed Amazigh handwritten character recognition system uses a neural network approach to recognize the characters, based on Feed forward Multi Layered Perceptron (MLP) network trained using back-propagation algorithm. In order to evaluate the performance of the proposed method, we compare it with pixel density features and Euclidean distance features methods, all the methods use the same database.

### 4.1 Multi Layer Perceptron

Our multi layer perceptron is a feed-forward neural network with one or more layers of nodes between the input and output layers. These in-between layers are called hidden layers. All neurons have a single sigmoid output. Each node in a layer is connected to the all nodes in the next layer. Using MLP in the context of a classifier requires all output nodes to be set to 0, except for the node that is marked to correspond to the class the input is from.

We have designed a simple unconstrained character recognizer based on a multilayer perceptron (MLP) with multiple hidden layers. Network output estimates a posteriori probabilities and the value of each output, necessary remains between zero and one because of the sigmoid function used (Figure 4).

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 Amazigh 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 [27].

The networks are trained and tested on different datas. Before training, the weights (connection strengths) in each network were independently set to random initial values.

The performance of the proposed method is examined in terms, Legendre moments order and neural networks size and architecture.

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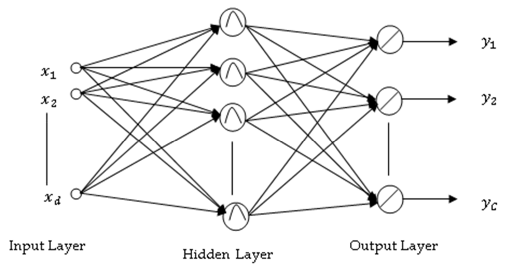

*Figure 4: Feed-Forward Multilayer Perceptron (AT&T and BeLL Laboartories)*

## 5. EXPERIMENTAL RESULTS

Our procedure of handwritten Amazigh character recognition is given below

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

A complete flowchart of handwritten Amazigh character recognition is given below in Figure 5

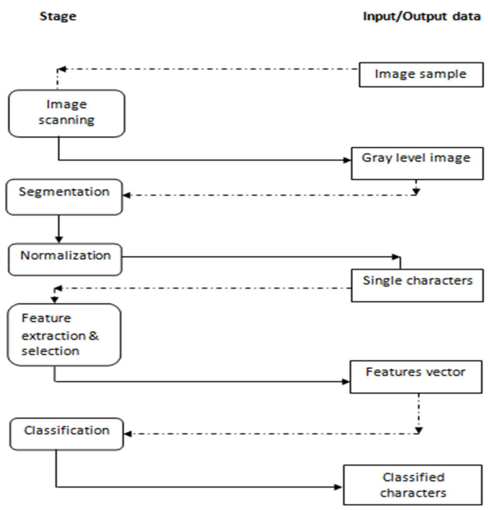

*Figure 5: Synoptic Diagram of The Proposed System*

The existing papers in the field of Amazigh recognition carried out completely different databases, it is then non convenient to compare our method with other works. We will hence describe some important results in the literature. In fact, The Recognition scheme proposed in [28], has an accuracy of 93.63%. The scheme proposed by B. El Kessab and al [29] is a hybrid model MLP/HMM and has an accuracy of 92.33%. They tested their scheme on 7200 samples of Amazigh character.

The experimental results will first show the performances of the proposed MLP with optimized set of the moment's features. An exhaustive exploration is studied where we will see the effect of Legendre moments order, the behavior of the proposed neural network with respect to two databases of different sizes. This will prove if the proposed method has great generalization ability. Then we will see the best neural network architecture for the problem at hand by varying the hidden layers and the nodes number in each one.

Finally, a comparison study is carried out with the pixel density features and Euclidean distance features methods

Experiments will test the classification power of the proposed neural network with respect to datas in our database composed of 7524 characters, 6600 characters for training and 924 for testing. At the training time, for each iteration, weights and bias will be updated, once there is a difference between the computed output and the target. Figure 6 shows recognition rate for different moment orders, of our neural network with one hidden layer of 400 nodes. Order 20 is the best order which correspond to the optimal one obtained by MEP.

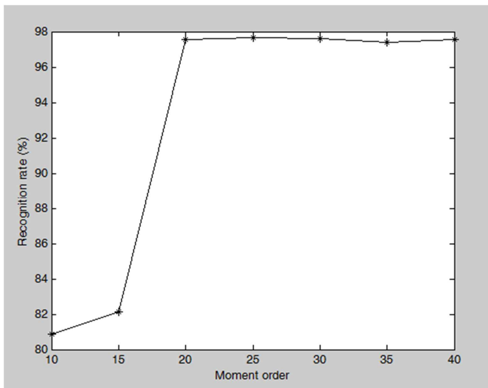

*Figure 6: Recognition Rate versus Moments Order*

This shows that the proposed method composed of feature selection by MEP and neural classifier gives good results. Note that the optimal moment order obtained is 20 that correspond to 231 input nodes of the neural network.

In order to see the best neural network architecture for the problem at hand, we will vary the hidden layers and the nodes number in each one. Table 4, presents the recognition and error rates with different hidden layers.

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*Table 4. Recognition Rate, Error Rate Versus Hidden Layers*

| Number of hidden layers | Recognition rate | Error rates |
|---|---|---|
| 1 | 97,62% | 2,38% |
| 2 | 94,5% | 5,5% |
| 3 | 91,3% | 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, 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.

In fact, this corresponds to the universal approximation capability UAC theorem that asserts that a single hidden layer of neurons would be sufficient for approximating any given function [30]. As such, the use of additional layers of hidden neurons might lead to fewer neurons being required, but the number of connections between these layers would necessarily increase, which in turn would lead to a more complex, unwieldy structure being evolved [31].

