Proceedings of Engineering & Technology (PET)
pp. 189-193

2nd International Conference on Automation,Control, Engineering and Computer Science (ACECS-2015)
Proceedings of Engineering & Technology (PET)

Online Arabic Handwriting Recognition Based on Classifier Combination

Mariem Gargouri[1] and Sameh Masmoudi Touj[2]
Research Unit of Advanced Systems in Electrical Engineering
National Engineering School of Sousse, Tunisia
[1]National Engineering School of Sfax, Tunisia
[2]High Institute of Computer Science, Tunis, Tunisia
[1]gargouri.mariem@gmail.com, [2]samehmasmouditouj@yahoo.fr

***Abstract*—Handwriting recognition is a rich and complex issue. Some of its problems include the large shape variations in human handwriting. Classifier combination contributes in increasing the classification accuracy compared to the performance of individual classifier. In this paper, we present an online handwriting recognizer based on classifier combination according to holistic approach. We propose two combination types: a combination between online recognition and offline recognition, and a combination between dynamic approach, structural approach and statistical approach. For feature extraction phase and classification phase, we use Point Features (PF) and Dynamic Time Warping (DTW) in dynamic approach, Freeman Chain code (FC) and Levenshtein Distance (LD) in structural approach, Zernike Moments (ZM) and Support Vector Machine (SVM) in statistical approach. In the combination phase, different methods are applied on the results provided by the three classifiers and different combinations are studied. The proposed framework is tested on ADAB database [6].**

Keywords*—*Arabic handwriting; online recognition; offline recognition; classifier combination; holistic approach

I. Introduction

The handwriting recognition system is a tool used by the computer to recognize the handwritten script. Compared to the input mode, the handwriting recognition can be classified into two classes: offline and online. The additional time information makes online recognition easier than offline recognition. After the binarization, the online recognition can also be treated as offline recognition. However, this is not the case for offline recognition. In addition to coordinate and time information, some devices can provide force and speed information. These can be useful for writer identification [3] but they present problems in handwriting recognition because of different resulting forms of writing.

Recognition systems are classified into two categories: holistic approach and analytic approach. The holistic approach [13-15] allows recognizing the word/sub-word without segmentation. For the analytical approach [7][9-12][16-18], each word is segmented into sub-units which are considered independently. On the one hand, holistic approaches generally offer better recognition rates than analytical approaches of the error term involved in the segmentation. On the other hand, analytical approaches are more powerful for large databases (Open-vocabulary) than holistic approaches (Closed-vocabulary). In Arabic language, the cursive aspect of the writing makes the segmentation in letters more difficult. Thus, holistic method becomes more effective. This approach deals with words like human vision. In the particular case of cities names recognition, holistic method is used to increase precision and speed [26].

Handwriting variations are very large. Therefore, handwriting recognition accuracy is not very satisfying using one feature set and one classifier. Classifier combination can lead to a significant improvement of the system’s overall performance than a single classifier in a recognition task. However, the most difficult problem is finding the best combination function. In order to perform the classifier combination, it must be created, for which different ways are possible. The most popular ways are based on different initialization, different parameter choices, different architectures, different classifiers, different training sets or different feature sets [29].

In this paper, we present an online Arabic handwriting recognition system based on parallel combination of three subsystems from three different approaches: dynamic approach (PF and DTW), structural approach (FC and LD) and statistical approach (ZM and SVM). According to different combination functions (Majority Voting, Weighted MV, Borda Count, WBC, Modified BC and Product), a comparative study of these approaches and there combinations is addressed. In addition, we detail techniques (Translation, Interpolation and Binarization) used in preprocessing phase.

The remainder of this paper is organized as follows: related work is addressed in Section 2. We present in Section 3 our framework. Section 4 details the experimental evaluation. Finally, the conclusion and the future work can be found in Section 5.

