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PERCEPTUAL RECOGNITION OF ARABIC LITERAL AMOUNTS

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Abstract. Since humans are the best readers, one of the most promising trends in automatic handwriting recognition is to get inspiration from psychological reading models. The underlying idea is to derive benefits from studies of human reading, in order to build efficient automatic reading systems.

In this context, we propose a human reading inspired system for the recognition of Arabic handwritten literal amounts. Our approach is based on the McClelland and Rumelhart's neural model called IAM, which is one of the most referenced psychological reading models. In this article, we have adapted IAM to suit the Arabic writing characteristics, such as the natural existence of sub-words, and the particularities of the considered literal amounts vocabulary.

The core of the proposed system is a neural network classifier with local knowledge representation, structured hierarchically into three levels: perceptual structural features, sub-words and words. In contrast to the classical neural networks, localist approach is more appropriate to our problem. Indeed, it introduces a priori knowledge which leads to a precise structure of the network and avoids the black box aspect as well as the learning phase. Our experimental recognition results are interesting and confirm our expectation that adapting human reading models is a promising issue in automatic handwritten word recognition.

Keywords: Handwritten Arabic words, reading models, perceptual or perception-oriented recognition methods, localist neural network, literal amounts, perceptual features

1 INTRODUCTION

Automatic handwriting recognition was initially considered an easy to solve problem, but has later proved to be very difficult [9]. Before attempting the machine recognition of handwriting and since humans are the best pattern recognizers, it is worthwhile considering the way that people read: What features are detected while reading? How do we access information concerning the identity of a word? Does perception of a word build up from the perception of its letters or by its global shape? etc.

For many years, psychologists have been investigating these questions and various reading models resulted from their work [7, 8, 22]. Even if these investigations are still in progress, and many theories and ideas are being debated, the handwriting recognition community can benefit from the current state of research on human reading, to achieve automatic word recognition [3]. In fact, writing features perceived by humans while reading are likely the best to use in machine recognition. In the same way, human mental identification of words can influence the architecture of the automatic recognition systems. New insights into handwriting recognition indicate that it seems appropriate to base automatic handwriting recognizers on psychological reading models. This recent issue led to the development of systems that are called *perceptual*, *perception-oriented* or *human reading inspired* [23].

Since the perceptual approach is our first motivation, we were influenced by the psychologists who state that *"converging evidence from behavioral and brain imaging studies supports a word recognition model closer in spirit to the interactive activation model (McClelland and Rumelhart, 1981) than to more recent (distributed) model"* [8]. That is why we have been strongly inspired by the perception model developed in 1981 by McClelland and Rumelhart in their psychological researches.

Among the psychological word reading models proposed in the literature [8], the most referenced one is the McClelland and Rumelhart's neural Interactive Activation Model (IAM) [13]. IAM was originally developed to explain the word superiority effect: *it is easier to recognize a letter in a word than in isolation.* IAM has three processing levels corresponding to different levels of abstraction (features, letters and words). The levels interact in a way that the results obtained at a certain level are used by the process at another level. Thus, the influence of lexical context is not explicitly modeled, but is an effect of the global architecture [23].

In this article, we propose a perceptual system for the recognition of Arabic handwritten words in literal amounts. Our approach is inspired by IAM, which was successfully adapted to recognize handwritten Latin words [3, 4, 5, 23]. This work represents a first attempt to adapt IAM to Arabic handwriting recognition, by taking into account the characteristics of Arabic writing, and focusing on the considered lexicon particularities.

The proposed classifier is a localist neural network (i.e. with local knowledge representation) including three hierarchically organized levels of cells, corresponding to features, sub-words and words. The second level, which corresponds to the Arabic natural sub-word concept, represents the first specificity of our approach compared to IAM. The second one results from our particular decomposition of the literal amounts vocabulary. These two specificities allowed us to build a classifier whose architecture best suits the characteristics of the considered Arabic words.

