Visual Aspect of Cursive Arabic Handwriting Recognition

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Abstract

In this paper, we discuss the visual aspect of Arabic handwriting; we notice that Arabic script has some characteristics common to Latin as well as some distinct ones. We consider the features which can generate visual index contributing to the description and distinction of words in a global classification scheme. We define classes of visual indices (*VIs*) for Arabic cursive handwriting; then we talk about their extraction. An approach to compute informative power using an entropy criterion of these *VIs* is proposed. The overall performance of the global recognition approach based on a Hidden Markov Model (HMM) module is presented.

keywords: visual indices, word description, Mutual Information computation, feature selection, Arabic handwriting recognition, HMM modeling.

1. Introduction

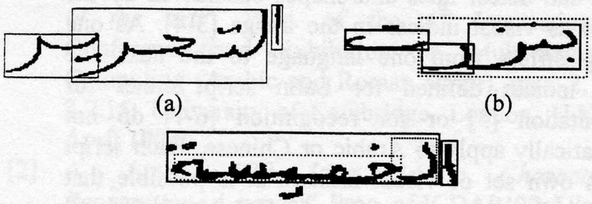
Since the appearance of the machine, man has been trying to mimic his own behavior. The need to understand how he functions pushed him to model mechanically not only his motion, but also the way he thinks. This curiosity reached the field of pattern recognition, and in particular automatic reading, and gave birth to hundreds of research studies [1]. Yet, the question remains: How does a human identify complex patterns while the machine, with all its computational power, is not capable of solving relatively simple problems? We will not attempt to answer such a question here, but we deduce that surely it is not by complex features (transforms and others [2]) that the humans can read. What we identify in the image of a word are relatively simple visual indices. Many studies define and detect lines and shapes considered by the authors as visual indices in the image [3-4]. As one writing differs from one language to the next, the visual indices defined for Latin script either for segmentation [5] or for recognition [6-7] do not automatically apply to Arabic or Chinese. Each script has its own set of visual indices. It is possible that similar indices appear in a set of scripts sharing visual similarities.

Our main interest is the optical reading of Arabic cursive handwriting. Arabic is the official script of Arabic and Persian countries which places it in a fairly high position on the ranking of the world's commonly used scripts. Still, the number of studies done on the field of Arabic writing recognition is relatively low [8-9]. Because Arabic writing is based on an alphabet and rules different from those of Latin, it is foreign writing for the majority of our scientific community. Arabic writing, both handwriting and printed, is semi-cursive. As shown in Figure 2, the word is a sequence of disjoint connected components called pseudo-words. Similarly, each pseudo-word is a sequence of completely cursive characters. Opposite to Latin, Arabic text is written from right to left. The Arabic alphabet contains 28 different characters. An individual character shape is directly related to its position in the pseudo-word, and is written in four different ways according to whether it is at the beginning, at the middle, at the end of the pseudo-word, or isolated. This rule is true except for six characters which can never be attached to their successors. The Arabic character set can be divided into 18 sub-sets. Each sub-set contains characters with identical dominant shape, also called main body.

Characters in a sub-set can be distinguished by the number and position of their dots (Figure 1).

Figure 1 : Example of Arabic text: a style close to handwriting; the right box contains a ligature composed of two different characters; the left box contains a word composed of three pseudo-words.

The semi-cursive aspect of Arabic handwriting is due to the notion of pseudo-word. In this study, it is replaced by another notion of tracing. The detected connected components can be pseudo-words (in the majority of cases, see Figure 2-a), portions of pseudo-words (Figure 2-c), or sets of pseudo-words (Figure 2-b), which gives importance to the notion of tracing.



(a) (b)

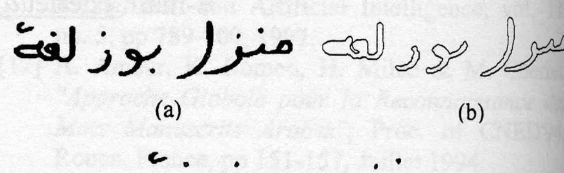
(c)

Figure 2 : Differences between the notions of pseudo-word and tracing: (a) correct writing when the detected tracings correspond to the pseudo-words (b) the first tracing to the right is composed of two pseudo-words; (c) the second pseudo-word on the right is composed of two tracings.