ISSN: 2356-5608

II. RELATED WORK

Table I presents a review of online Arabic handwriting recognition systems. A recent survey done by Tagougui *et al.* [19] reviews the status of research. Surveys on problems of writing on digital surfaces, segmentation, feature extraction and recognition techniques for Arabic script can also be found in [21-24]. The large public corpus ADAB [10-13][16][17] available of on-line handwriting is composed by 17 210 Arabic words from 937 Tunisian town/village names [6]. Recently, new databases AltecOnDB [8] and Quranic Handwritten Words [20] have emerged.

TABLE I. REVIEW OF ONLINE ARABIC HANDWRITING RECOGNITION SYSTEMS

Authors	Method	Database	Accuracy
Abdou and Fahmy [7]	chain code features + HMM model + DTW	20000 samples from 340 students	79%
Abdelazeem and Eraqi [9]	Geometric features + holistic approach for delayed stroke detection + HTK	ADAB database for training 300 Arabic personal names for test	92.50%
Biadsy et al. [14]	Geometric features + holistic approach for word-part recognition using HMM + word-part dictionary and the letter-shape model	3200 words for training 2358 words for test with 10 writers	95.44 % word part based
Saabni and El-Sana [15]	Holistic approach + dynamic time warping classification.	600 word parts written by 6 persons	Between 86 and 90 %
Kherallah et al. [18]	Combining visual coding and genetic algorithm	500 words written by 24 persons	97 %
Razzak et al. [27][28]	Combining online and offline, combining fuzzy rules and HMM.	1,800 ligatures by 15 trained users	87.6 % and 74.1 %
Eraqi and Abdelazeem [10]	Grapheme segmentation + offline features + Fuzzy SVM	ADAB database	87%
AbdelAzeem and Ahmed [11]	Online and offline features + online HMM and offline HMM fusion		97.78%
Kour and Saabne [12]	Morphological features + k-NN		76%
Saabni and Sana [13]	Hierarchical clustering, Principal component analysis, and K-means clustering		about 80%
Tagougui et al. [16]	Beta-Elliptical + MLPNN/HMM combination		96.40%
Boubaker et al. [17]	Grapheme segmentation + HTK + Fuzzy rules		Between 54.26 and 87.13%

III. FRAMEWORK LAYOUT

The steps of our online handwriting recognition system are: Preprocessing, Feature Extraction and Classification. The final decision is given by a parallel combination of the three approaches: dynamic approach, structural approach and statistical approach, using different combination functions. In this section, we discuss the general flow of our online recognizer and its various modules, as shown in Fig. 1.

A. Preprocessing

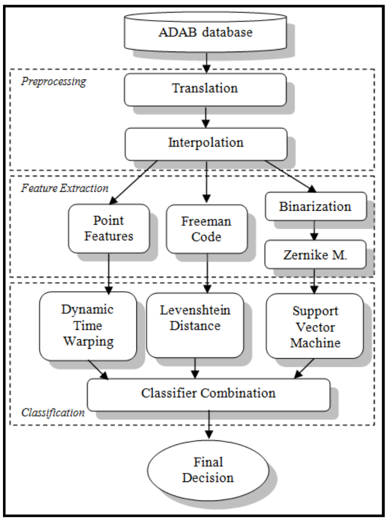

Fig. 1. Proposed system outline.

1) Translation: In writing, the user may start from any place in the digitizer. Translation is applied in order to compensate this variation.

$$x_i' = x_i - X_{min}. \quad (1)$$

$$y_i' = y_i - Y_{min}. \quad (2)$$

where X_{min} and Y_{min} are the minimums of x and y respectively of the handwriting trajectory $(P(x_i,y_i))$.

2) Interpolation: Any script written with high speed will have some missing points and gaps between the points. Interpolation is applied to regenerate them between each two consecutive points $p_i(x_i,y_i)$ and $p_{i+1}(x_{i+1},y_{i+1})$ (see Fig. 2) [2].

