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Handwritten Characters Classification Using Neural Networks and Moments Features

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ABSTRACT: *This paper presents unconstrained handwritten Amazighe character recognition based upon orthogonal moments and neural networks classifier. The proposed system extracts moments features from character images. A total of 6600 images were considered for experimentation and overall accuracy found to be 97.46%. The novelty of the proposed method is independence of size, slant, orientation, and translation. The performance of the proposed method is experimentally evaluated and the promising results and findings are presented. Our method is compared to an Euclidian distance criterion and K-NN classifier algorithm, results show performances of our method.*

Keywords**:** *Neural Network, character recognition, orthogonal Moments*

I. Introduction

Character recognition is one of the most challenging topics in pattern recognition, In the past several decades, a large number of OCR systems have been developed for natural languages [1-3]. Handwritten character recognition is difficult due to the large category set, wide variability of writing styles, and the confusion between similar characters.
Artificial neural networks trained with back propagation algorithm are frequently used in the field of pattern recognition and have shown its power and good performance for pattern recognition. However, the performance of those classifiers is strongly affected by the quality of the representation of the pattern i.e. features. Consequently, we present an efficient feature extraction method based on orthogonal Legendre moments.
Hu [4] first introduced the use of seven invariants moments which are defined on moments of the image as features for pattern classification. These moments are nonlinear and invariant under translation, rotation, scaling, and image reversal. Where lower orders of moments are not enough to classify patterns, higher orders will be used, although, the higher orders resulted in higher sensitivity.
In this paper, we use the Maximum entropy principle MEP as feature selection criterion which produces finite optimal moment orders carrying out only moments of low orders containing sufficient and pertinent information needed for classification.
Our classification method is used with different network topologies, compared to other methods as minimum mean distance, nearest neighbor.
In general, the overall recognition process can be divided into 3 main sections, namely segmentation, preprocessing, and classification [6]. Segmentation requires isolating the characters individually before they are fed to the preprocessing unit where the important features of characters (feature extraction) are identified. Finally, classification process is done by determining the category or the group of each character used during the recognition process.
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.

II. Database preparation

2.1. Amazighe language

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 [5]. 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
As far as the alphabet is concerned, and because of historical and cultural reasons, Tifinaghe has become the official graphic system for writing Amazighe [6]. 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: □ □(g^w) and □ □(k^w).[7]. The Fig.1 represents the repertoire of Tifinaghe which is recognized and used in Morocco with their correspondents in Latin characters.

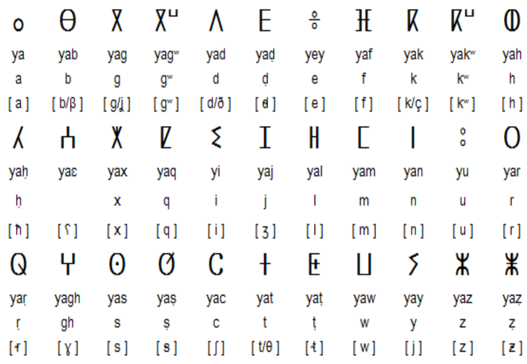

Figure 1: Neo-Tifinaghe alphabet as used in Morocco with their Correspondents in Latin Characters.

2.2. Data collection

Our 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 of unconstrained handwritten characters including 7524 isolated characters, gathered from 57 different and independent writers, 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. 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. 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.

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 Fig. 2. 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.

The characters prepared as explained in previous Section, are scanned using a scanner and these characters will be segregated according to their own character group. One example is shown below in Fig. 2.

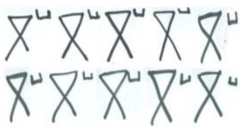

Figure 2: Sample of character

Note that the scanned images are in RGB scale.

These images have to be converted into grayscale format before further processing can be done. Using appropriate grayscale thresholding, binary images are to be created.

Figure 3: Binary image of sample character

Fig. 3 shows the generated binary image using image processing tool box in MATLAB and 8-connectivity analysis.

III. 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 [8-9]. The invariant properties of moments are utilized as pattern sensitive features in classification and recognition applications [10,11].

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,

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

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

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

3-1-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 :

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

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

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

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 [12], [13], [14]. 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 [12].

