International Journal of Modern Engineering Research (IJMER)
www.ijmer.com Vol.2, Issue.2, Mar-Apr 2012 pp-436-441 ISSN: 2249-6645

Handwritten Amazigh Character Recognition System Based on Continuous HMMs and Directional Features

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ABSTRACT

This paper proposes a global approach to the recognition of handwritten Amazigh characters. The method used is based on continuous Hidden Markov Models and directional features. The input provided to our system is a vector of features extracted directly from an image of Amazigh characters using sliding windows technique based on hough transform. The obtained vector is translated into a sequence of observations that is used for the learning phase. This task involves several of processing steps, typically, pre-processing, normalization, skeletonization and features extraction. Finally the class of the input characters is determined by the Viterbi classifier. The experimental result indicates the promising prospect of this approach.

Key words- **Handwritten Amazigh characters, Hidden Markov Models, Directional features.**

I. INTRODUCTION

The off-line recognition of handwritten characters is one of the hottest subjects in pattern recognition. This field has a number of applications such as reading addresses on envelopes, amounts on bank checks, and so on. These various applications need a particular and small lexicon from specific domains. Several approaches have been used so far for Latin and Arabic script recognition, some of them are based on Hidden Markov Model [1][2][3][4][5][6]. Furthermore the Amazigh (Tifinagh) characters recognition remains less explored. Indeed, research done up to now is very limited, but there are few attempts. In the literature devoted to Amazigh, we find approaches based on statistical, geometrical and syntactical approaches [7][8][9][10][11]. For more details on the survey of this language refer to [12].

The Figure 1 represents the repertoire of Tifinagh which is recognized and used in Morocco with their correspondents in Latin characters. 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).

Fig 1. Tifinagh characters adopted by the Royal Institute of Amazigh culture with their correspondents in Latin characters

The automatic treatment of this script compared with other types of writing (Arabic and Japanese) appears simple. Indeed, the Amazigh alphabet is never cursive, which facilitates the operation of segmentation. The Amazigh script is written from left to right; it uses conventional punctuation marks accepted in Latin alphabet. Regarding the figures, it uses the Arabic Western numerals. The majority of graphic models of the characters are composed by segments. Moreover, all the segments are vertical, horizontal, or diagonal.

The use of HMMs discrete to these handwritten characters is limited to our previous contribution [10]. This method is based on a discriminating model which associates one or more model by class. We obtained a recognition rate 90,4% on a handwritten character database [13]. The recognition errors are assigned, in the one hand, to the methods used for the estimation of the probabilities of the observation symbols, and secondly, to the topology models. The introduction of continuous HMMs (CHMMs) and the use of other model architectures can reduce the error rate of our system.

In order to improve the performance of our system, we suggest to address the problem of Amazigh handwritten characters recognition by Continuous Hidden Markov Models with various topologies per model.

The remaining parts of this paper develop as follows. Section (2) briefly introduces the conventional hidden Markov models whereas section. Section (3) presents an overview of our system. As to section (4), it sheds light on the pre-processing techniques and methods. Section (5) presents the process of extracting vector features and generation of the sequences of observations from an image of Tifinagh letter. Section (6) is focused on the learning and classification steps. In addition, section (7) is concerned with the numerical results. The paper finally concludes with an analysis of the results and a description of future work.

II. THE BASIC CONCEPTS OF HMM

An HMM is a doubly stochastic process with an under-lined stochastic process (Markov chain) that is not observable (it is hidden), but can only be observed through another set of stochastic processes that produce the se-quence of observed symbols. The elements of the first order HMM are formally defined as follows :

N : the number of states;

T : the number of observations or possible symbols;

q_t : the state of the system at the time t;

M : size of the observed sequence;

$A=\left\{a_{ij}=p\left(s_j/s_i\right)\right\};\ \sum_{j=1}^{N} a_{ij}=1$: is the matrix of the probability of transitions;

$\Pi=\left\{\pi_i=p\left(s_i\right)\right\};\ \sum_{i=1}^{N}\pi_i=1$: is the vector of the initial probabilities;