In contrast to classical neural networks, cells in localist neural networks correspond to concepts and links are established to express relationships between these concepts. Moreover, connection weights are not randomly assigned, then modified during a training phase, but they are fixed to express contributions between neurons, according to a priori knowledge. Consequently, the learning phase is avoided.

When a word image is presented to the system, the perceptual features (i.e. ascenders, descenders, loops and diacritical dots) of its sub-words are extracted and gradually given (i.e. sub-word by sub-word) as input to the classifier. The recognition phase chooses and rates possible word candidates, using perceptual cycles. Each cycle contains two processes: bottom-up and top-down. During the bottom-up process, the information propagates from the lower (feature) level to the higher (word) level, and vice versa in the top-down process. After a few cycles, an ordered list of possible lexicon words is obtained.

The remainder of this article is structured as follows: in Section 2, we present the IAM reading model and its adaptation to Latin word recognition. The most significant characteristics of Arabic writing are summarized in Section 3. An overview of the proposed system is given in Section 4, and Section 5 is dedicated to our vocabulary decomposition. The next sections (6 and 7) describe the recognition model architecture and behavior. Finally, we discuss some experimental results and compare the proposed approach to our previous work on the same application domain. This discussion is followed by a conclusion and some perspectives.

2 IAM READING MODEL AND ITS ADAPTATION TO LATIN WORD RECOGNITION

McClelland and Rumelhart assume that perceptual processing takes place within a system in which there are several levels of processing, each concerned with forming a representation of input at a different level of abstraction [3, 13]. IAM is a neuron-like system containing three hierarchical levels: features, letters and words with feedback between them. Communication between levels is excitatory and inhibitory. This model was used to find one missing letter in a four-letter word. The words consisted of printed letters described with very simple features: horizontal, vertical and diagonal strokes [4, 5, 13].

McClelland and Rumelhart presented many psychological justifications of the IAM architecture [3, 13] and several existing Latin word recognition systems were inspired by this attractive model [23]. These systems generally present a recognition cycle divided into two parts: a bottom-up and a top-down process. The bottom-up process consists in extracting global features which are not expected to give the identity of a letter, but only to account for the global shape of the word. This representation is used to create a short list of candidates among the lexicon elements by selecting only the words with a compatible shape (e.g. the presence of an ascender will allow to discard all the words of the lexicon that do not contain letters with ascenders). In some cases, the short list contains only one word and the recognition process is completed, in other cases, several words are selected and the top-down process is needed. It consists of verifying or looking for the letters that compose each candidate of the short list. This approach does not need the recognition of all the letters of the word and when the short list contains only one word, it is not necessary to recognize any letter. This technique is based more on the discrimination between the words of the lexicon than on their recognition. Therefore, it is effective in applications that involve a static lexicon [23]. To the best of our knowledge, the closest recognition system to IAM is Percepto [5] where Côté et al. deal with Latin handwritten words and introduce into their model additional characteristics specific to cursive script [3, 4, 5, 23].

3 ARABIC WRITING CHARACTERISTICS

Arabic characters are used in the writing of several languages such as Arabic, Persian and Urdu. It is estimated that there are more than one billion Arabic script users in the world [6]. Unlike Latin, Arabic is written from right to left in cursive script, according to a baseline, and is such that words are separated by spaces. Among the 28 basic Arabic letters, 22 are cursive letters while 6 are non-cursive; they are not connectable with the succeeding character. Thus, an Arabic word may be decomposed into more than one sub-word, each represents one or more connected letters.

The shape of an Arabic character depends on its position in a sub-word, a character has up to four different shapes depending on it being isolated (isolated form, IF), connected from the left (beginning form, BF), connected from the right (end form, EF), or connected from both sides (middle form, MF). This fact increases the number of Arabic character classes from 28 to around 100 (see Table 1).

In addition, the character size (height and width) varies across different characters and across different shapes of the same character. Several characters can combine vertically to form a ligature, especially in typeset and handwritten text. Some Arabic characters may have exactly the same main body shape, and are distinguished only by the presence or absence of diacritical dots, their position (above or below) and their number (up to three) like the characters ba, ta, tha in Table 1.

