Arabic Handwritten Words Recognition Based on a Planar Hidden Markov Model

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Abstract: *Off-line recognition of handwritten words is a difficult task due to the high variability and uncertainty of human writing. The majority of the recent systems are constrained by the size of the lexicon to deal with and the number of writers. In this paper, we propose an approach for multi-writers Arabic handwritten words recognition. The developed method uses multiple sources of information at the description and the classification levels. A hybrid planar Markovien modelling permitting to follow the horizontal and vertical variations of the writing has been adopted. This modelling is based on different levels of segmentation: horizontal, natural and vertical. The process of segmentation conducts to the decomposition of the writing in a limited set of elementary entities, with simplified morphologies specific to every horizontal band. The choice of different type of primitives is then imposed in order to assure an efficient description. Different architectures of modelling proved also to be indispensable. The classification is finally achieved using a Planar Hidden Markov Model.*

Keywords: *Off-line Arabic handwriting recognition, planar hidden Markov models, segmentation, multiple sources of information.*

Received July 2, 2004; accepted September 172004

1. Introduction

In the field of document recognition, many improvements have been made during the last decade. However, automatic recognition of handwritten words remains a challenging task, especially for Arabic handwriting. The handwriting recognition either on line or off-line refers to two different modes of Optical Character Recognition (OCR), each having its own hardware and recognition algorithms [8]. According to the mode of data acquisition, shapes of characters vary significantly and recognition problems differ sensibly.

The automatic recognition of handwritten digitized cursive script is performed after the writing is completed. It finds its field of application in various domains. We especially mention bank check reading, mail sorting, forms processing in administration and insurance. Off-line handwriting Arabic OCR (AOCR) has been a subject of great interest, however, the different works remain in the experimental state and no Arabic commercial product is available. In spite of the achieved progress, some meaningful hypotheses are often introduced (level of noise, number of writers, size of the vocabulary…) in order to obtain satisfactory results; hence the off-line handwriting AOCR is mainly experimental prototype.

The latest research has generally used structural features such as ascenders, descenders, loops and diacritics [2, 10, 17] or directional information [26]. It has used either global [21] or analytic [13] approaches based essentially in implicit vertical segmentation of the word into graphemes (characters or sub-characters). In fact, Arabic script letters are written cursively from right to left by using either horizontal and vertical ligatures or natural disconnection because some specific letters cannot be connected on their left side. Hence Arabic script is rather semi-cursive in the sense that a word can be composed of one or several parts which we shall call sub-words.

In our approach, we propose to take into consideration horizontal and vertical variation of the writing not only during the feature extraction step but also through the model's architecture, that's why we opted for a Planar Hidden Markov Modelling (PHMM) [4, 12]. The retained architecture is formed by five horizontal secondary Hidden Markov Models (HMMs) representing the logical variations zones relative to Arabic handwriting. Zones correspond to: Upper diacritics, upper extensions, median zone, lower extensions and lower diacritics (Figure 2). Accordingly, a two level segmentation stage is performed. It includes a horizontal segmentation step to delimit the different horizontal zones and a vertical segmentation step to segment the median zone into graphemes. The segmentation points, which are encoded according to their nature, are finally used for chronological duration computation. The segmentation data is then labelled to serve as a starting point for the following recognition steps.

The results descended of the segmentation process are distributed in the different logical variations zones: The extracted graphemes present structural and morphological specificities inherent to each logical zone. Thus, we opted for a specified characterization, adapted to the nature of the existing information in every level of variation. In fact, the use of multiple sources of information represents one of the advisable orientations in pattern recognition and especially in AOCR [3]. We also opted for different architectures for the secondary HMMs. Therefore, we defined an analytic Markovien model constituted of a succession of elementary models capable to follow the variations of the central band. Right-left HMMs, using a double set of observations, have been used for the other bands. The decision is finally achieved thanks to the principal vertical model.

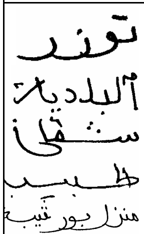
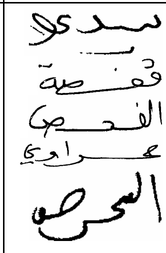
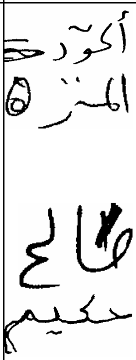
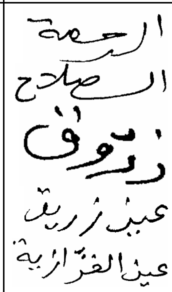
In the following section, we expose briefly the field of Arabic handwriting and its inherent problems. The developed approach is addressed in section 3. Section 4 is devoted to the segmentation process. The description of the obtained data is discussed in section 5. Section 6 is concerned with the different HMMs architectures. The experiments are the subject of section 7. Conclusion and some perspectives are assessed in the last section.