IV. Classification and recognition

4.1. Minimum Mean Distance

Minimum mean distance is a conventional nonparametric statistical classifier. At first, it makes mean feature vector of each class using training samples. Then in the testing stage, it assigns an unknown input pattern to the class which has minimum distance with corresponding mean feature vector among the all classes. Different definitions of distance can be used practically e.g. Euclidian distance, city-block distance, and so on.

In the minimum distance classifier, each character class, *Ck*, is represented with the sample means, *μk*, learned from the training examples. When a new example is given, it is compared to each character class by calculating the Euclidean distance. The example is assigned to class *k* for which the distance is minimum.

The training example of class *k*, *ck*, with the smallest distance to the test example, *a*, is the nearest neighbour of *a*, the equation is shown below:

$$d(a, c^k) = \sum_{i=1}^{m} (a_i - c_i^k)^2 \quad (12)$$

4.2. K-Nearest-Neighbor (KNN)

Nearest neighbor rule is also a conventional nonparametric statistical classifier. In training stage, it stores all training samples in a table. Then in testing stage, it assigns an unknown input pattern to which class has minimum distance to a training sample of that class. Just such as minimum mean distance classifier, different definitions of distance can also be used here.

We used Legendre moments based features for recognition of Amazighe characters. In this work, we have considered only isolated characters.

K-Nearest-Neighbor (KNN) classifier is an effective technique for classification problems in which the pattern classes exhibit a reasonably limited degree of variability. The K-NN classifier is based on the assumption that the classification of an instance is most similar to the classification of other instances that are nearby in the vector space. It works by calculating the distances between one input patterns with the training patterns. A K-Nearest-Neighbor classifier takes into account only the k nearest prototypes to the input pattern. Usually, the decision is determined by the majority of class values of the k neighbors.

In the K-Nearest neighbor classification, we compute the distance between features of the test sample and the feature of every training sample. The class of majority among the k-nearest training samples is based on the Euclidian minimum distance. The classification is carried using K-NN as follows:

Algorithm

Input: Isolated Binary Amazighe character Images

Output: Recognition of the Character
Method: Legendre Moments, and K-NN Classifier
1. Preprocess the input image to eliminate the noise using median filter.
2. Fit the bounding box on an input image and crop the image, then resize it to 100x100 pixels.
3. Extract the moment based features stored in a feature vector.
4. A Euclidian distance criterion and K-NN classifier used to classify the test sample
5. Stop

4.3. Multi Layer Perceptron

Artificial neural network (ANN) has been inspired from biological neural structure of human brain. Although ANN is a very simple abstraction of its biological counterpart, it has been interested a lot because of its extensive power in pattern classification and clustering in the resent years [15]. 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. 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 expect for the node that is marked to correspond to the class the input is from. That desired output is 1. MLP training is done using an iterative gradient descent procedure known as back-propagation algorithm [16].
Neural network is widely used as a classifier in many handwritten character recognition systems [10, 17]. Also, due to the simplicity, generality, and good learning ability of neural networks, these types of classifiers are found to be more efficient [10]. 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 [18, 19].
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 [20].

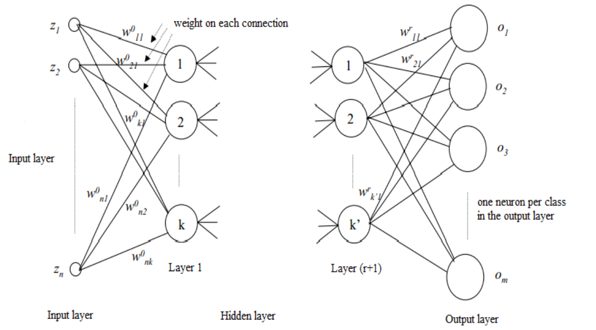

Figure 4: Multi-layer-Perceptron neuronal network

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

$$o_i = \varphi(a_i) = \varphi(\sum_{k=1}^{N}(w_{ik} z_k)) \qquad (13)$$

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 :

$$\varphi(x) = \begin{cases} -1, & x < \theta \\ +1, & x \geq \theta \end{cases} \qquad (14)$$

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 Amazighe character recognition is given below in Fig. 5.