Arabic writing can be vowellized, with diacritical short vowels written as small strokes above or below the characters. A different short vowel on a letter can change the meaning of a word. In contemporary Arabic, these signs are only used in books teaching systematic reading and writing, readers are accustomed to reading unvowellized texts by deducing vowels from context [1].

Over the centuries, Arabic calligraphers have developed many writing styles. Some of them are geometrical, decorated, braided or embellished like the Kufi style.

Letter	IF	BF	MF	EF
Alif	ا	ا	ـا	ـا
Ba	ب	بـ	ـبـ	ـب
Ta	ت	تـ	ـتـ	ـت
Tha	ث	ثـ	ـثـ	ـث
Jeem	ج	جـ	ـجـ	ـج
Hha	ح	حـ	ـحـ	ـح
Kha	خ	خـ	ـخـ	ـخ
Dal	د	د	ـد	ـد
Thal	ذ	ذ	ـذ	ـذ
Ra	ر	ر	ـر	ـر
Zay	ز	ز	ـز	ـز
Seen	س	سـ	ـسـ	ـس
Sheen	ش	شـ	ـشـ	ـش
Ssad	ص	صـ	ـصـ	ـص

Letter	IF	BF	MF	EF
Dhad	ض	ضـ	ـضـ	ـض
Tta	ط	طـ	ـطـ	ـط
Ttha	ظ	ظـ	ـظـ	ـظ
Ain	ع	عـ	ـعـ	ـع
Ghain	غ	غـ	ـغـ	ـغ
Fa	ف	فـ	ـفـ	ـف
Qaf	ق	قـ	ـقـ	ـق
Kaf	ك	كـ	ـكـ	ـك
Lam	ل	لـ	ـلـ	ـل
Meem	م	مـ	ـمـ	ـم
Noon	ن	نـ	ـنـ	ـن
Ha	ه	هـ	ـهـ	ـه
Waw	و	و	ـو	ـو
ya	ي	يـ	ـيـ	ـي

Table 1. Different shapes of Arabic characters

Others have round shapes and are more legible like the Naskh style which became a standard font both for printed and handwritten Arabic [2].

4 OVERVIEW OF THE PROPOSED SYSTEM

Our system is developed for off-line recognition of handwritten words in Arabic literal amounts (see Figure 1). In the following, we discuss briefly the preprocessing and feature extraction preliminary phases. Algorithms are described in [19, 20]. The images of amounts are first binarized using a histogram thresholding method [14], then smoothed [12] and segmented into word images. Contours of these words are traced according to Freeman code directions [12, 14]. Features are then extracted and used as input for the recognition module. This module, which is a perceptual classifier, corresponds to the vocabulary decomposition (see Section 5), and consists of a neural network with local knowledge representation, giving as output an ordered list of word candidates (see Figure 1). The complexity of the used algorithms is generally linear. It is a function of the amount image size in the preprocessing phase. During contour tracing, the complexity depends on the number of pixels belonging to contours in a word image. Features extraction complexity is based on the number of contours. The complexity of the classification phase is a linear function of the number of sub-words and their corresponding features.

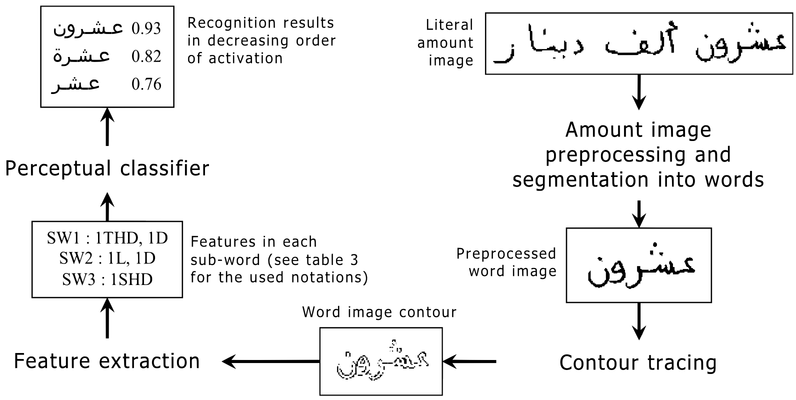

Fig. 1. Overview of the proposed system

Concerning the feature choice, evidence from psychological studies of reading indicate that humans use perceptual high level features such as ascenders, descenders and word length in addition to letter identities in fluent reading [10, 16]. Several of these features have found application in computer systems for handwritten words recognition [11, 21]. This is why we have retained this kind of features for our system.