$B=\left\{b_i\left(o_k\right)=p\left(o_k/s_i\right)\right\};\ \sum_{k=1}^{T} b_i\left(o_k\right)=1$: are the probabilities of the observation symbols with $b_j(o_k)$ are practically estimated by an M mixture of multivariate Gaussian distributions:

$$b_j\left(o_t\right)=\sum_{k=1}^{M} C_{jk}\mathcal{N}\left(o_t,\mu_{jk},\sigma_{jk}\right)\ 1\le j\le M,\ \sum_{k=1}^{M} C_{jk}=1$$

$$\mathcal{N}\left(o_t,\mu_{jk},\sigma_{jk}\right)=\frac{1}{2\pi\sqrt{\left|\sigma_{jk}\right|}}\exp\left(1/2\left(o_t-\mu_{jk}\right)\sigma_{jk}^{-1}\left(o_t-\mu_{jk}\right)^T\right)$$

: denotes a normal Gaussian distribution;

c_{jk} :The weight of the k^{th} mixture component;

μ_{jk} : Mean vector associated;

σ_{jk} : Covariance matrix associated.

The parameters of an HMM can be denoted by $\lambda = (N, M, A, B, \Pi)$. There are three basic algorithms that establish the use of HMM, for-ward-back algorithm, Viterbi algorithm and Baum-Welch algorithm [14].

III. THE WHOLE RECOGNITION SYSTEM

Figure 3 illustrates the block diagram of the proposed system. The system is divided into steps. All of them are performed prior to training and testing process, and includes: image acquisition, pre-processing and features extraction. The objective is to acquire the character image, pre-process it and then decompose it into vertical bands. Each bands image is transferred into a sub-sequence of features.

Those directional features are extracted from vertical windows along the line image using the Hough transformation. Then the sequences of observations are generated. In the training step, we involve the Hidden Markov Model of each character, with a Baum-Welch process, by the various sequences of observations. The classification is done by the search for the characters discriminating models and we decide for the class of the character.

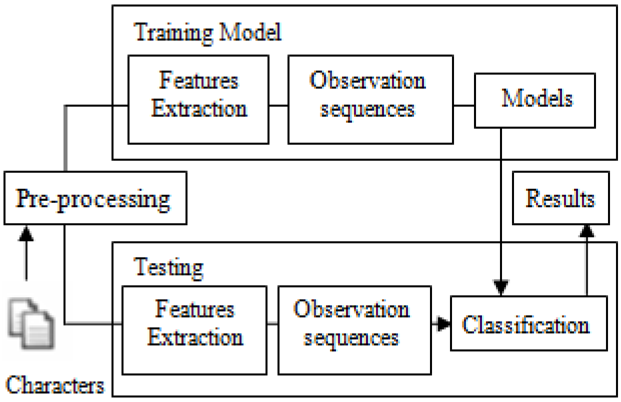


Fig 2. System overview

IV. PREPROCESSING

The variability in the Tifinagh handwritten characters to be recognized becomes more prominent. This situation complicates the recognition process. To adapt the characteristics of the Amazigh handwritten characters to our recognition system, eliminate noise in the image and simplify subsequent treatments, a number of pre-processing operations are applied. As the binarization, smoothing, normalization, skeletonization.

The binarization enhances the useful information from the background of the image; the choice of threshold is important. As a result, we use Otsu's algorithm [15] which chooses the threshold to minimize the interclass variance of the black and white pixels.

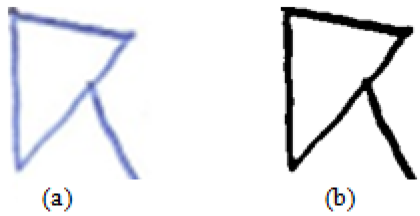


Fig 3. Results of binarization Otsu algorithm to the character « ⴽ » (a) input letter; (b): binarization (level= 0.8196)

The operation of smoothing is applied to remove noise introduced by the image acquisition systems.