This paper is divided into two main parts. After a brief summary on the preprocessing and the detection of the information areas in the images, we introduce in the first part the different visual indices and the extraction process. The second part is a comparative study of the contribution of the different detected visual indices in description of words. The first study is based on the entropy criterion (Mutual Information). We study the impact of fusing similar indices on the global classifier performance (leading to index discrimination). In the second study, we have used Hidden Markov Models HMM for selection of visual indices. We terminate this paper with a general conclusion.

2. Detection of areas of interest and word straightening

Detection and localization of the different connected components of the word is achieved by the extraction of the image external contours. These components represent two types of image information: tracings and diacritics [10], (Figure 3). For the latter, we detect the global baseline and the word middle zone [11] based on heuristic rules containing essentially distance criteria comparing component relative position to the baseline and the middle zone.



(a) (b)

(c)

Figure 3 : Detection and separation of information areas of the image: (a) word image; (b) external contours of tracings; (c) diacritics (dots)

By analysis of the tracings, we can detect the baseline of the word as being the sequence of straight line segments joining together the local minima of the contours (after filtering those outside the middle zone). The slope of these line segments differs from the slope of the reference baseline of the word. To strengthen the detection of features, we straighten the image of the word ; we use the method of slight correction, described in [12].

3. Extraction of Visual Indices

We mentioned that our images could be decomposed into two main information areas: tracings and diacritics. Each of these areas contains its own set of visual indices:

3.1 Area of tracings

This is the richest of indices; it contains the majority of the image information. Also, we can frequently encounter words with no diacritic, but never a word without tracings. It presents the main area of the word. The visual indices from this area are of two types, defined as regularities and singularities [13]. The first type groups indices extracted from the middle zone: loops, valleys and inter-tracing spacing; the second type includes the prominent features: alifs [10], ascenders, descenders and tanks (see §3.1.2).

Among the features of this area, we distinguish those which can be extracted directly (like loops) from those which can only be extracted after a signal analysis describing the general shape of the tracings and its two distinct areas: middle and prominent zones (Figure 4). To detect these visual indices (except for loops and alifs), we proceed with a signal extraction qualified as useful which contains sample pixels of top contour (from different tracings).

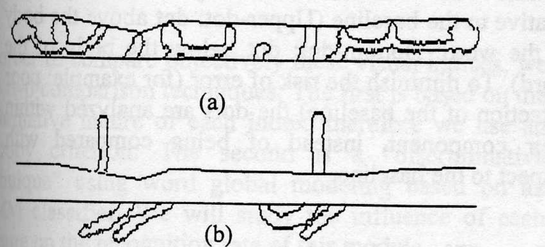


Figure 4 : The two areas of the tracings: (a) middle zone; (b) prominent zone.

3.1.1 Alifs

An alif is a special character intrinsic to Arabic writing and generally appears in the shape of a vertical or slightly inclined line (Figure 5). These characters cannot be attached to the previous or the next character; they can only appear isolated. Their morphological properties make them easy to extract and simple to recognize [10]. We believe they are powerful visual indices and in our study, they contribute valuable information and influence greatly the recognition performance.

Figure 5: Some examples of alifs

3.1.2 Prominent zone

The prominent zone contains features of 3 types: ascenders, descenders, and tanks. Ascenders and descenders are undeniably the most used features in the field of Latin writing recognition [4-7]. The feature detection is achieved by the useful signal analysis. This signal is extracted from the upper contours of the tracings, and describes the general shape of the word [14]. An *upward* terminating outside the middle zone generates an ascender. Also, a downward terminating outside the middle zone (within a certain ''security'' margin), if it corresponds to the last significant state of the signal, indicates a descender (Figure 6).

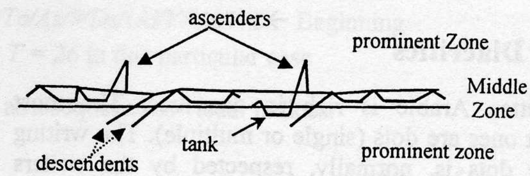


Figure 6: Features localization

Tanks are particular cases of descenders (Figure 6) appearing in characters such as *Sine*, *Lem*, *Noun*, and *Khaaf* (Figure 7), when written at the end of a tracing or isolated. We call them tanks because they represent descenders terminating inside the middle zone, which gives them the shape of a tank.

