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▶ **To cite this version:**

Hanen Khlif, Sophea Prum, Yousri Kessentini, Slim Kanoun, Jean-Marc Ogier. Fusion of Explicit Segmentation Based System and Segmentation-Free Based System for On-Line Arabic Handwritten Word Recognition. 5th International Conference on Frontiers in Handwriting Recognition (ICFHR 2016), Oct 2016, Shenzhen, China. pp.399-404, 10.1109/ICFHR.2016.0081 . hal-03030186

HAL Id: hal-03030186
https://hal.science/hal-03030186

Submitted on 8 May 2022

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Fusion of explicit segmentation based system and segmentation-free based system for on-line Arabic handwritten word recognition

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***Abstract*— The complexity and viariability of the Arabic handwriting makes difficult the implementation of an efficient recognition system through the use of a unique recognition engine.. In this paper, two handwriting word recognition systems are combined in order to take advantage of their complementarities. The first one is a segmentation free based system that uses the generative classifier HMM. The second system is discriminative based. Relying on analytical approach, it proceeds with explicit segmentation of words into graphemes. Different combination strategies are compared including sum, product, Borda count and Dempster-Shafer rules. The experimental results conducted on ADAB database demonstrate a significant improvement of recognition accuracy of 5% compared to the segmentation free based system and 9% compared to the analytical based system.**

Keywords- on-line handwriting Arabic word recognition segmentation free; analytical approach; HMM; SVM; information fusion;

I. INTRODUCTION

This paper deals with on-line Arabic handwriting recognition system, which becomes a fundamental service in our modern society. Handwriting recognition can be defined as the process of transforming text represented in the spatial form into its symbolic representation [1]

In the literature, handwriting recognition can be divided in two categories, depending on the nature of the input. First, off-line recognition which is essentially based on the treatment of texts that are generally captured by scanned images; and on-line recognition which is generally based on digital pens or tablets, for which a chronological sequence of coordinates is usually produced. The set of sequences represents a pen movement that can scale on the mapped screen surface. This mapping (time, coordinates and sequence) is captured in a real-time. As a consequence, online handwriting recognition technology has a great potential for improving human machine interaction.

Over the past few years, many techniques have been proposed in the literature. There are a huge number of researches which have dealt with Latin and Chinese handwriting recognition. However, only a few of these researches have considered Arabic language.

In Arabic language, words are written in a cursive style, from the right to the left. There is no discreet type of handwriting. In addition, each letter can be written in four different shapes according to its positions in the word. Furthermore, the Arabic language contains some diacritics, hence reversing or even changing word meaning by a simple sign change. Consequently, handling such a complex script with large lexicon is a challenging task for existing handwriting recognition systems.

Two approaches have been used for handwritten word recognition [2]: the global approach that considers each word as a class [3, 4, 5] and the analytic approach that involves segmentation and recognition processes to determine the sequence of characters forming the input word [5, 6, 7, 8].

A recent survey on on-line Arabic handwritten recognition has been presented in [9]. A segmentation-based recognition method operating at a stroke level and having Segmentation Points (SPs) has been proposed in [7] in the context of online cursive handwritten word recognition system. The authors have used first an algorithm that works at stroke level by segmenting it into letters. Then, HMM is used to classify the sub-strokes to letters using the Hu features. The letters candidates and their scoring have been used to determine the best set of SPs. In [10], the authors have proposed two stages for the on-line Arabic handwritten text segmentation system based on Hidden Markov Model (HMM). In the first stage, SPs were nominated before being validated in the second stage, using a rule-based engine. The system has been experimented on a self-collected database named OHASD. In [11], the authors have designed a system for Arabic personal names based on HMM and trained with the ADAB-database using two different methods: manually segmented characters and non-segmented words. In [12], a combination of HMM and sliding window have been used to recognize Arabic word with three features (the local angle, super segment, and loop presence). In [8], the authors have presented a system of character recognition based on support vector machine (SVM) and using a new feature called relative context (RC). RC was obtained from the relative pairwise distances and the angles of the writing trajectory.