For one hidden layer, we will vary the nodes number to see the effect of hidden nodes to the recognition rate. Figure 7 exhibits recognition rate versus total number of nodes for the test data.

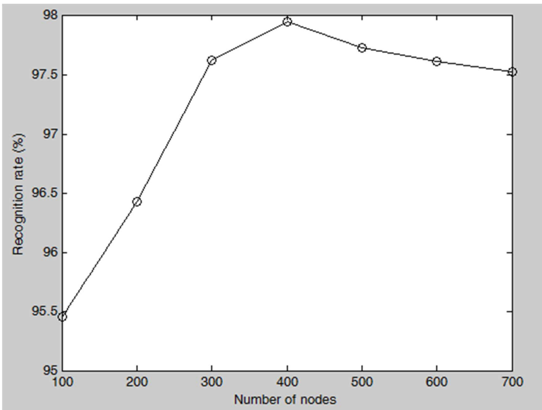


*Figure 7: Recognition Rate versus Total Number of Nodes*

Recognition rate reaches the best value with 400 nodes, and while this number of nodes increases the ability of recognition decrease, it is due to overtraining.

In Table 5, we present error rate obtained for each character of the alphabet. These results correspond to our system with on hidden layer of 400 nodes.

All performances are about 95%, and the differences depends on the shape of each character.

*Table 5: Recognition Rates For Amazigh Letters.*

| Character | Error rate (%) | Character | Error rate (%) |
|---|---|---|---|
| ⴰ | 2,38 | ⵊ | 2,16 |
| ⴱ | 2,27 | ⵍ | 1,84 |
| ⴳ | 1,84 | ⵎ | 2,49 |
| ⴳⵯ | 4,11 | ⵏ | 2,06 |
| ⴷ | 2,06 | ⵓ | 1,62 |
| ⴹ | 3,9 | ⵔ | 4,55 |
| ⴻ | 2,49 | ⵕ | 1,3 |
| ⴼ | 2,71 | ⵖ | 1,08 |
| ⴽ | 2,16 | ⵙ | 4,55 |
| ⴽⵯ | 3,14 | ⵚ | 2,16 |
| ⵀ | 3,79 | ⵛ | 2,27 |
| ⵃ | 2,06 | ⵜ | 1,73 |
| ⵄ | 2,81 | ⵟ | 4,22 |
| ⵅ | 2,81 | ⵡ | 2,92 |
| ⵇ | 1,62 | ⵢ | 1,3 |
| ⵉ | 2,27 | ⵣ | 3,14 |
| | | ⵥ | 3,9 |

Table 6 shows the comparison between methods based on pixel intensity features and Euclidean distance features associated with MLP and our proposed method. we find that results are less better than those obtained by our classifier. Moreover, the two other methods requires more time.

*Table 6. Comparison Between The Two Methods and Our Method.*

| Recognition method | Recognition rate (%) |
|---|---|
| Density pixel features + MLP | 94.68 |
| Euclidean distance features + MLP | 95.23 |
| Proposed method | 97.77 |

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*Table 7. Results Of Handwritten Recognition Accuracy Using MLPN*

| Input of the MLPN | No. Of hidden units | No of epochs | Recognition Accuracy(%) | |
|---|---|---|---|---|
| | | | Training Data | Testing Data |
| 231 | 100 | 1000 | 99.2 | 95.45 |
| | 200 | 1000 | 98.7 | 96.42 |
| | 300 | 1000 | 99.5 | 97.61 |
| | 400 | 1000 | 99.8 | 97.94 |
| | 500 | 1000 | 99.7 | 97.72 |
| | 600 | 1000 | 99.7 | 97.61 |
| | 700 | 1000 | 99.7 | 97.50 |
| Average | | | 99.47 | 97.11 |

In our experiments, we are interested in determining how well the recognizer works for a new user under classification method.

Table 7 indicates network results for different states. For MLP network with 100 to 700 nodes in hidden layer and with equal iterations, and we see that network with 400 nodes gives the best recognition rate of 96% in test set.

The found nodes number correspond with the well-known first and third rule enounced in [31], usually used to decide the number of neurons in the hidden layer:

- The number of hidden nodes should be less than twice the input layer size.
- The number of hidden nodes should be in the range between the size of the input layer and the size of the output layer.
- The number of hidden neurons should be 2/3 of the input layer size, plus the size of the output layer.

It is important to note here that the system performs extremely well with recognition rates ranging between 93% and 99% on different nodes and the overall recognition is 93.88%. This is a very good performance taking into account the fact that we have a limited number of samples in each class and that we have not used any noise filtering techniques. The recognition on the training data is also extremely high, 99.4%, which represents a very good training performance.

By analyzing the results, it shows that insufficient hidden nodes will cause under fitting where the network cannot recognize the characters because there are not sufficient adjustable weights to model the input-output relationship. Excessive hidden nodes will cause over fitting where the network fails to generalize.

## 6. CONCLUSION

In this paper we have explored an off line system for the recognition of the handwritten characters. The work involved is divided in two big parts:

- The realization of a system of isolated characters recognition: in this case, the study is based, mainly, on the evaluation of neural network performances, trained with the gradient back propagation algorithm. The used parameters to form the input vector of the neural network are extracted on the gray level images of the characters by Legendre moment method, moments features are optimized by maximum entropy principle.
- Evaluating the system with different databases by extension to the widen database by taking in account a bigger number of writers and writing instruments.

This paper can contribute to reduce some of the confusions found in Amazigh handwritten recognition systems. The results obtained by using our approach demonstrating by experiments are very encouraging and promising; therefore, this kind of approach can improve the performance of the
system. However, we foresee the following evolution possibilities:

- the validation of our approach in a different database;
- To improve our system by automating segmentation algorithm;
- Present a method to optimize neural network by new pruning technique

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