Among the Arabic writing properties (see Section 3), the ones which interested us during our study are:

- Arabic is written from right to left.
- It presents several shapes for a same letter according to its position in a word.
- The sub-word concept is natural in Arabic and most of the writers respect it.

The analysis of these specificities, particularly for the literal amounts vocabulary, permits us to proceed to an important step of our work: the decomposition of the considered vocabulary according to the number of sub-words, then the extraction of features (ascenders, descenders, loops and diacritical dots) within these sub-words. Figure 2 illustrates perceptual features in an Arabic word. These features are extracted from the contours of a preprocessed word image: the loops correspond to internal contours and the number of ascenders and descenders is deduced from the presence of given Freeman code sequences in the primary contour. Diacritical dots correspond to small secondary contours (relatively to the primary one), their position (high or low) is determined according to the baseline and their type is evaluated by heuristics on the stroke thickness [18, 20]. The feature description of the word given in Figure 2 and obtained using the notations explained in Table 3 is: 2SW, 2L, 1A, 1D, 1SHD, 0SLD, 0DHD, 1DLD, 0THD

The recognition method is based on some ideas presented in the IAM reading model and its adaptation to Latin handwritten word recognition: Percepto [5], but

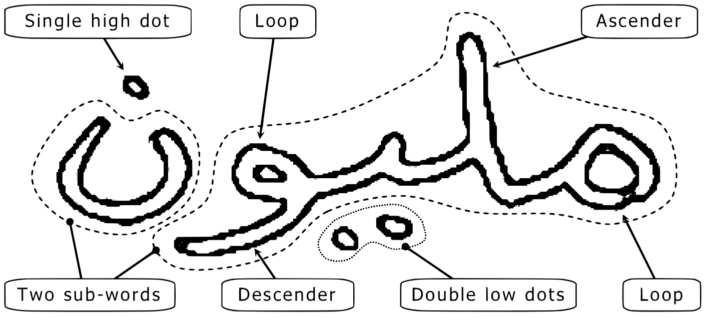

Fig. 2. Features of an Arabic word

we have included in our classifier some characteristics specific to Arabic handwritten script and to the literal amounts vocabulary. Therefore, our perceptual classifier has the following properties:

- Its inputs are perceptual features in Arabic writing (ascenders, descenders and diacritical dots for each sub-word).
- It consists of a neural network with local knowledge representation.
- There are three levels of processing: features, sub-words and words (the sub-word concept is natural in Arabic).
- Its architecture results from our vocabulary decomposition (see Section 5).
- The inhibition mechanism (used in IAM) is discarded in order to keep all the information available until a decision on the identity of the unknown word is finally made.
- Propagation of activation is gradual between adjacent levels, following several bottom-up and top-down processes.

5 DECOMPOSITION OF THE VOCABULARY

Real world exemplars of a handwritten word may be modeled as distortions of an ideal exemplar of the word which can be represented by its printed form. Thus, to simplify our explanations, we illustrate them with printed Arabic words, but our recognition experiments have been carried out on handwritten samples. The Arabic check amounts lexicon contains 48 words and each word is composed of up to four sub-words (see Table 2).