From the above review, it can observe that there are many on-line Arabic handwriting recognition systems with different classification techniques and feature extraction methods. However, it is noticed that many researchers have found appropriate combinations of different classifiers aiming at providing better recognition results. Generally, there are two main categories of approach for information combination: feature combination representation and decision fusion based approach. The first approach joins

different features before using the classifier. The method of the second approach is based on the combination of decisions independently of the different information sources. Among the methods we can cite majority vote [13], borda count [14], linear combination of the confidence value [15], and Dempster Shafer theory [16].

In this work, an information fusion of the two different analytical systems is proposed to build an online Arabic handwritten word recognition system. These two systems are combined in order to take advantage of their complementarities. First, they use different segmentation methods. The first system relies on segmentation-free strategy while the second system relies on explicit segmentation using segmentation/recognition strategy. Secondly, these systems rely on different classifier. The first system relies on generative HMM model while the second system relies on discriminative SVM classifier. Thirdly, these systems use complementary methods for extraction features. The first system relies on local on-line features extracted from each point of the input signal while the second system relies on the combination of on-line and off-line features. The detail presentation of these methods is presented in section II. and III. Respectively

The rest of this paper will be organized as follows. Section II presents the first system relying on a segmentation free approach. Section III presents the second system on analytical approach. Section IV introduces the combination methods which allow the fusion of the output of both systems. Ultimately, the experimental results are revealed in section V.

II. SYSTEM BASED ON SEGMENTATION FREE APPROACH

The First system relies on segmentation free approach with a generative classifier HMM. The architecture of this system is illustrated in Fig. 1. First, the preprocessing phase is used to reduce the effect of the handwriting device noise and the handwriting irregularity. Then, numerous features are extracted from the preprocessed handwriting signal and are used to train the HMM models in the training step. Afterwards, an embedded training phase is introduced. Finally, a recognition phase where handwriting input is decoded and recognized using the training output. The output of system is the top scoring hypotheses of the handwriting input.

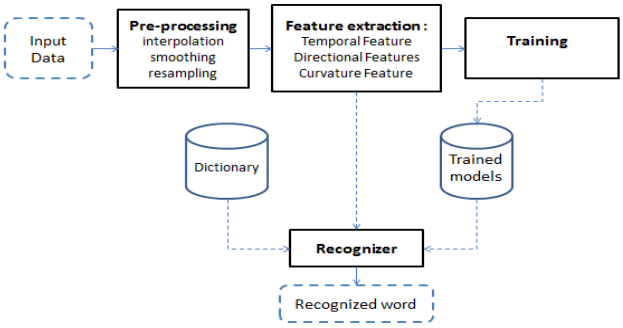


Figure 1. Architecture of system based on segmentation free approach

In the following sub-sections, each component of this system will be detailed.

A. *Preprocessing*

Preprocessing is the first step to recognize words in the suggested system. Given the input handwriting signal, the preprocessing method is applied in order to remove the noise caused by the acquisition device and normalize the online signal respecting the writer's speed. In this system, four commonly used methods (size normalization, interpolation, smoothing and resampling) are applied.

B. *Feature extraction*

Feature extraction is a very important process in the general problem of classification and handwriting recognition. It consists in extracting the measures of the entries to differentiate classes. In this system, from each point of the input signal, a vector of 7 features is extracted: (coordinates, direction, curvature, Pen Down or Pen Up). These features can be classified as temporal features, directional features and curvature features, as presented in the following paragraphs

1) Temporal Features: First, an online signal is represented by a sequence of points P(x (t), y (t)), where t represents time. The sequential nature of the information acquired by the tablet is preserved to provide a better recognition rate. At this level, different parameters of the pen status are detected: horizontal position x (t), the vertical position y (t) and the time t. Then, to specify the state of the pen at a point , the information of pen's movements is detected (pen-up and pen-down) and allows to define a new feature or a new point at the character level.