Fig 4. Results of smoothing algorithm to the character « ⴽ »; (a) input letter; (b): after smoothing

The normalization task is necessary to bring the same size to the characters 96×96. These characters can have different sizes that will influence the parameters stability caused by the variability of styles or by the expansion /

reduction operations of image size; these operations are performed by the size normalization algorithm [16].

The skeletonization or Thinning is an important pre-processing step for many image analysis operations. The main objectives of thinning in image processing and pattern recognition are to reduce data storage while at the same time retaining its topological properties, to reduce transmission time and to facilitate the extraction of morphological features from digital patterns. Thinning reduces the amount of data to be stored by transforming a binary image into a skeleton, or line drawing. The thinning algorithm used herein for testing is the Rutovitz algorithm [17]. This algorithm is selected for its preservation of connectivity and topology of the characters. Figure 5 shows a sample input character image and the results of skeleton algorithm.

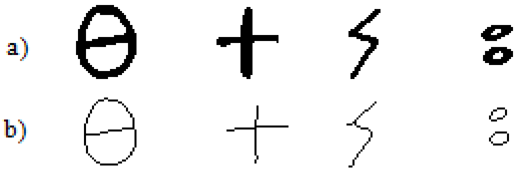


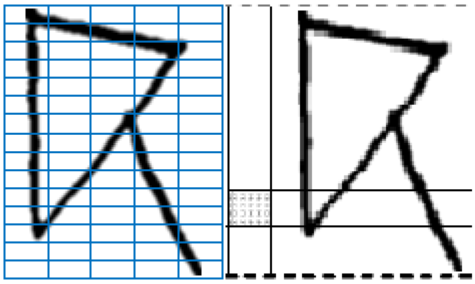
Fig 5. Results of skeleton Rutovitz algorithm to the characters « ⵚ », « ⵜ », « ⵣ », « ⵓ » (a) input letter; (b): skeleton

V. EXTRACTION OF PRIMITIVES

In order to build the directional feature vector sequence, the image is divided into vertical and horizontal windows or frames. The sliding window is shifted along the word image from left to right. According to the size of the images' characters (96 × 96 pixels), we obtained, in total, 16 horizontal and 16 vertical bands and the intersections of these bands form 256 cells; each one has 6x6 pixels (see figure 6). For each area, we calculate the presence rates of the six orientations and we determine the dominant direction based on the Hough Transform. This algorithm gives a set of discriminating characteristics using the character pixels representation that facilitates recognition [18]. The steps of the Hough algorithm are summarized below:

> Initialization of t the Hough Transform accumulator
>
> For each black pixel of the image $\left(x_i, y_i\right)$
>
> $0 \le x_i \le n$ et $0 \le y_i \le m$, with n is width the image and m its height.
>
> $0 \le \theta \prec 180^\circ$
>
> $\rho_k = x_i \cos\theta_k + y_i \sin\theta_k$
>
> To increment the cell of the table of accumulator corresponding to the couple $\left(\rho_k, \theta_k\right)$.

In the experimentation, the displacement $\Delta\theta$ is equal to 30, consequently the Hough accumulator will contain information on of the six orientations (0°, 30°, 60°, 90°, 120° et 150°). Finally, we memorize these dominant directions which will be used for the generation of observations.



(a) (b)

Fig 6. Dividing the image into windows and cells

VI. GENERATION OF THE OBSERVATIONS SEQUENCES

For the generation of the sequence of observations' task, we select the minimum of the primitives representing the dominant directions. In each area, we consider the rate of the dominant direction. Thereafter, we represent, by a symbol in the sequence of observations, a set of adjacent areas that have same rates considered from the left to the right. The symbols which can be emitted are 6 corresponding to the 6 basic orientations (cf figure 7).