The possible occurrence numbers for each feature within a word of the chosen lexicon is given by the Table 3. For instance, the last line in this table, concerning the THD (triple high dots) numbers ($x = 0..2$), indicates that we can find, in the lexicon:

Number of sub-words	Words				
1	عشر	تسعة	سبعة	ستة	خمسة
				و	سنتيم
2	عشرة	ثمانية	ثلاثة	اثنا	احد
	مائة	تسعون	سبعون	ستون	خمسون
	تسعمائة	سبعمائة	ستمائة	خمسمائة	مائتا
	ملايين	مليونا	مليون	الفا	الف
			سنتيمات	ملايير	مليار
3	ثمانون	ثلاثون	عشرون	اربعة	اثنان
	الاف	الفان	ثمانمائة	ثلاثمائة	مائتان
		مليارا	دنانير	دينار	مليونان
4		جزائري	ملياران	اربعمائة	اربعون

Table 2. Arabic literal amounts vocabulary

- Words which have 2 THD ($x = 2$) such as words in Figure 3 a)
- Words which have 1 THD ($x = 1$) such as words in Figure 3 b)
- Words which have 0 THD ($x = 0$): the remaining 37 words of the lexicon

a) ثلاثة , ثلاثون , ثلاثمائة

b) عشر,عشرة, عشرون, ثمانمائة

ثمانون, ثمانية, اثنان, اثنا

Fig. 3. Words containing THD

Code	Meaning
xSW	Sub-words Number ($x = 1..4$)
xL	Loops number ($x = 0..3$)
xD	Descenders number ($x = 0..2$)
xA	Ascenders number ($x = 0..3$)
xSHD	"Single High Dot" number ($x = 0..2$)
xSLD	"Single Low Dot" number ($x = 0..2$)
xDHD	"Double High Dots" number ($x = 0..2$)
xDLD	"Double Low Dots" number ($x = 0..2$)
xTHD	"Triple High Dots" number ($x = 0..2$)

Table 3. Features in the words of Arabic literal amounts vocabulary

We have decomposed the set of possible sub-words into four groups according to their position in the corresponding words (from right to left) as shown in Table 4. For instance, the first group contains all the sub-words (SW) which can occur in the first position (most right one) of one word (or more) in the lexicon.

Group	Sub-words of the group				
1 (25 SW)	عشر	تسعة	سبعة	ستة	خمسة
	تسعو	ثلا	ملا	تسعما	سنتيم
	سنتيما	ما	خمسو	جز	ثما
	مليا	خمسما	مليو	سبعو	سبعما
	ا	و	د	ستو	ستما
2 (23 SW)	ثو	نية	ئتا	ثة	حد
	ينا	ثنا	ئة	ثما	نو
	نما	ن	يير	يين	لف
	ت	ة	نا	لفا	لا
			ا	ر	و
3 (10 SW)	ئة	بعما	بعة	بعو	ن
	نير	ر	ف	ئر	ا
4 (3 SW)			ي	ئة	ن

Table 4. Decomposition of the sub-words of the vocabulary into groups

While analyzing Table 4, we notice that for a given group of sub-words it is not necessary to associate the set of all possible occurrences of features, but just those that really exist in the considered group. Table 5 summarizes the features which are present in each group of sub-words. Note that we have focused on the detected features in the sub-words (when they are correctly written), the feature absence (0 occurrence) is not expressed in Table 5, to simplify our purpose and, later, our classifier architecture. With these new assumptions, the description of the word in Figure 2 is transformed to:

- For the 1st sub-word SW1: 2L, 1A, 1D, 1DLD
- For the 2nd sub-word SW2: 1SHD

6 CLASSIFIER ARCHITECTURE

For the recognition phase of our system, we have chosen a **neural network** with **local representation** of knowledge [4, 5] because there is a limited set of concepts (features, sub-words, words) and the connections between neurons can be established according to the interpretation of their relation. Therefore:

- We can introduce *a priori* knowledge in the network.
- It is possible to explain step-by-step the behavior of the network: it is a transparent system, not a black box (like the classical neural networks with distributed representation).
- There is no modification of connection weights.
- It is not necessary to use extensive database to train the system (there is no training).