2) Directional Features: this method consists in extracting local writing direction features at each point P(t) = (x (t), y (t)) at instant (t). This method has been described in [17]. For each point P(t), cosinus and sinus of writing direction angle are extracted as follows:

$$\cos\alpha_t = \frac{\delta x(t)}{\delta s(t)} \quad \text{and} \quad \sin\alpha_t = \frac{\delta y(t)}{\delta s(t)}$$

Where $\delta s(t)$, $\delta s(t)$ and $\delta y(t)$ are defined as follows:

$$\delta s(t) = \sqrt{\delta x^2(t) + \delta y^2(t)}$$
$$\delta x(t) = x(t-1) - x(t)$$
$$\delta y(t) = y(t-1) - y(t)$$

3) Curvature Features: The curvature at point (x (t), y (t)) is represented by the cosinus and sinus of the angle Φ defined by the following three points [17]:

(x (t-2), y (t-2)), (x (t), y (t)), (x (t+2), y (t+2))

The features (cos(Φ) and sin(Φ)) can be computed by:

$$\cos\Phi = \cos(t-1)*\cos(t+1)\ \sin(t-1)*\sin(t+1)$$
$$\sin\Phi = \cos(t-1)*\sin(t+1)\ \sin(t-1)*\cos(t+1)$$

C. *HMM Training*

After the preprocessing and feature extraction phases, this step consists in creating (training) HMM model for each character class. In the proposed system, a left to right HMM is considered. As mentioned earlier, the shape of each Arabic character is changed according to its position in the word. Therefore, to represent the 28 Arabic characters in different positions in a word (beginning, middle, end word position), there are HMMs for 69 unique models. Each character model is composed of 5 emitting states. The Gaussian Mixtures (6 per state) are used to model the observation probabilities. An embedded training with Baum-Welch algorithm is applied on word examples where all character models are trained in parallel. The system builds a word HMM by the concatenation of the character HMM corresponding to the word transcription of the training sample.

D. *HMM decoding*

In the recognition phase, features vectors extracted from a word image are passed to a network of lexicon entries formed of words HMM built by the concatenation of their character HMM. The character sequence providing the maximum likelihood identifies the recognized entry. Word recognition is achieved with the Viterbi algorithm.

The overall recognition process is presented in Fig. 2.

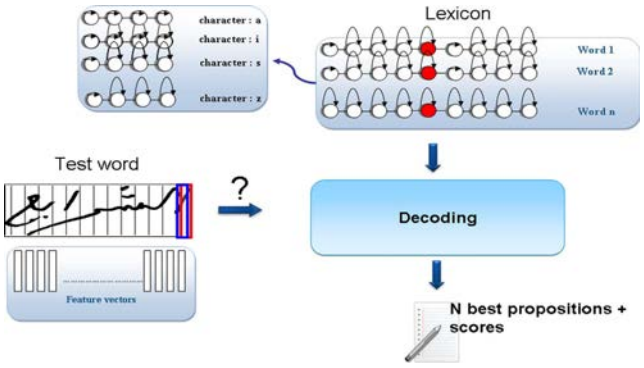


Figure 2. Handwriting word recognition scheme using HMM

III. RECOGNITION SYSTEM OF ARABIC SCRIPT BASED ON ANALYTICAL APPROACH

The second system relies on explicit grapheme segmentation and SVM-based single character recognition. Word recognition is achieved with an efficient dynamic programming method similar to the Viterbi algorithm. This system has been used for on-line handwritten word recognition for English and French languages that rely on Latin character set. The details of this system are presented in [18].

The global view of this system is illustrated in Fig.3. More specifically, given an input handwritten signal, pre-processing methods are applied. For a fair comparison with the HMM-based system, the same pre-processing methods are used (see Section II). The normalized signal is then segmented into a set of graphemes to be further used to create a lattice of L levels. Each node of the lattice is considered as a candidate character. For each node of the lattice, a set of on-line and off-line features are extracted. Next, a single character recognizer is used to emit recognition hypotheses for each node. In the last stage, a word decoding process is used to find the most probable words.