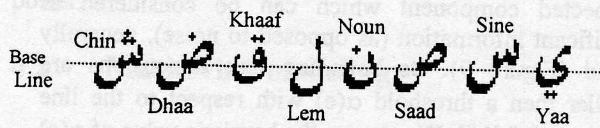


Figure 7: Characters having a tank when written at the end of a pseudo-word or isolated

3.1.3 Middle zone

In this zone, apart from already detected loops, we are looking for informative indices, such as valleys and inter-tracing spacing. Arabic writing being semi-cursive, the characters inside a given tracing are inter-connected by links. These line segments have the shape of small valleys linking two summits. The number of valleys per tracing reflects approximately the number of characters. This information is important to enrich knowledge of word tracings. The valleys are represented by flat shaped segments inside the middle zone, followed by an upward.

Inter-tracing spacing are natural separators between characters of the same word entity. The notion of tracing or pseudo-word, intrinsic to Arabic handwriting, implies necessarily taking them into consideration in the modeling. Also, these spacings are easily detected by their visual aspects of discontinuity in the word entity (Figure 8). We have to distinguish between two spacing types: long and short. The first type normally represents the inter-pseudo-word spacing, whereas the second represents intra-pseudo-word spacing (Figure 2).

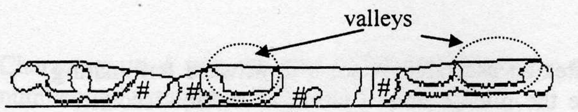


Figure 8: Features of the word middle zone: inter-tracing spacing are represented by ``#".

3.2 Diacritics

Handwritten Arabic is rich in diacritics. The most pertinent ones are dots (single or multiple). The writing of these dots is, normally, respected by the writers because dots distinguish characters having the same main body. As shown in the word images in this paper, half of the characters in the Arabic alphabet contain dots, written either above or below the main body. Also, these dots appear outside the information area (tracings), and are simple to detect by their visual aspect. However, the single dots are small, and sensitive to acquisition noise.

We define a single dot as being the smallest connected component which can be considered as significant information (as opposed to noise), generally round (Figure 9). Its bounding box dimensions are smaller then a threshold $\alpha(e)$ with respect to the line thickness "e" [15]. We choose the heuristic value of $\alpha(e)$ as 2.5.

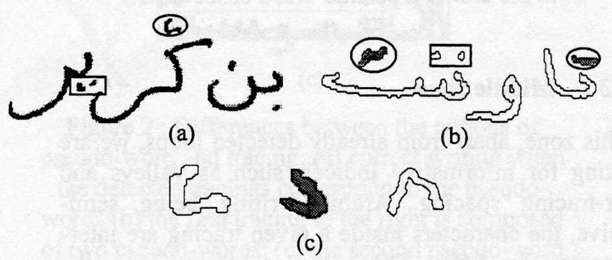


Figure 9: Some samples of simple and multiple dots: (a) example of triple dots (b) example of double dots (c) general shapes taken by triple dots

On the other hand, multiple dots are more complex shapes because they are groupings of the dots of a character. This grouping is due essentially to the writing style. Even if their shapes are simpler in printed characters, still they are sometimes not distinguishable and inseparable from other diacritics. Multiple dots come in two types: double (Figure 9-b) and triple (Figure 9-a). Double dots are groupings of two dots and can appear above or under the baseline; triple dots are groupings of three dots. Figures 9-c shows the variability in which triple dots are presented on a single character. These triple dots cannot be written above the baseline. We use simple features (number of transitions per line/column, open loops) and heuristics to distinguish between the different diacritics. As we mentioned before, in the case of handwriting, the diacritics are complex that we decompose each of these two types into their number of single dots. To refine the word description and to increase the information value of the features, we separate them into two distinct visual indices according to their position relative to the baseline (Upper-dot: dot above the body of the word; Bottom-dot: dot below the body of the word). To diminish the risk of error (for example: poor detection of the baseline) the dots are analyzed within their component, instead of being compared with respect to the baseline.