4^{th} group (4 features)	3^{rd} group (8 features)	2^{nd} group (9 features)	1^{st} group (11 features)
1SHD	1SHD	1SHD	1SHD
1DHD	1DHD	1DHD	1DHD
1DLD	1SLD	1DLD	2DHD
1L	1L	2DLD	1SLD
	2L	1THD	1THD
	1A	1L	1L
	1D	1A	2L
	1DLD	2A	1A
		1D	2A
			1D
			1DLD

Table 5. Sub-word groups and their corresponding features

Our network includes three levels of cells (or neurons), hierarchically organized at feature, sub-word and word levels. Using the vocabulary analysis results presented in the previous section, the obtained network structure is shown in Figure 4.

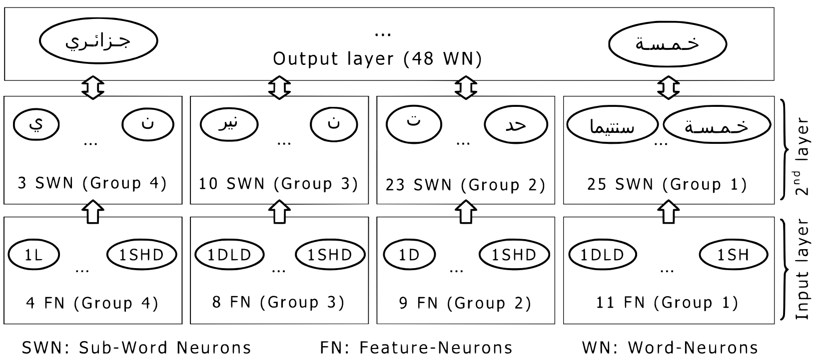

Fig. 4. Structure of the proposed localist neural network

Unlike the IAM model (see Section 2), the connections in our network are **only excitatory**. There is no inhibition in our system, as in several psycho-physiological systems, because of the nature of handwritten cursive script (noisy and unstable information). We reward occurrence of events but not their absence; thus, possible solutions are kept and not eliminated too early in the decision process.

- Connections between the corresponding groups in feature and sub-word levels are unidirectional (see Figure 4).
- Connections between sub-word and word levels are bi-directional (see Figure 4).
- Neurons are not connected within the same level.

- There is no connection between levels which are not adjacent (no direct link between feature and word neurons).

The neurons are pre-linked according to a priori knowledge. Two lexicons join the adjacent layers of cells:

- A feature_sub-word lexicon: containing information about the features which are theoretically present in each sub-word (in corresponding groups).
- A sub-word_word lexicon: containing information about all the sub-words which theoretically constitute a given word (bottom-up links) according to their position and on all the words which contain a given sub-word (top-down links).

Connection weights are not randomly assigned then modified during a learning phase (like in *classical* neural networks with distributed knowledge representation), they are fixed to express contribution relation between neurons according to a priori knowledge: that is why the proposed network can be called *pseudo-neuronal*. There is **no learning** and weights are **fixed** according to the following formulas.

- Weight of a connection between Feature and Sub-word neurons: $w_{FS} = 1/NF$ where NF is the number of features present in a given sub-word.
- Weight of a connection between Sub-word and Word neurons: $w_{SW} = 1/NS$ where NS is the number of sub-words constituting a given word (bottom-up link).
- Weight of a connection between Word and Sub-word neurons: $w_{WS} = 1/NW$ where NW is the number of words containing a given sub-word (top-down link).

7 CLASSIFIER BEHAVIOR

Interaction between units consists of excitatory activation of a neural type. Each cell or neuron i has a momentary activation $A_i(t)$, varying between 0 and 1 according to the following formula, adapted from the IAM model [5]:

$$A_i(t+1) = 0.93A_i(t) + \sum_j w_{ij} \cdot A_j(t)(1 - A_i(t))$$

where $Ai(t+1)$ is the new value of activation at time $t+1$; $Aj(t)$ is the activation of a neighbor j of the unit i and w_{ij} is the weight of the connection from unit j to unit i.

The transmission of information within the three levels of the system is allowed by two complementary processes: bottom-up and top-down processes, in which activation at one level spreads to neighboring level. A perceptual cycle is completed when a bottom-up process is followed by a top-down process.