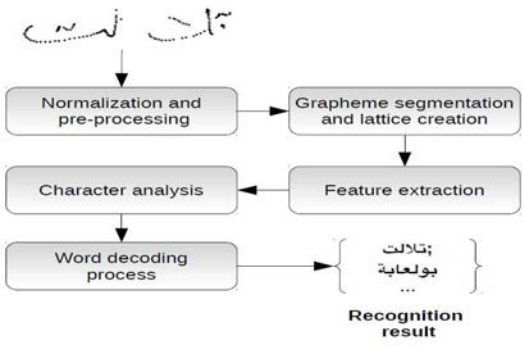


Figure 3. Global overview of the system based on analytical approach

A. *Segmentation and lattice creation*

The normalized signal (resulting from the previous step) is over-segmented into a set of graphemes. In the suggested system, a grapheme is defined as the set of all the consecutive points of a given stroke located between a local minimum and a local maximum (following the y coordinate)

These segmented graphemes are used to create a lattice of levels which represents all the possible concatenations of graphemes [18]. A node in the lattice may be a grapheme or a concatenation of graphemes. Each node is considered as a candidate to be a character and is therefore introduced as the input of the single character recognizer whose role is to generate character hypothesis of each node.

B. *Feature extraction*

In order to benefit from the advantages and complementarity of different feature extraction methods, this system uses the combination of on-line features and off-line features. From the input on-line signal (the signal containing in each node), a set of on-line features, mainly inspired by [19], are extracted. These features represents the number of strokes, the information of starting and ending points of the signal (x, y coordinates, gradients at the starting and ending points).

The off-line features can be computed from the image generated artificially by connecting the consecutive points in the input signal. Nine families of off-line described statistical and structural features are used. These features consist in 5 families of global features (Hu invariant moments, projection, profile, Zernike and Radon moments) and 4 families of local features (intersection with straight lines, local extrema, points/junctions and holes and concave arc). These off-line features have been successfully used for off-line character recognition problem [20] and other pattern recognition problems [21].

In total, a set of 254 features is obtained. This large set of features may contain some insignificant features, as well as

some redundant features. This kind of features may increase the computational time, and sometime degrade the effectiveness of the classification system. In order to circumvent these problems, the Sequential Forward Floating Search (SFFS) Feature Selection method is used to reduce the size of this vector by removing the insignificant features. The detail description of these features is presented in [22].

C. *Single character recognition system (SCR)*

Support Vector Machine (SVM) is used as the discriminative classifier to crate our SCR. As mentioned earlier, the Arabic language is composed of 28 standard character classes. However, the shape of each character changes according to its position (start, middle, ending and isolated) in the word. Therefore, there is a high variation of shape in each class which will decrease the classification performance. To deal with this problem, characters can be categorized in 4 classes according to their position in the word: start-characters, middle-characters, ending-characters and isolated-characters.

Nevertheless, it is worth mentioning that this SCR is used to recognize each node in the lattice. In fact, it can be specified in advance if each node situates at the beginning, in the middle or at the end of the input word, according to its position in the lattice. Yet, it cannot be known in advance if each node is an isolated character or not. For these reasons, three different SCR systems are to be created. The first SCR considers the starting and isolated-characters (50 classes) and is used to recognize nodes at the beginning of the lattice. The second SCR considers the middle and isolated-character (61 classes) and is used to recognize the node and the middle of the lattice. The third classifier considers the ending and isolated-characters (58 classes) and is used to recognize the character at the end of the lattice.

D. *Word decoding*

Given a lattice G of graphemes corresponding to a word to be recognized, the word decoding step consists in searching an optimal path for each word [22] in a given lexicon, and calculating its recognition score. This word decoding process relies on dynamic programming.

IV. FUSION OF EXPLICIT SEGMENTATION BASED SYSTEM AND SEGMENTATION-FREE BASED SYSTEM

This section presents the proposed methods used to information fusion of systems based on segmentation free and analytical approach. As presented in the previous section, these two systems rely on different segmentation methods, feature extraction methods and classifiers. The goal is to combine the outputs of these systems in the best way in order to take advantage of the complementarities of these two systems.