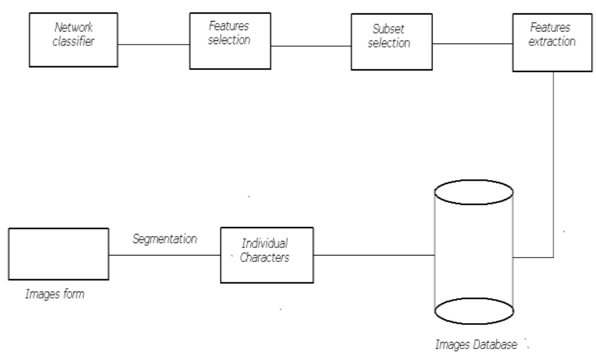

Figure 5: System for Amazighe character recognition

V. 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. 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 classifiers, the classifier recognition rate (%) is considered as the number of recognized characters in the training (test) phase over the total number of characters.

Table1: The results of error rate classification of different classifiers

Uttilized classifier	**Error rate classification(%)**
Minimum Mean Distance(MMD)	83,5
Nearest Neighbor Rule(NN)	94,5
Artificial Neural Network(ANN)-Multi layer perceptron	97

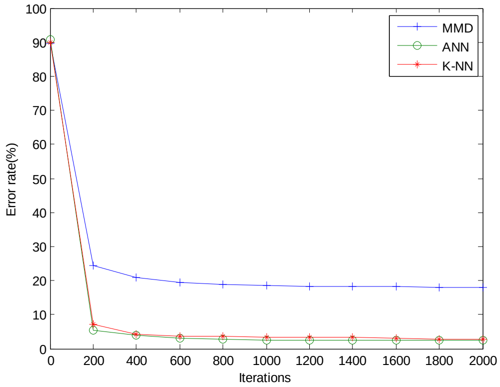

Figure 6: Error rate for the same set of characters of different classifiers: MMD, K-NN and ANN

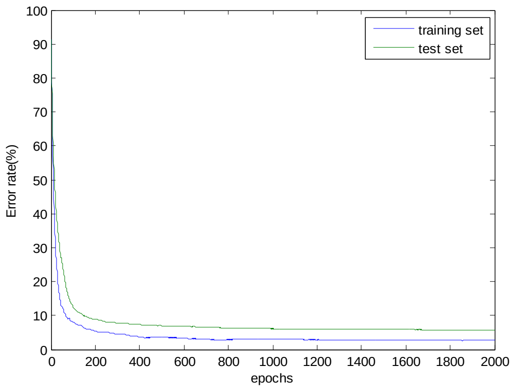

Fig 7. shows that our combined method of neural networks and moment features, gives the best results than the other methods in terms of recognition rate

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 Fig. 6.

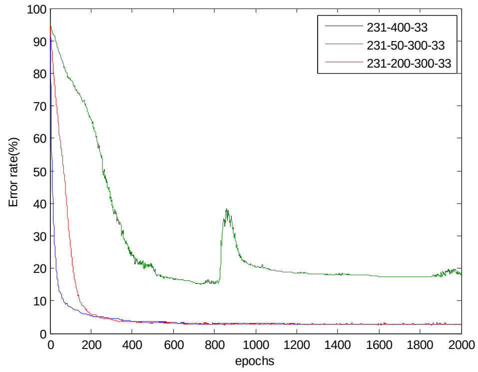

Figure 8: Error rate of different architectures for moment order set to 20

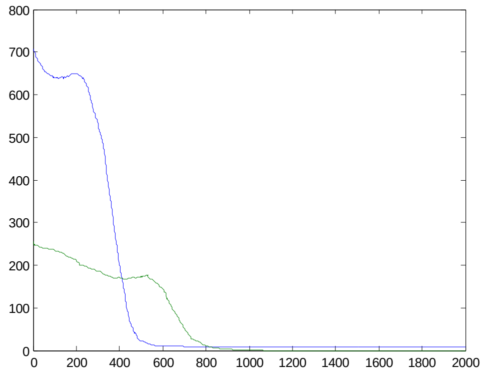

Figure 9: recognition rate of training set of the same architecture and two different samples

The recognition converges faster when the number of samples 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.

VI. 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 without any preprocessing of characters images set.
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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