Graph based Method for Online Handwritten Character Recognition

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Abstract: In this research, we attempt to propose a novel graph-based approach for online handwritten character recognition. Unlike the most well-known online handwritten recognition methods, which are based on statistical representations, we set forward a new approach based on structural representation to overcome the inherent deformations of handwritten characters. An Attributed Relational Graph (ARG) is dedicated to allowing the direct labeling of nodes (strokes) and edges (relationships) of a graph to model the input character. Each node is characterized by a set of fuzzy membership degrees describing their properties (type, size). Fuzzy description is invested in order to guarantee more robustness against uncertainty, ambiguity and vagueness. ARGs edges stand for spatial relationships between different strokes. At a subsequent stage, a tree-search based optimal matching algorithm is explored, which allows the search for character structures i.e the minimum cost of nodes. Experiments performed on ADAB and IRONOFF datasets, reveal promising results. In particular, the comparison with the state of the art demonstrates the significance of the proposed system.

1 INTRODUCTION

Graphs have emerged as an active area of research aims to model structural relations of objects and patterns. The graph's ability to model different parts of an object as well as its bases on sound mathematical background can be invested in many diverse fields (Baldini et al., 2019; Lee et al., 2018). In the domain of handwritten character recognition, graph drew the attention and whetted the interest of numerous researchers.

The use of a graph-based handwritten recognition induces the need to formulate two main required operations: transforming handwritten graphs into feature vectors and calculating the graph similarity. From this perspective, the common task is to compare graphs to find the similarities between them. This is known as graph matching (GM). Basically, two types of graph matching were adopted by researchers(Yan et al., 2016). The exact graph matching refers to the search for an exact replication of the test graph in the template graph as well as the conservation of all relationships presented in test one. The complexity of the exact graph matching has not yet been specified to be P or NP(Conte et al., 2004), but there are polynomial algorithms for solving the isomorphism problem of certain graph categories. A well-known method is based on the depth-first search (backtracking) with a forward checking method which greatly reduces the number of backtracking steps. The inexact graph matching provides a distance value that indicates graph dissimilarity(Bengoetxea, 2002). One of the most flexible and versatile approaches to inexact graph matching is graph edit distance(Abu-Aisheh et al., 2017). However, the latter suffers from its high complexity that limits its applicability to graphs with small size. For this reason, a number of methods addressing the high computational complexity of graph edit distance computation has been established, e.g. (Darwiche et al., 2019).

Moreover, in recent years many tree-based methods(Abu-Aisheh et al., 2015) have become of great interest to researchers since computational time and even the explored search space can be manageable with the impact of the quality of the provided matching solution. Therefore, the primary motivation of the paper lies in tree-based methods which can be explored in GM computation. Besides, owing to the variability and ambiguity of handwritten character strucure (for example: disorder, imprecision, connection, etc) the use of fuzzy graph-based description could be extremely helpful to add flexibility against

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these errors. In this paper, we propose a novel fuzzy graph-based handwritten method that takes advantage of the aforementioned tree technique and fuzzy logic concept merging them together with a Weighted Euclidean Distance (WED) to matching two characters graphs. Finally, we shall use the fuzzy attributed relational graph (FARG) matching algorithm to recognize online hand written characters. The rest of this paper is organized as follows. Section 2, presents a brief description about related works. Section 3, illustrates the graph used to represent the handwritten character and presents the graph matching algorithm. In section 4, the experimental evaluation is elaborated on ADAB and IRONOFF datasets. Finally, section 5 wraps up the conclusion and provides new perspectives for future works.

2 LITERATURE REVIEW

Great attention has been paid to graph based method in many application fields. Among them, we can cite: image analysis (Clément et al., 2018), etc. For instance, a few attempts are performed in online handwritten character recognition research with graph representation or relative concepts. One of the pioneer attempts to use graph in online handwritten character recognition was carried out by Si-Wei Lu et al.(Lu et al., 1991). To obtain an efficient recognition system and avoid much of the combinatorial explosion in the graph matching, the author resorted to a two-level hierarchical graph representation for handwritten Chinese characters. The two-level graph has a special structure: the lower level is composed of nodes that denote the strokes of a character to which they attributed through the irrespective orientation on the one hand. The edges denote relations between nodes according to the type of junction on the other. Finally, an error-tolerant graph matching for classification framework is provided. This attempt is also conducted with (Huang et al., 1993) to recognize Chinese characters. Indeed, any character class will be described by a graph where the stroke's points represent the nodes and relation between them is defined by an edge. A constraint-based optimization problem is formulated using a relaxation matching for resolving issues in pattern recognition. Resting upon Chinese characters, in(Suganthan and Yan, 1998) a method for recognition of hand printed Chinese characters is defined. Hopfield networks have been used to solve graph matching problem. In both references (Rocha and Pavlidis, 1994) and (Rocha and Pavlidis, 1995) the task of recognizing machine printed distorted characters in text lines is tackled. Unlike all graph methods each node corresponds to a branch, an ending, a turning points or a sharp corner and the edges represent strokes. Recognition task of text lines turns into an error-tolerant subgraph isomorphisms from character prototype graphs to text line graphs. In this case, the benefits recorded compared to feature-based methods are typically two fold: First, making optical character recognition to be independent of segmentation. Second, handling both touching and broken characters. Ref (Chakravarthy and Kompella, 2003) also tackled the online handwritten recognition problem using graph-based shape representation. In this work, the authors aim to build graphs from a handwritten shape. In this sense, they opted first for creating a vector out of seven Structural Properties (SP) related to the shape of handwriting: interior, end, bump, cross, dot and various other characteristic shape points of the trace of a handwritten text. Thereafter, each handwritten character is represented by a graph with SP design the nodes and edge served as a link between nodes. (Al Mubarok and Nugroho, 2016) proposed a method using the skeleton structure of character as a way to design graph where edges were identified into shape types and nodes were detected with line simplification algorithm. The graph matching issue is converted into hierarchical approach and is concepted with the subgraph isomorphism principals. To the knowledge of the underlying authors, these methods are still far away of being able to deal efficiently with a large and multilingual dataset of complexe characters. Thus, we evolve a fuzzy matching algorithm for graph-based handwriting recognition. The proposed matching algorithm permits efficiency more regarding the variability of characters, as well as the imprecision and the ambiguity of their structures.