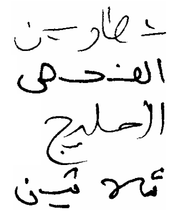
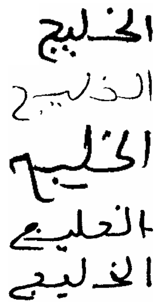
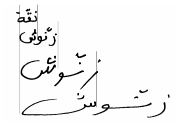
2. Off-Line Arabic Handwriting Recognition

Generally speaking, the off-line handwriting recognition, represents the most challenging OCR problem because of the different variations of writings and the absence of dynamic information relative to the different considered shapes [6, 19]. In order to resolve these problems, many approaches have been proposed. The majority of the developed systems have been inspired by works on human reading modes [7]. In this context, several classifiers have been tested such as 1D HMMs with different topologies corresponding to different levels of perception in the works of Miled [13]. Transparent neural network classifiers were proposed in [10, 18]. Analytic approaches have also been adopted in the works of Atici [1] and Pechwitz [14].

Different criteria can condition the complexity of handwriting OCR systems (infinite variations of shapes resulting from the writing habit, style and other conditions of the writer as well as other factors such as the writing instrument, writing surface, scanning methods [20], fusion of diacritical points, overlapping and touching of sub-words...and of course the machine's character recognition algorithms [11]). Following, we will focus in particular on problems related to the intrinsic writer's variations. These problems are generally the most complex, especially in the case of Arabic. According to the conducted study, the important problems are related to writing discontinuity and slant, overlapping and sub-words touching, shape discrimination and variations in sub-word sizes. The diacritical marks cause serious problems as well, Table 1 illustrates the main problems related to the off-line Arabic manuscript.

Table 1. Examples of problems related to the off-line Arabic handwriting.

Sub-Word Connexion	Variable Elongation	Corrected Writings	Multiple Slants
			

Writing Discontinuity	Multi-Writers Aspects	Dimension Variations
		

3. The Developed Approach

The principal purpose of our approach is to decompose the writing into a limited set of elementary entities dispatched in different logical zones and having much more simplified morphology than the original word. Therefore, we decided to divide the writing into its five logical horizontal bands corresponding to upper diacritics, ascenders, median zone, descenders and lower diacritics. The segmentation process allows us then to reduce the complexity of the treated shapes (Figure 1). A PHMM based architecture is adopted, it has been proved to be well adapted to this decomposition into several bands.

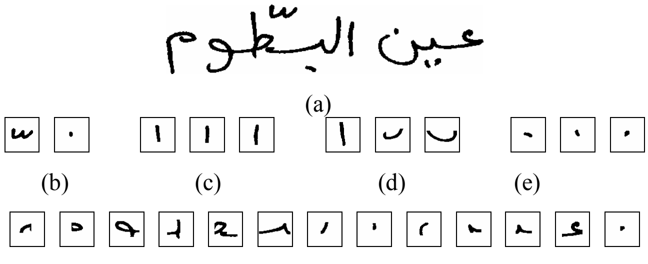


Figure 1. (a) Original image of the city name "عين البطوم" and the extracted graphemes belonging to, (b) upper diacritics, (c) ascenders, (d) descenders, (e) lower diacritics, and (f) median zone.

PHMM is a HMM whose emission probabilities are also modelled by HMM's [5, 9, 16]. The retained architecture has a vertical principal model composed of seven super-states: Beginning, end and five intermediate super-states associated to the different logic bands of variations of the Arabic script (median zone and upper/lower extensions and diacritics zones) [4, 12]. As shown in Figure 2, jumps between super-states are allowed which seems to simulate efficiently the presence and/or the absence of either diacritics or stems and descenders and the pertinent presence of the median information zone, as well as distortions of handwriting. Secondary models are of two types: One relative to the middle zone and the other to zones delimiting extensions (ascenders and descenders) and diacritics. HMM median zone model illustrates the vertical segmentation process behaviour of this logical band.