The first step consists in selecting top N recognized words given by segmentation free and analytical based systems. Then, both outputs are combined together using different methods to deliver the new score for each word hypotheses. Finally, the list of hypotheses is sorted to have the list of the TOP N best classes as shown in Fig. 4

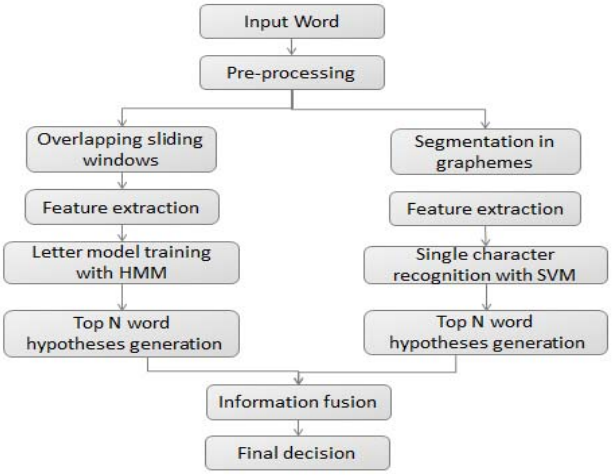


Figure 4. Fusion of explicit segmentation based system and segmentation-free based system

To achieve this, we apply the following combination rules:

- Simple combination rules: sum and product rules to find the separate combination function for each class

- The rank-based combination methods: Borda count represents the combinations of medium, since the calculating rank requires comparing the original score with other scores produced during the same identification trial. The final output label for a given test pattern n is the class with the highest rank sum[23]

- DST (Dempster-Shafer theory) aims at combining the classifiers we have presented in a previous work [16, 23, 24]. It consists in different step: First, for each of the Q classifiers, the likelihoods are normalized so that they sum up to one over the whole set of classes. Second, a mass function is derived from each of the Q classifiers. Third, the accuracy rates of the classifiers (derived from a cross validation procedure) are used to weigh each mass function in relation to the reliability of each classifier. Fourth, the Q mass functions are combined together. Finally, a probabilistic transform is applied, and the so-derived probability values are sorted decreasingly to provide the TOP N list. More details can be found in [23], [24]

V. EXPERIMENTS AND ANALYSIS

The systems based on segmentation free and the analytical approaches are evaluated against other state of art HRW systems. There are applied using ADAB database of Tunisian town names. It comprises around 11024 samples written by more than 170 different writers divided to 4 sets.

El Abed et al. [25] held the first competition on ADAB database at 10th International Conference on Document

Analysis and Recognition (ICDAR), three data sets were provided for training (sets 1, 2 and 3) and set 4 was used for testing the systems. The results of set 4 for all the competing systems are shown in Table1.
Our experimentation using ADAB where 8024 samples are used for training and 3000 are used for testing with a lexicon constituted of 706 words is shown in Table II and Table III. We evaluate 2 different groups of operations which are:

- Testing individual systems separately.
- Testing the different fusion methods: the sum rule, product rule, Borda count and DST.

The recognition rate given by the system based on analytical approach is 81,33% while the one given by the system based on segmentation free approach is 85,3% on the same test dataset. The best recognition rate is obtained by using the Borda count and DST that give a gain of 5% compared to the system based on segmentation free approach and 9% compared with the system based on analytical approach. Besides, it is observed that the sum and product rules give a more interesting result than individual systems. But the most important thing is that all combination rules improve the performance system.

To evaluate our systems with the stat of the art, we are testing individual systems and the different fusion methods in the same condition of competing systems in ICDAR 2009.