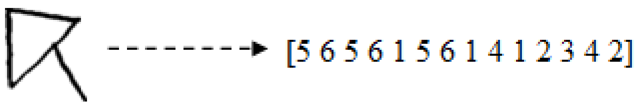


Fig 7. Sequence of the character k (ⴽ)

VII. HIDDEN MARKOV MODELS RECOGNIZER

When considering the alphabet such as those involved in the recognition of Tifinagh characters, it is possible to build a different model for each character. Therefore, our handwriting modelling is carried out at the character as whole. This approach is called discriminating hidden Markov model. In this strategy, for each class of the problem (each letter of the alphabet) a model is constructed. Then for recognizing an input letter, the score for matching the character to each model is computed. The class related to the model that has the maximum score gives the result of recognition. In the literature, various models and architectures were proposed for the use of the hidden Markov models in the handwritten recognition [19][20]. In our work, we opted for a left-right topology where the number of states is strictly lower than the number of horizontal bands of the character (see figure 8). Thus, the bands of the extremities supply no observation. Indeed, the number of states per hidden Markov models is equal to all models.

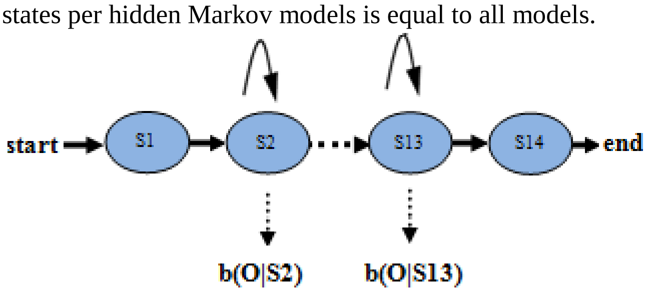


Fig 8. Left to right HMM topology for character models

6.1 Learning

The images of characters are translated into sequences of observations, which must be deducted from the model that generated them. Once the topology of the model is chosen, each letter has its own model. Therefore, the learning allows to estimate the probabilities of the inputs, the transitions and the emissions which model the characters. To do this, we use the standard procedure of Baum-Welch [20][21]. This iterative procedure is used to train the HMM characters to adjust their parameters.

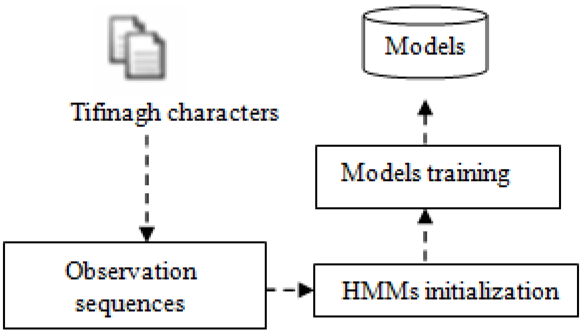


Fig 9. Learning overview

The algorithm will re-estimate the Hidden Markov Model of each character until the probability of generating the sequence of observations is maximal. The best Hidden Markov Model found is recorded to form a database of learning (cf Figure 9).

6.2 Classification

In the learning step, we obtain so many hidden Markov models as the number of characters. The recognition is made at first by the search of the discriminating model among every selected hidden Markov models of each character. We calculate, by the Viterbi algorithm [21], the probability of the observations sequences of the character to be recognized that the models can generate. Afterward, we have a set of models where every model is associated with a score. The elected model is the one possessing the biggest score (see figure 10).

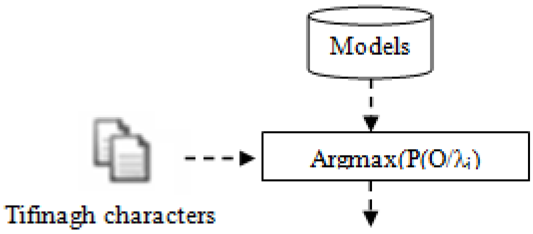


Fig 10. Classification overview

VIII. Experimental results

A series of experiments have been performed to evaluate the effectiveness of the proposed approach. These experiments were performed on database of isolated Amazigh handwritten characters (AMHCD) [13]. This database contains 780 variations for each character led to an overall of 24180 isolated Amazigh handwritten characters (780 × 31). Some Amazigh handwriting samples are given in Table 2.