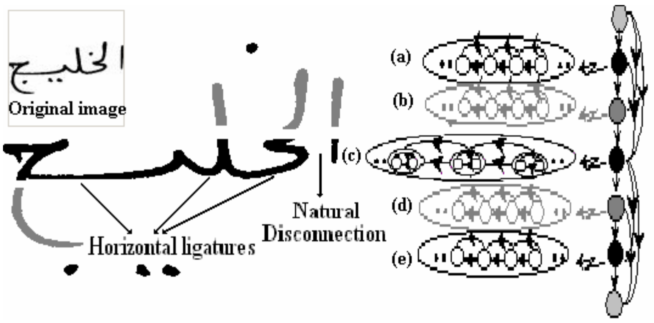


Figure 2. The proposed PHMM architecture: (a) upper diacritics, (b) upper extensions, (c) median zone, (d) lower extensions, (e) lower diacritics.

The proposed PHMM architecture depends greatly on a segmentation process at different levels; we distinguish horizontal, natural and vertical segmentation. In the following, we discuss the different segmentation steps.

4. Segmentation Procedure

The segmentation is achieved into four principal steps. They are the extraction of connected components, the horizontal segmentation followed by the vertical segmentation stage and the procedure of chronological duration computation. Finally, segmentation data is labelled and stored.

4.1. Connected Components Extraction

Connected components are extracted and then processed to extract their basic contour. Each contour is then filtered to reduce it to one-pixel width. An algorithm of contour following is then applied to detect and count closed contours within each component. The Freeman chain-code of the obtained closed contours is determined considering the clockwise sense; which allows us to distinguish between upper and lower contours according to specific contour directions. The resulted information is structured hierarchically to be used subsequently during the different segmentation steps.

4.2. Horizontal Segmentation Stage

In this stage, we extract two kinds of information associated respectively with diacritics and principal tracing. Diacritics occupy two logical bands situated all sides of the tracing, while tracing could be naturally divided into three zones associated with the middle band, upper extensions and lower extensions. The tracing zones are separated by horizontal frontiers.

4.2.1. Diacritics Pre-Detection

In this step components are analyzed according to their size. Small ones are pre-classified as being diacritics components. Among them, we eliminate those containing a loop inner contour.

4.2.2. Horizontal Frontiers Detection

Only the principal tracing is concerned with this step, hence the identified diacritics are first eliminated, then we compute the horizontal projection histogram of the remained tracings. The obtained pixels densities associated to the contingent presence of loops and/or the character "ا", are used to compute the upper and lower rough limits of the median zone.

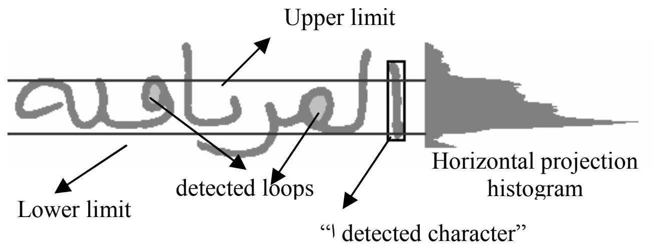


Figure 3. Example of rough horizontal limits detection for the city name "المرناقية".

To separate efficiently the logical horizontal bands, the obtained limits have to be refined. Thus, for each principal tracing component, we do the following treatments:

- We detect local maximums and minimums in respectively the upper and lower contours.
- We remove both maximums and minimums being far from the obtained rough limits according to pre-defined thresholds.

Finally, we join the remaining maximums by following the contour pixels below them to form the upper horizontal frontier. Then, we join the remaining minimums by following the contour pixels over them to form the lower horizontal frontier.

If the considered component doesn't contain any valid maximum and/or minimum, we consider the continuity of the frontiers of the nearest component from the right. If we deal with the first right component, we consider the nearest left component (see component 1 in Figure 4).

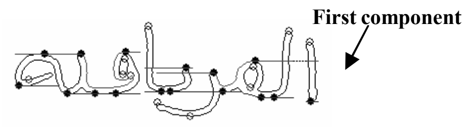


Figure 4. Example of horizontal frontiers detection for the city name “المرناقية ”.

4.2.3. Horizontal Bands Separation

The horizontal logical zones are separated according to the diacritics classification result and the obtained horizontal frontiers of each principal tracing component (Figure 5). The relative height of each band is finally computed.

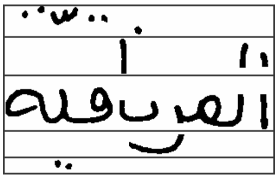


Figure 5. Horizontal bands separation in the case of the city name “المرناقية”.