The Algorithm of Interpolation

For each $stroke_k$ *from the data*
If $[d(p_i , p_{i+1}) < threshold]$
$I = (y_{i+1}-y_i)/(x_{i+1}-x_i)$
$x_j = x_i + step$
do
$y_j = I * (x_j - x_i) + y_i$
$x_j = x_i + step$
$add((x_j, y_j), stroke_k)$
until $x_j = x_{i+1}$

The *threshold* is the minimum distance between two consecutive points p_i and p_{i+1}, and the *step* is the distance between the new points. In our case, we have chosen *threshold=1*, *step=1* and Euclidian distance. Firstly, interpolation is performed following the *x-axis*. Secondly, interpolation is performed following the *y-axis* with the same method.

Fig. 2. The word "Bouaoun" (بوعوان) before and after interpolation.

3) Binarization: The given online trace $(P(x_i,y_i))$ is converted to a bitmap image (see Fig. 2), as shown in the next algorithm.

The Algorithm of Binarization
smp=[(x1,y1); ….;(xK,yK)];% the size of smp is (K,2)

```
smp=[(x1,y1); ….;(xK,yK)];% the size of smp is (K,2)
xmax=max(smp(:,1));
ymax=max(smp(:,2));
img=zeros(ymax,xmax);
for m=1:K
  if smp(m,1)>0 && smp(m,2)>0
    img(smp(m,2), smp(m,1))=1;
  end
end
imwrite(img);
```

B. Feature Extraction

Point Features and Freeman Chain Code were applied on the online coordinates *($P(x_i,y_i)$)* whereas Zernike Moments was applied on the offline image of each word.

1) Point Features: We define a set of 5-features of a point: x normalized (3), y normalized (4), local direction cosine (5), local direction sine (6), and the local curvature cosine (7) [3].

$$x_n = x/X_{max} \tag{3}$$

$$y_n = y/Y_{max} \tag{4}$$

$$dx_i = x_i - x_{i+1}$$

$$dy_i = y_i - y_{i+1}$$

$$ds_i = \sqrt{dx_i^{\,2} + dy_i^{\,2}}$$

$$\cos(\alpha_i) = dx_i / ds_i \tag{5}$$

$$\sin(\alpha_i) = dy_i / ds_i \tag{6}$$

$$\cos(\phi_i) = \cos(\alpha_i)\cos(\alpha_{i+1}) + \sin(\alpha_i)\sin(\alpha_{i+1}) \tag{7}$$

where X_{max} and Y_{max} are the maximum of x and y respectively of the handwriting trajectory *($P(x_i,y_i)$)*.

2) Freeman Code: This representation is based on 8-connectivity of the segments. The direction of each segment is coded by using a numbering scheme (Fig. 3).

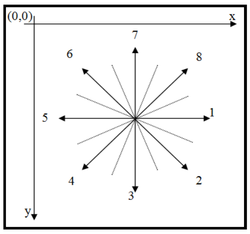

Fig. 3. 8-directional Freeman chain codes.

3) Zernike Moments: Zernike introduced a set of complex polynomials $V_{nm}(x,y)$ which form a complete orthogonal set over the unit circle interior $(x^2+y^2)=1$ in the coordinated polar. The ZM A_{nm} of order n with repetition m of an image $f(x,y)$ are defined as follows (* denotes complex conjugate) [26]:

$$A_{nm} = \frac{n+1}{\pi}\sum_{(x,y)\in I} V_{nm}(x,y)^* * f(x,y) \tag{8}$$

$$V_{nm}(x,y) = \sum_{s=m}^{n} \frac{(-1)^{(n-m)/2}((n+s)/2)!}{((n-s)/2)!((m+s)/2)!((s-m)/2)!} r^s * e^{-im\theta} \tag{9}$$

C. Classification:

In the classification phase, we implemented three different classifiers: DTW, LD and SVM [1]. In fact, we chose DTW and LD because they don't require that the compared vectors have the same size. For dynamic and structural approaches, test sample is not compared with all training samples but it is only compared with representative patterns of classes. We selected, as representative pattern, the sample smp_i which minimizes the sum of distances to the other samples of the same class C_i.

$$smp_i = \arg\min_{smp_p \in C_i}\left(\sum_{smp_q \in C_i} D(smp_p, smp_q)\right) \tag{10}$$

While there are many classification schemes in the literature, SVM is chosen for this research for the following reasons: (i) SVM has a strong theoretical background, (ii) SVM can be applied to large database, (iii) SVM algorithm is flexible, and (iv) SVM is very accurate.