First, meaningful features such as ascenders, descenders, loops and diacritical dots are extracted from the image of an unknown handwritten word and gradually presented to the classifier. In the bottom-up process, sub-words compatible with the features are activated (feature level toward sub-word level). Following the same process, activated sub-words trigger the words they are related to.

When the bottom-up process is completed, the top-down process begins. The activated words generate sub-word hypotheses which are verified against the features. If the features matching the sub-word hypotheses are present in the unknown pattern, the hypotheses are validated and the corresponding detectors are activated. Hypothesis generation is therefore the way additional contextual information is brought back to the sub-word level and then to the feature level. Because the activation changes gradually over time, the neurons need several perceptual cycles before they can reach an activation level high enough to decide on the identity of the unknown word. In our application, the system converges toward a solution (saturates) after two to five cycles. The convergence means that the activation of the word-neurons reach their final (maximal) values and that it becomes possible to establish a list of candidate words in decreasing order of activation. The word having the highest activation value among the candidates is selected as a recognition result.

8 RESULTS AND DISCUSSION

To evaluate the performances of our approach, we tested it on a database containing 4800 words (the 48 words of the vocabulary, written by 100 scriptors). About 91.81 % of these words were assigned to the correct class (well recognized) while 3 % were assigned to an incorrect class (bad recognition), with 3.94 % of rejected words and 1.25 % of ambiguous words.

A word is rejected or not recognized when there is not an output neuron (word neuron) sufficiently activated. The activation must be greater than an experimentally determined threshold (0.5 in our case) to retain the corresponding word as a valid response; otherwise, it is rejected. This problem occurs when several features are missed (due to the writer style) and especially when the separation between the sub-words is not done correctly by the writers. The bad recognition occurs when a tested word is assigned to another class than the expected one. The ambiguity occurs when two (or more) word neurons have the same greatest activation value among the outputs. We have noticed that these two problems are generally caused by degradation of loops or diacritical dots due to thickness of the stroke, to the writer style or to the heuristics used in our algorithm for diacritical type evaluation.

Our opinion is that the field of off-line Arabic handwritten word recognition is not mature enough to enable a deep and significant comparative study. In fact, the description and comparison of experimental results achieved by other systems (dealing with a similar recognition problem) are not interesting at this stage for the following reasons:

- The off-line Arabic handwritten word recognition problem has been addressed by a restricted number of researchers when compared to the work conducted on Arabic printed characters or words and handwritten characters [6].

- The few systems that deal with handwritten words use proprietary databases. Some recent work has been carried out on a new public database [15, 17] but using a different lexicon (than the one considered in this paper) including Tunisian city/village names.
- The proposed methods in Arabic handwritten word recognition systems were not investigated and tested up to their limits, they went through preliminary experiments only.
- Performance of a system depends on many factors besides the recognition method used. A complete word recognition system relies on several modules (preprocessing, segmentation, feature extraction, post-processing. . .) and its recognition results are influenced by those obtained at each stage. In addition, the chosen feature set contributes, in a major way, to the final performance.

Consequently, to evaluate the recognition method proposed in this article, we have decided to describe some experimental results obtained by other knowledge/neural based systems, developed in our laboratory for the recognition of Arabic literal amount words [18, 19, 20]. To enable the classifier comparison, we used the same preprocessing algorithms in these systems. In addition, the chosen features were the perceptual high level ones, their extraction algorithms were identical as well as their testing database which contains 4800 words (the 48 words of the vocabulary, written by 100 scriptors).

In Table 6, we give a brief description of each classifier. The table shows that the localist neural network presented in this article gives better results than two distributed representation neural networks as well as than knowledge-based classifier for our application. Perceptual classifier performances are equivalent to those of neuro-symbolic one, probably because the two classifiers integrate, by two different ways, a priori knowledge into the network structure. A significant additional advantage of the classifier proposed in this paper is the fact that it does not require any training while this phase is necessary for the neuro-symbolic classifier, but takes about 10 times less than the distributed neural networks.