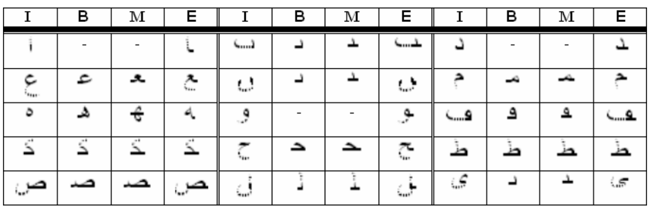
4.3. Vertical Segmentation Stage

This procedure concerns only the median zone. It aims to detect natural separations between the median entities (natural segmentation) and anchor points belonging to different ligatures (vertical segmentation).

4.3.1. Natural Segmentation

Natural segmentation concerns natural separation between connected abstract entities, which could be characters or portions of characters called also pseudo-characters (PCs). Therefore a pseudo-character alphabet is defined for median zone modelling (Table 2). The Natural Segmentation points (NSP) are obtained using the classical vertical projection (Figure 6).

Table 2. Pseudo-character alphabet (I: Isolated, B: Beginning, M: Median and E: End according to the position into the median zone).



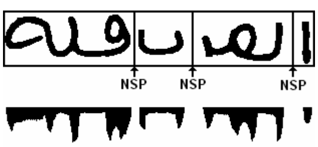


Figure 6. Sample of natural segmentation result in the case of the city name “المرناقية”.

4.3.2. Vertical Segmentation

The vertical segmentation delimits the different sub-word pseudo-characters. The segmentation points are called Vertical Segmentation Points (VSP) and are obtained as following: We detect the upper contour local minimums and we retain only those belonging to the median zone (Figure 7-a). A local minimum is considered as a VSP only if a significant variation is observed in the vertical histogram starting from the last detected VSP (Figure 7-b).

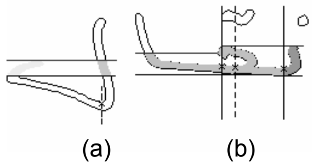


Figure 7. VSP detection: (a) Invalid minimum: Outside the median zone (b) Invalid minimum: Redundancy.

At the end of the segmentation procedure, the NSP are considered among the set of the vertical segmentation points.

4.3.3. Duration Modelling

At the end of the vertical segmentation process, the word image is divided into different type of patterns (diacritics, entities corresponding to higher and lower extensions, pseudo-characters). The delimited vertical bands corresponding to the median zone are subsequently used as a chronological reference mark for the computation of the duration between patterns (connected entities) in either diacritics or extensions zones (Figure 8).

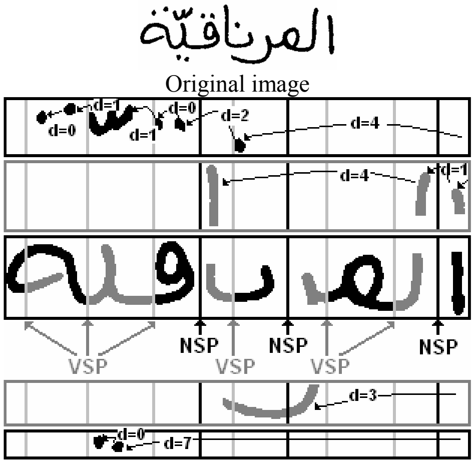


Figure 8. Sample of vertical segmentation result: VSP/NSP detection & durations computation.

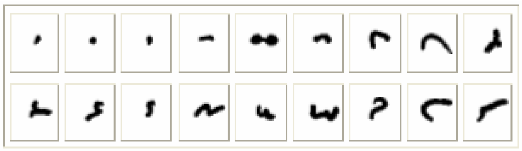
5. Features Extraction

After the segmentation process, we obtain a set of graphemes of different kinds. Accordingly, different techniques of features extraction are adopted.

5.1. Diacritics Description

The diacritics belong to both the upper and lower bands. However, we notice some differences between the classes of diacritics of these two bands. For example, signs such as “ـّ” and “ـَ” and triple dots don’t belong to lower diacritics. Table 3 presents some basic shapes of the diacritics issued from the segmentation stage. The description of these entities is done according to structural features relative to dimensional and pixels density criteria.

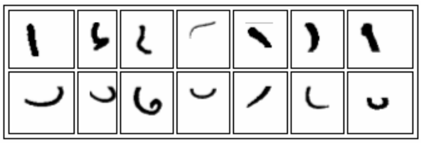
Table 3. Samples of some diacritical graphemes.