D. Classifier Combination

Three types of classifier outputs are considered: abstract level (a single class), rank level (ordered sequence of candidate classes) and measurement level [25]. For each level, we tested different combination functions: Majority Voting and Weighted Majority Voting (abstract level), Borda Count, Modified Borda Count and Weighted Borda Count (rank level), and Product (measurement level).

1) Majority Voting (MV): It considers only the most likely class provided by each classifier and chooses the most frequent class label among this crisp output set (in (11) $\omega_j=1, r_{ij}=1$).

2) Weighted Majority Voting (WMV): It multiplies each vote by a weight before the actual voting. The weight for each classifier is obtained by its accuracy (in (11) ω_j=3 2 1 or 2 1, $r_{ij}=1$).

3) Borda Count (BC): Borda count adds the ranks in the N-best lists of each classifier (in (11) $\omega_j=1$).

4) Modified Borda Count (MBC): DTW and LD results followed Borda count method, but we kept SVM voting.

5) Weighted Borda Count (WBC): It is similar to weighted majority vote (in (11) ω_j=3 2 1 or 2 1).

6) Product: It is measurements m_{ij} product (13) after the normalistion (12). For SVM, we set $mea_{ij}=1/v_{ij}$ where v_{ij} is C_i vote. We retain the class with the lowest measurement.

$$r(C_i) = \sum_{j=1}^{L} \omega_j r_{ij} \tag{11}$$

$$m_{ij} = \frac{mea_{ij}}{\sum_{i=1}^{C} mea_{ij}} \tag{12}$$

$$P(C_i) = \prod_{j=1}^{L} m_{ij} \tag{13}$$

where C is classes' number, L is classifiers' number, r_{ij} and mea_{ij} are rank and measurement assigned by the classifier e_j for the class C_i respectively, $r(C_i)$ is new rank, m_{ij} is the normalized measurement, ω_j is the weight of classifier e_j.

IV. Experimental Results

From the ADAB database [6], we extracted 1141 samples handwritten by 52 different writers. The written text was from

163 Tunisian town/village names. Each name was repeated 7 times (3 samples for testing and 4 samples for training). These samples can be composed by 1, 2 or 3 words.

Firstly, we tested dynamic approach, structural approach and statistical approach (see Table II). For this last, ZM order is 6 (feature vector size is 16). Then, we experimented the combination of the three approaches using different combination functions. For BC method, the candidate classes' number $N=5$ was determined empirically. Recognition rates are presented in Table III. The best recognition rate 97.98% was given by our proposed Modified BC.

TABLE II. RECOGNITION RATES OF DIFFERENT CLASSIFIERS (%)

Approach	Rate
Dynamic (Dyn)	84.75%
Structural (Str)	72.39%
Statistical (Sta)	**88.16%**

TABLE III. RECOGNITION RATES OF DIFFERENT COMBINATIONS (%)

Classifier Combination	Combination function					
	MV	***WMV***	***BC***	***MBC***	***WBC***	***Product***
Dyn + Str	79.22	84.75	82.29	82.29	86.59	84.05
Dyn + Sta	87.55	88.16	**96.49**	***97.98***	96.58	**96.40**
Str + Sta	81.33	88.16	82.29	93.86	93.33	92.64
Dyn + Str + Sta	**90.18**	**91.49**	95.44	97.63	**97.80**	96.23

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we presented a parallel combination of three different approaches: dynamic approach, structural approach and statistical approach for online handwriting recognition according to holistic approach. We experimented different combination functions on ADAB database. The best recognition rate 97.98% was given by the combination of dynamic approach and statistical approach using Modified BC and the recognition rate 97.80% was given by the combination of three approaches using Weighted BC. We used a small corpus (1141 names' city), so we aim to widen the database. In future work, we will test others combination functions or generic classifiers (neural networks). We will also experiment the combination between analytic approach and holistic approach.

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