9 CONCLUSION AND PERSPECTIVES

In this article, we proposed a perceptual or human reading inspired system for the recognition of handwritten words in Arabic literal amounts. The analysis of Arabic writing particularities and the study of the considered lexicon lead us to decompose our vocabulary according to the sub-word concept, natural in Arabic words.

The proposed classifier is a neural network with local representation where a priori knowledge is hierarchically represented by the neurons and their fixed weight connections. Our network includes three levels of cells, organized at feature, subword and word levels. Interaction between them consists of excitatory activation of a neural type.

When an unknown word image is presented to the system, the perceptual features of its sub-words (ascenders, descenders, loops and diacritical dots) are first

Classifier type	Classifier description	Training phase	Recognition rate
Symbolic knowledge-based classifier	Uses a set of hierarchical rules reflecting a classification of the words according to their features [18].	No	$\approx 82\,\%$
Neural with distributed knowledge representation (MLP1)	MLP1 is a fully connected three layer neural network (Multilayer Perceptron) with distributed knowledge representation and randomly generated initial weights. Input layer: 30 neurons corresponding to the possible occurrences of perceptual features in a word. Output layer: 48 neurons corresponding to the words of the lexicon. Hidden layer: 38 neurons, size heuristically determined, then experimentally modified.	Yes	$\approx 84.5\,\%$
MLP2	MLP2 has a description similar to MLP1, except for the size of input and hidden layers. Input layer: 32 neurons corresponding to the possible occurrences of perceptual features in each sub-word position (from 1 to 4, as in Figure 4). Hidden layer: 40 neurons, size heuristically determined, then experimentally modified.	Yes	$\approx 87\,\%$
Hybrid neuro-symbolic classifier	The symbolic (theoretical) knowledge is expressed as a set of hierarchical rules reflecting a classification of the words according to their features. This knowledge is translated into a knowledge based artificial neural network (KBANN) using a translation algorithm. This algorithm defines the network architecture (neurons and connections) and fixes the initial set of weights [19, 20]. • Input layer: 30 neurons corresponding to the possible occurrences of perceptual features in a word. • Output layer: 48 neurons corresponding to the words of the lexicon. • 3 intermediate layers: with 4, 9 and 4 neurons respectively, corresponding to hierarchical classes and subclasses in the lexicon.	Yes (about 10 times less than MLP1 and MLP2)	$\approx 92\,\%$
Neural with local knowledge representation	The perceptual classifier described in this paper (see Figure 4).	No	$\approx 91.81\,\%$

Table 6. Description of five knowledge/neural based classifiers for the recognition of Arabic literal amount words

extracted and gradually given as input to the recognition phase. A cyclic process is then used to choose and rate possible word candidates. The bottom-up process enables filtering words according to observed features that are compatible with sub-words at given locations. The top-down process is used to validate or reject active words according to the existence (or absence) of features that are required to create the temporary missing sub-words. After a few cycles, an ordered list of possible lexicon words is obtained. The word having the highest activation value among candidate words is selected as a recognition result. Thus, the behavior of the system can be explained step by step and a training phase is not needed.

By choosing a local representation instead of a distributed one for our model, we are not in the main stream of 'classical' neural recognition methods, but we are closer to human perception of reading. In fact, the obtained results are interesting and coherent with human psycho-perceptual model because errors made by the system are like those observed by humans: confused words are generally part of a same perceptual family.

As many research works, the proposed method can be improved in several ways:

- By using additional features to resolve ambiguities.
- By evaluating the impact (positive or negative) of adding a letter level to the proposed network (between feature and sub-word levels).
- By integrating the proposed classifier into a multiple classifiers system for Arabic word recognition. The components of this system may use different representations of the word image (many kinds of features) and a large variety of recognition methods.
- By using multiple sources of knowledge, such as syntactic and semantic information on the literal amount, as well as the corresponding numeric amount recognition results, to increase recognition rates.

We are also thinking about the adaptation and the evaluation of the proposed method for the recognition of other restricted Arabic lexicons like country names or city names in a given country.

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