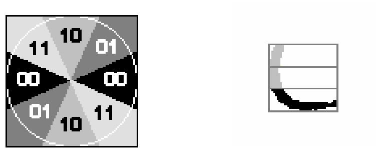


5.2. Extensions Description

The extensions belong to the two bands beyond the median zone. The extracted entities differ greatly by their morphological shapes, dimensions and thickness. However, we notice that the basic differences are of a directional nature (Table 4). Thus, we used the directional information to describe these entities. We distinguish four ranges of orientations (Figure 9-a). Each extracted grapheme is subdivided into three equal horizontal bands. For each band, we compute the dominant direction by using a technique based on the Hough transform and detailed in [26] (Figure 9-b).

Table 4. Samples of some extensions graphemes.





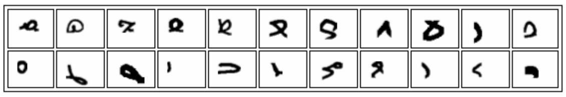
(a) (b)

Figure 9. Sample of extensions description: (a) considered directional ranges (b) sample of a grapheme: the extracted code is 10 10 00.

5.3. Median Zone Description

The median zone is known by its wealth in information. Thus, we opted for the use of two kinds of primitives to be extracted. On the one hand, we used two structural primitives relative to the presence of loops and a part of the character “ ا ” in the grapheme. On the other hand, we have used a set of six primitives describing the behaviour of the segmentation process: the nature of the segmentation points all sides the grapheme (NSP or VSP), the possible connection of the grapheme with upper and lower extensions and the possible presence of diacritics over and below the grapheme, which yields at the end to a set of eight primitives. The obtained descriptors allow us to characterise the continuity of the information between the different levels of abstraction in the word image.

Table 5. Samples of some median zone graphemes.



6. HMMs Architectures

Taking in consideration the inherent differences between the different horizontal bands, we define two HMM’s architectures for the secondary models: An analytical architecture for the median zone and a right/left architecture with a double set of observations for the other horizontal bands. The vertical model having a top to bottom topology is finally trained statistically on the whole training database.

6.1. Median Zone Modelling

It is generally established that the median zone is often highly deformed, thus in order to have a soft and elastic model, we opted for an analytical modelling representing the behaviour of the segmentation process instead of modelling the median zone information. Therefore the states of the retained model do not represent pseudo-characters but rather graphemes descended of the vertical segmentation process. Nevertheless, we use a model for each word class of the considered vocabulary. Thus, the final model of the median zone is a fusion of models associated with different levels of abstraction. These models characterise the behaviour of the segmentation process in relation to the Pseudo-Character (PC) on the one hand, and the succession of two PCs (bi-gram) on the other hand.

6.1.1. The PC Model

Because a PC might be segmented into at most two graphemes, we associate a two state sequential model (a state by grapheme) for each PC class. Figure 10-a shows the PC model. The model parameters are:

- *Pr1* (α): The probability that the *PC* α is composed by only one grapheme.
- *Pr2* (α): The probability that the *PC* α is decomposed into two graphemes. This probability is directly deduced from the first one.

6.1.2. The Bi-Gram Model

This model illustrates the behaviour of the segmentation process being given a bi-gram (α, β). Therefore, we have as much models of bi-gram as we have a succession of two PCs in the training data base. The bi-gram model must take into consideration all the possibilities of the bi-gram segmentation. A sequential two state model is thus associated with bi-grams (Figure 10-b). The transition probabilities between the model states are defined as follows:

- *Pr1 (α, β)*: The probability that the bi-gram (*α, β*) is composed by only one grapheme after the segmentation (case of sub-segmentation).
- *Pr2 (α, β)*: The probability to segment the bi-gram (*α, β*) into two graphemes.

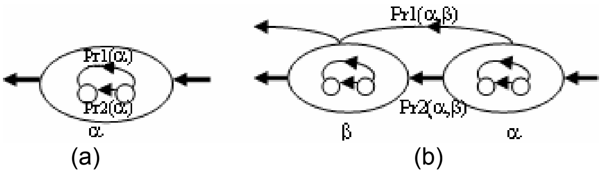


Figure 10. (a) Pseudo character α model (b) bi-gram (α, β) model.

These parameters are estimated on the whole tagged training database.

As already mentioned, the state represents graphemes and not PCs. Therefore, the number of states corresponding to the median zone is a model dependent and varies from one word class to another. The number of states is equal to the number of the different graphemes issued from the vertical segmentation [24]. The evaluation of the transitions probabilities between the models states is computed according to the formula:

$$a_{ij} = a_{inter}(I, j) \,.\, a_{intra}(j)$$

The observations are directly produced by the states. The probabilities of the symbols emission are estimated statistically on the entire training database.