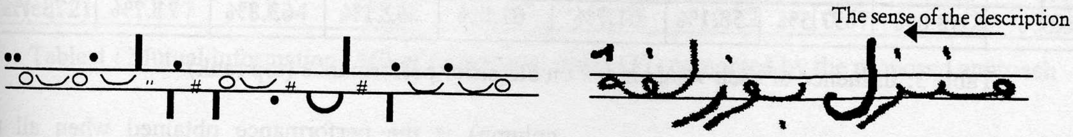
3.3 Word description

The visual indices described above represent the set of features used in word description. The words are represented by a chronological observation sequence (visual indices in Figure 10).

The description direction follows the proper Arabic reading/writing direction, which is from right to left. The literature provides studies [16] presenting the reading direction as being from the exterior to the interior; we find in [7] an application for this method, but in our study we use the conventional direction and describe the word in a *"first come, first served"* fashion. We use the horizontal axis as a chronological axis to order the observations provided by the two different information zones. The tracing zone indices do not cause any problem as they already appear in chronological order (memorized in the signal pixels). The difficulty arises with the insertion of diacritic indices into the observation sequence. To solve this problem, caused by the heterogeneity of the information, we calculate the centers of gravity of the information and compare their positions in the image represented by the visual indices (Figure 10).
Finally we present in Table 1 the set of visual indices, localized and extracted from Arabic handwritten words, and their codes.

VI	Valley	Space	Upper dot	Bottom dot	Ascender	Descender	Loop	Alif	Tank
code	*V*	#	*Ud*	*Bd*	*As*	*Ds*	*L*	*Al*	*Ta*

Table 1: Visual index codes.



Ud/Ud/L/V/L/Ud/V/As/#/Ds/Ud/#/L/Ds/V/Dd/#/Ta/As/#/Ds/Ud/V/Ud/V/L ← Beginning

$y_1^T = (y_1, y_2, \ldots, y_{T-1}, y_T)$ where $T = 26$ in this particular case

Figure 10: Examples of word presentation as a sequence of visual indices.

4. Visual index evaluation

In order to compare objectively these visual indices, we use two comparison techniques. The first is based on the informative nature of each index; therefore we use an entropy criterion. The second is a "discriminative technique" using word global modeling based on an HMM classifier. We will study the influence of each feature on the recognition rate of this module.

We have used in this case a database constructed in the laboratory of PSI-La3i (University of Rouen) containing 10620 sub-images of handwritten words. The lexicon size of this database is of 232 word classes.

4.1 Mutual Information

Regarding the informative power of each visual index, we use the entropy criterion based on mutual information [17] with respect to the sequences observed during training. The computation of the mutual information looks easy in the case of feature vector descriptions of patterns [19]. But how can one compute the informative power of each feature in the case of sequential description of patterns (words)?

In [18] the author proposes using the occurrence number of each feature as information to compute its informative power. For example, take the following sequence representing a word (Tunis) from the database:

$$Ud\,/\,V\,/\,Ud\,/\,L\,/\,Ds\,/\#/\,V\,/\,Ud\,/\,V\,/\,V\,/\,Ta$$

Given that we are studying the visual index "*Ud*", this sequence, noted j, generates the code $N_j^{Ud} = 3$

The mutual information (*MI*) between the lexicon Ω and the set of the different codes N_j^k that can be generated by a visual index k can be written as:

$$MI(\Omega,k) = \sum_{m_i \in \Omega} \sum_{N_j^k} P(m_i, N_j^k) \log \frac{P(m_i, N_j^k)}{P(m_i)P(N_j^k)} \quad \text{(eq. 1)}$$

To clarify matters, we assume that the visual indices are independent of each other. The MI is computed using the entire database (10620 sub-images).

In Table 2, the visual indices are presented in increasing order with respect to their informative power.

4.2 Markovian modeling

A Markovian model is a stochastic process with a finite set of N different states defined by :

1- The transition probability matrix $A = \lfloor a_{ij} \rfloor$ where a_{ij} is the probability of being in state j at time t while knowing that we were in state i at time t-1:

$$a_{ij} = P(q_t = j \,/\, q_{t-1} = i) \quad 1 \le i \le N,\ 1 \le j \le N$$

2- The state initial probability vector $\Pi = [\pi_i]$:

$$\pi_i = P(q_1 = i) \quad 1 \le i \le N$$

Notice that $q^N{}_1 = (q_1, q_2, \ldots, q_N)$ is a chain of t states describing a Markov Model.