TABLE I. ADAB SET4 RESULTS (ICDAR 2009)

System	Method	Top 1	Top 5	Top 10
MDLSTM-1	NeuralNet	95.70	98.93	100
MDLSTM-2	NeuralNet	95.70	98.93	100
VisionObjects-1	NeuralNet	98.99	100	100
VisionObjects-2	NeuralNet	98.99	100	100
REGIM-HTK	HMM	52.67	63.44	64.52
REGIM-Cv	VC	13.99	31.18	37.63
REGIM-CvHTK	HMM&VC	38.71	59.07	69.89

TABLE II. RECOGNITION RATE OF SYSTEMS BASED ON ANALATYCAL AND SEGMONTATION FREE APPROACHES

Recognition Approach	Method	Top 1	Top 5	Top 10
Analytical approach	SVM	81.33%	86.86%	89.43%
Segmentation free approach	HMM	85.30%	91.26%	93.33%

TABLE III. RECOGNITION RATE OF THE INFORMATION FUSION

Information Fusion Methods	Top 1	Top 5	Top 10
Sum Rule	87.90%	92.46%	92.73%
Product Rule	87.60%	92.46%	92.73%
DST	90.26%	95.33%	95.77%
Borda Count	90.30%	93.10%	93.6%

TABLE IV. RECOGNITION RATE WITH ADAB SET4

Recognition methods	Top 1	Top 5	Top 10
SVM	66.8	80.5	83.1
HMM	80.1	92,3	94.1
Sum Rule	81.4	87.5	88.1
Product Rule	81.4	87.5	88.1
DST	83.9	92.8	93
Borda Count	81.4	87.5	88.1

From the results shown in Table I and Table VI, we can see how encouraging our system performance compared to the state of the art systems. Results show that the complementarities between both systems improve results because of the use of different characteristics (Offline that treat generally the form and Online that treat the trajectory of the signal). However, we can see that the treatment of Delayed Strokes is a messing operation in the system that can ameliorate the recognition rate.

The following figure presents different examples in which the global system using the combination provides a correct recognition while one of the combined systems fails to recognize a word. Fig. 5(a) shows that the system based on segmentation free approach cannot distinguish between « ـهـ » and « « ـهـ » because of the similarity between the two characters differing in the occlusion. In the second example the letter «ذ» is considered as « ـذ» and « ـذ» as « ـه», hence highlighting the influence of diacritics processing performed by the system without removing them. With the system based on analytical approach Fig.5(b), recognition errors come from segmentation errors.

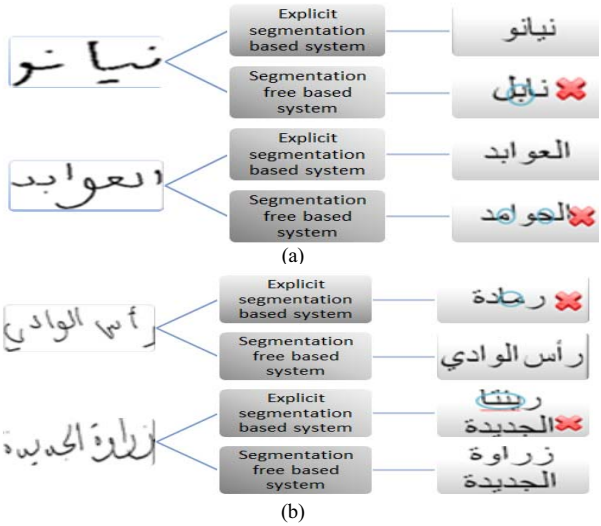


Figure 5. Examples of samples corrected recognitionally by the combination methods and confused by the individuals systems

VI. CONCLUSION

In this paper the outputs of the system based on segmentation free approach and the one based on analytical approach for Arabic on-line handwritten word recognition have been combined. Four of the existing methods (sum rule, product rule, Borda count and DST) are used to combine both systems. The recognition rate achieved by this information fusion by any of these combination methods is much better than the recognition rate given by any of the individual systems used solely.

In this work, the fact that the information fusion with different features improves the final recognition accuracy has been demonstrated.

This work can be extended to a combination which takes into consideration the decision of the system based on segmentation free approach depending on the confidence score obtained from the system based on analytical approach. Thus, the best accuracy can be reached to increase word recognition rate.

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