For the example given in Figure 11, the computation of the transition probabilities is as follows:

$$a_{ij} = a_{inter}(i, j) \,.\, a_{intra}(j) = Pr1(\beta) \,.\, Pr2(\beta, \gamma)$$
$$a_{jk} = a_{inter}(j, k) \,.\, a_{intra}(k) = Pr2(\gamma) \,.\, 1$$

6.2. Extensions and Diacritics Zones Modelling

The model architecture is a sequential right/left HMM allowing states jumps (Figure 12). The state represents the existing information composed of patterns which might correspond either to extensions or diacritics. The observation stands for the type of patterns. The length between two successive patterns being in the same band is represented by an observation emitted along the transition between states. The jump of states represents the possible absence of information (distortion, missing…). The model parameters are estimated by Baum-Welch algorithm [13]. Otherwise, it is interesting to observe that the structure of the model well encodes the topology of the word. Indeed, the fact of taking into consideration the length between two successive patterns enables to localize the information in its context. Besides, it puts in evidence the correlation that exists between entities being located in different zones, particularly, the continuation existing within extensions and the median part of the associated characters.

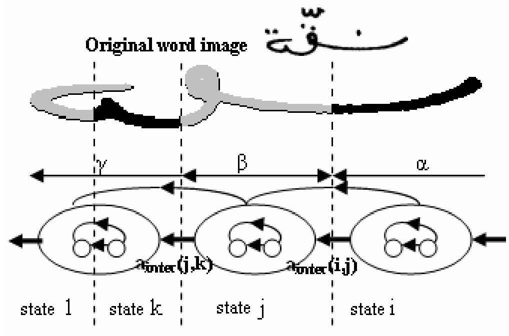


Figure 11. Median HMM states of the city name “نقة”.

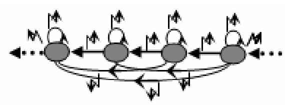


Figure 12. Diacritics and extensions zones HMMs architecture.

7. Experiments

The tests have been done on a corpus of Tunisian city names that is extracted from the IFN/ENIT database [15]. Our choice has been carried on city names of variable frequencies to show the capacity of the adopted approach to overcome the problem of lack of information. We used the samples of the sub basis “a” (1167 samples of a corpus of 25 city names with 8381 extracted graphemes) for the training and those of the sub basis “b” (1180 samples) for the test. In order to show the contribution of the central band in the discrimination between the handwritten words, we first used only the model of the median zone in the classification process. The rate of recognition achieved on the test basis is 73% [23, 25]. The average rate of recognition obtained for the city names of least frequencies (less than 25 samples by sub basis) passed from 44% while using a classical right/left HMM architecture to 72% while using an analytical HMM what justifies the choice of the method. Tests for the classification using the planar model in its totality gave results of 88,7% what shows the contribution of the other horizontal zones as well as the vertical model in the discrimination between the samples. We note that the obtained results are encouraging compared to those obtained by the approach of Pechwitz *et al.* based on a semi-continuous 1-dimensional HMM. The recognition rates that they have obtained on the IFN/ENIT database vary between 81,5% and 85% by using baseline estimation and the rates are up to 89% only by using a supervised ground truth baseline information [14].

8. Conclusion and Perspectives

In this paper, we proposed a planar modelling approach that is based on Hidden Markov Models. The use of hybrid model as well as multiple sources of information at the level of the description permitted us to surmount the major problems of morphological variations of handwritten Arabic efficiently. The adopted planar modelling permitted to put in evidence the five horizontal bands of variation of the Arabic writing and to take into consideration the different types of morphological variation relevant to this script. During the segmentation phase, the different delimited bands are subdivided into a set of graphemes. These graphemes present varied topological and morphological specificities and that drove us to adopt different techniques for their description. A technique of classification by structural criteria has been judged suitable for the different diacritical components characterization. The specific orientations of the different graphemes of the extensions zones guided us rather to the extraction of directional primitives by using the standard Hough transform. For the median zone, considering its wealth in information and the complexity of its associated patterns, we opted for the combination of structural and topological information that reflects the behaviour of the segmentation process. The different sequences of observations descended from the different zones of variation are used thereafter to train the secondary corresponding HMMs. A vertical model having top to bottom topology has permitted at the end the correlation of the different secondary models results. The obtained results are encouraging and show the efficiency of the use of multiple sources of information at different levels.

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