In our experiment, 16120 character images (i.e. 2/3 the AMHCD) from the portion of AMHCD were used to train the HMMs models. The other character images (i.e. 1/3 the AMHCD) were used to test identification performance. Some results according to the number of states and the number of mixtures are listed in Table 1, Figure 11 and Figure 12. Note that the number of states in our modeling represents a series of vertical bands.

This experimental results illustrate that this proposed approach for the handwritten character Tifinagh is more promising than our previous approach which is based on HMM discrete[10] and which gives a rate of 90, 4% of good recognition.

TABLE 1
Recognition rate on database AMHCD

Number of states	6	8	10	12	14
Number of mixtures	1-2	1-2	1-2	1-2	1-2
Recognition rate	96, 21%	96 , 56%	96 , 88%	97 , 3 8%	97 , 89%

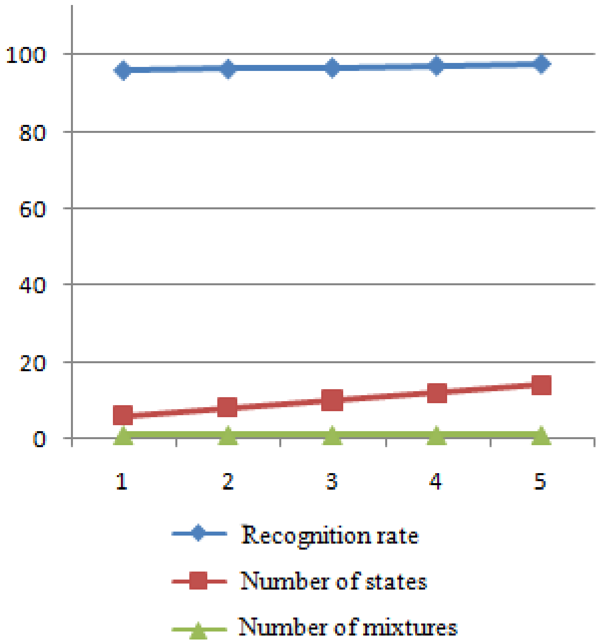


Fig 11.Tthe progressing recognition rate according to the number of states with one mixture