In addition to parameters A and Π, an HMM is described by the matrix B of observation probabilities of the symbols following the system's state:

3- $B = \lfloor b_j(k) \rfloor$ where $b_j(k)$ is the probability the state j generates the symbol k ($k \in [1, M]$);

$$b_j(k) = P(y_t = k \,/\, q_t = j) \quad 1 \le j \le N;\ 1 \le k \le M$$

where M is the number of possible observations.

VI (*k*)	#	*Bd*	*V*	*Ud*	*L*	*Ds*	*Al*	*As*	*Ta*
MI (eq. 1)	0.56	0.48	0.43	0.42	0.28	0.24	0.21	0.15	0.12

Table 2 : Mutual information (*MI*) of each visual index (*VI*) computed by the method proposed in [18]

	All VIs	VIs - Ud	VIs - Bd	VIs - #	VIs - As	VIs - V	VIs - L	VIs - Ds	VIs - Al	VIs - Ta
τ_{reco}	76.5%	55.0%	57.5%	58.1%	61.7%	61.8%	62.1%	63.8%	71.7%	73.4%

Table 3: Influence of each visual index on classifier performance (top rank)

Eventually a vector Γ of final state probability can be defined as:

$$\Gamma = [\gamma_i] \text{where } \gamma_i = P(q_T = i) \quad 1 \le i \le N$$

An HMM λ is totally defined by the parameters A, B and Π; we can add the final probability vector Γ to reinforce the decisions. An HMM λ is noted as: $\lambda=(A, B, \Pi, \Gamma)$.

HMMs are soft elastic models widely used in speech recognition [20], and since the beginning of the decade they are imposing themselves in writing recognition [21]. We note that there are some derivations of HMM described in [22-24], for example. This modeling tolerates variability in the writing, and adapts perfectly to our type of data. The only problem is that we have a relatively large lexicon (232 classes of words), and few samples per word classes. The model's topology is a classic right to left one (see Figure 11). The estimation of the model parameters is done by the *Baum-Welch* algorithm.

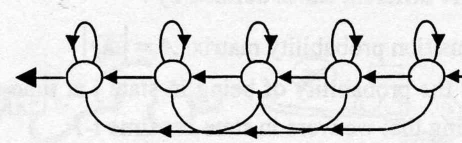


Figure 11: A right to left HMM (5-state model)

Decision : The decision model is a maximum likelihood module where the word is attached to that class M_i which maximizes $P(y_1^T / \lambda_i)$ where $y_1^T = (y_1, y_2, ..., y_T)$ is the observation sequence (visual indices) generated by the word:

$$k = \arg\max_i P(y_1^T / \lambda_i)$$

In our experiments, we studied the influence of each visual index on the system performance. In each experiment, we describe the database words by all visual indices except the one being studied.

Table 3 presents the performance variation of the classifier with respect to the removed visual indices from the feature set. To respect the same experiment conditions as in §4.1, all the database is used for training and also for testing. Our reference (first column) is the performance obtained when all the visual indices are used in our description.

We notice a large difference between the *VI* list order obtained by the discriminative technique (Table 3) and the informative ordered list (Table 2). In fact, the use of visual indices occurrence number [18] decreases the quality of their informative power. We deduce that occurrence number information does not reflect the information used by an HMM modeling. To overcome this problem, we propose a new approach to compute the mutual information in this kind of pattern description.

4.3 Proposed approach to compute MI

The feature vector describing a word, in an HMM modeling, is a sequence of variable length which derives its descriptive power in the order of appearance of the visual indices. This kind of description complicates the computation of the mutual information due to the number of possible combinations (all possible sequences), which requires a large database. In practice such a database is difficult to obtain. To simplify the computation of *MI*, we transform each sequence of visual indices (describing a word) into a binary vector indicating the presence or the absence of a given *VI* in each possible position in the word. Let's take the previous example representing a word (Tunis) from the database:

Ud / V / Ud / L / Ds /# / V / Ud / V / V / Ta

Given that we are studying the visual index "*Ud*", the sequence generated would be the following:

(1,0,1,0,0,0,0,1,0,0,0) and noted by : $(s_1^k, s_2^k, ..., s_L^k)$ where L is the length of the sequence and k represents the *VI* "*Ud*".