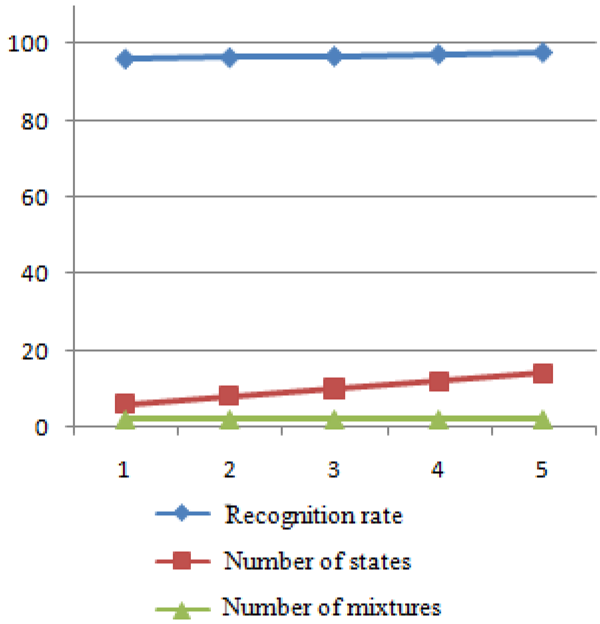
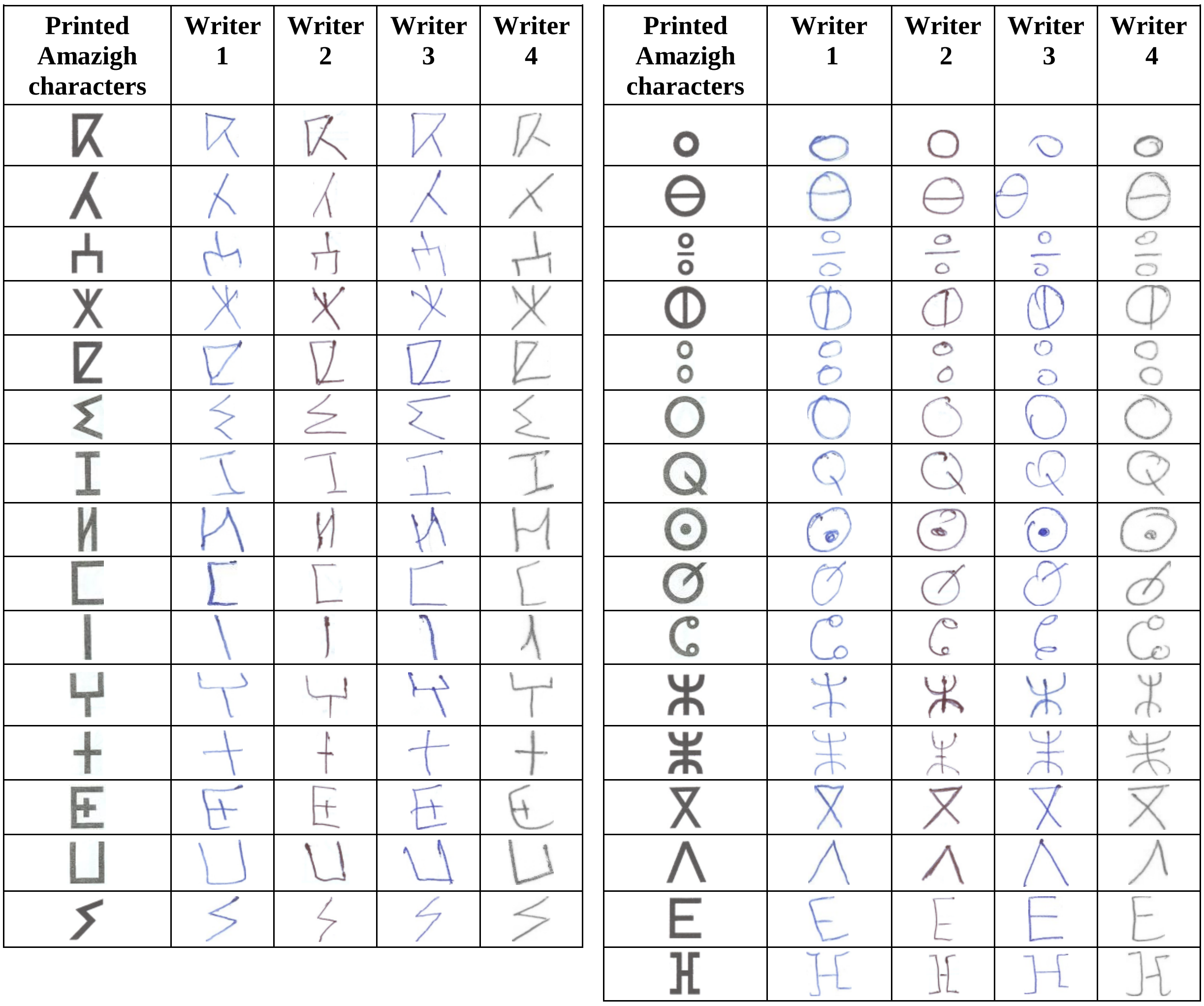


Fig 12. The progressing recognition rate according to the number of states with 2 mixtures

TABLE 2. Handwritten Tifinagh characters



IX. CONCLUSION AND PERSPECTIVES

In this article we have developed a system for recognition of off-line handwritten Amazigh characters using Continuous hidden Markov models as a classifier. We focused on main goal is to Apply a Markov classifier not used so far in the handwritten Amazigh recognition field and analyzing its performance. The results obtained are promising. However, the discrimination of these models is not very good because each hidden Markov models uses the learning of a single character. The error rate was recorded mainly due to the bad writing and learning data. In the future works, we will improve this approach by combination with other classifiers and adding a stage of post-treatment. Indeed we will use neural networks for the estimation of the probability of observation symbols for each hidden Markov models, because one of the hidden Markov models weakness due to this estimation.

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