The mutual information (*MI*) between the lexicon Ω and the set of the different positions s_j^k that can be taken by a *VI* k can be written as:

$$MI(\Omega, k) = \sum_{m_i \in \Omega} \sum_j P(m_i, s_j^k) \log \frac{P(m_i, s_j^k)}{P(m_i)P(s_j^k)} \quad \text{(eq. 2)}$$

where m_i describes all word classes of the lexicon Ω and j describes all the possible positions in the word's sequences of the visual index k. This solution reduces the number of estimated parameters.

Table 4 presents the list of visual indices in increasing order with respect to their informative value computed by the proposed approach.

VI (k)	V	Ud	Bd	#	Ds	L	As	Al	Ta
MI in (eq. 2)	1.17	1.14	1.12	0.99	0.73	0.72	0.67	0.42	0.27

Table 4 : Mutual information (*MI*) of each visual index (*VI*) computed by the proposed approach

The analysis of these results (Table 4) proves that the proposed approach has a better estimation of the *VI* (features in a general case) informative order than the method proposed in [18] (Table 2) compared with the "discriminated technique" (Table 3).

The analysis of the previous results proves the importance of the diacritics in the word descriptions. They are considered as the second and the third most informative indices by the entropy criterion (Table 4), these results are confirmed by their influences on the performances of the HMM based classifier (Table3).

Finally, we point out that if we don't take into consideration the valleys, we find approximately the same order of *VI* given by both the "discriminated technique" and the proposed *MI* criterion.

5. HMM performance

In this study, our goal is to optimize word description with respect to the performance of the classification module. To pursue this line, we study whether all the set of visual indices are useful for word description. We merge certain visual indices which have the same global shape and characteristics, and see their influence on the recognition rates. For these experiments 2/3 of the database (7080 words) is used for training, and 1/3 of the database for testing (3540 words).

First, we study the performance (τ_{reco}) of a classifier, based on HMM word modeling, considering the set of all *VIs* (Table 5). We remember that the word model topology is a classic right to left (§ 4.2).

	top1	top2	top3	top4	top5
τ_{reco}	63.9%	73.1%	77.7%	80.4%	82.3%

Table 5: Classifier performance (top rank)

Second, we study the influence of merging similar *VI* on classifier performance. In the following studies, the results of Table 5 serve as reference.

We notice that the alifs and ascenders are the less informative visual indices (with the tanks) according to the entropy criterion, and they also have the same shape. Table 6 shows the performance of the recognition module after the fusion of these two *VIs*. We point out that a diminution of 2% in the first choice (top1) caused by this fusion

	top1	top2	top3	top4	top5
τ_{reco}	62.1%	71.6%	75.2%	77.6%	79.2%

Table 6: Classifier performances after the fusion of two visual indices: alifs and ascenders

The same experiment is done for descenders and tanks, because first the tanks are the less informative *VI*, and second they have the same characteristics.

The fusion of these two visual indices decreases the performance of the classifier by 5.5% in the first choice (Table 7).

	top1	top2	top3	top4	top5
τ_{reco}	58.4%	67.7%	71.9%	74.3%	76.0%

Table 7: Classifier performances after the fusion of two visual indices: tanks and descenders

From these two experiments we deduce that to optimize the words description, we must take into consideration the set of all visual indices.

6. Conclusion

In our process, we distinguish two types of visual indices: *VIs* extracted from the tracing zone, and *VIs* extracted from the diacritic zone. We have described the word as a sequence of visual indices. The performances of word description is evaluated using an HMM global word modeling. We have also proposed an approach to compute the mutual information in the case of a word description by a sequence of observations, and studied the informative power of each visual index in solving the Arabic handwritten word recognition problem.

The results obtained by the fusion of similar visual indices, which are the less informative indices, confirm that the set of all visual indices is necessary to optimize the performance of the global classification module. This study shows also the importance of the diacritics information in the description of Arabic words.

Finally, the recognition rates of this global classifier are about 88% in the 10th choice (top 10), and about 98.5% in the 120th choice. We think that this classifier can reduce our Arabic word lexicon if we use a strategy combining the two classification approaches: global and analytical.

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