3 GRAPH REPRESENTATION OF HANDWRITTEN CHARACTERS

3.1 Introduction of Fuzzy Attributed Graph

The notion of Attributed relational graph (ARG) was introduced in 1983 by Tsai and Fu for pattern analysis task (Tsai and Fu, 1983). The nodes of the graph indicate the different components of objects while the edges denote the relations between these components. More recently, this definition has been extended to a Fuzzy Attributed Relational Graph (FARG) by attaching fuzzy attributes to its nodes and edges. FARG was introduced by Chang and Cheung (1992)(Chan and

Cheung, 1992). These references (Jouili et al., 2009; Luqman et al., 2013) are suggested for supplementary reading on ARG and FARG respectively and their applications.

3.2 Graph Generation

An online character pattern is composed of a sequence of an arbitrary number of strokes. A stroke is defined as an elementary drawn between pen up and pen down. A handwritten character is approximated by a graph where stroke is denoted with node. These nodes are linked by an edge that represents the relations between them. For a handwritten character that is composed of n strokes, its associated graph is also composed of n nodes (same number of strokes) and n(n- 1)/2 edges. An example of nodes and edges numbers is illustrated in figure 1.

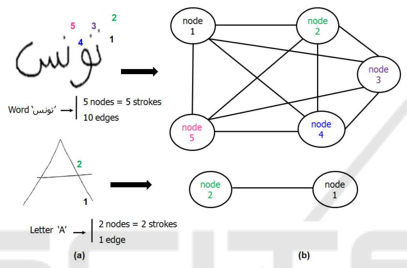

Figure 1: (a) An example of a handwritten character, (b) Its corresponding graph.

3.3 Computation of Node Attributes

Two nodes attributes are used namely type and size.

3.3.1 Stroke Type Attribute

Based on the βeta-elliptic model, each script in the segmentation step is modeled in the dynamic domain by a series of βeta profiles and in the static domain by a series of elliptic arcs. The reader is referred to (Bezine et al., 2007) for more details. Firstly, for each elliptic stroke we assigned an Elementary Perceptual Code (EPC) (Njah et al., 2012). However, to solve the problems of perception and uncertainty of assessed EPC, we opted for fuzzy logic representation(Njah et al., 2012). Based on the human vision we cannot perceive these EPCs. What we can perceive is restricted to some general forms labeled Global Perceptual Codes (GPCs)obtained with the combination of fuzzy EPCs. Due to the variety of possible combinations concerning either the number or the type of EPCs that form a GPC, we opted to use the Genetic Algorithms (GAs) to detect GPCs easily. Figure 2 exhibits the different GPCs, their classification and the corresponding shapes.

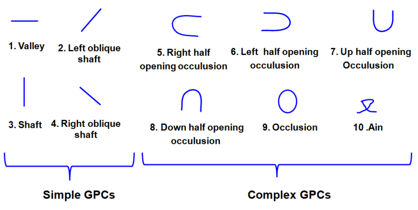
1. Valley
2. Left oblique shaft
5. Right half opening occulusion
6. Left half opening occulusion
7. Up half opening Occulusion
3. Shaft
4. Right oblique shaft
8. Down half opening occulusion
9. Occlusion
10 .Ain
Simple GPCs
Complex GPCs

Figure 2: List of GPCs.

3.3.2 Size Type Attribute

The following equation is used to compute the size of handwritten stroke :

$$d = \sqrt{(x_l - x_f)^2 + (y_l - y_f)^2} \quad (1)$$

Where (x_f, y_f) and (x_l, y_l) denote respectively the start and end point coordinates. The membership functions for the linguistic values of this feature are identified over the domain [0, 1]. The domain is then divided into 5 fuzzy regions. In order to get more significant regions and minimum overlapping sets between them. The linguistic labels associated with it are Very Small (VS) , Small (S) , Medium (M), Big (B) and Very Big (VB) as depicted in figure 3 .

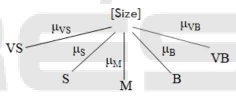

Figure 3: Size representation.

3.4 Computation of Edge Attribute

3.4.1 Spatial Relations

Same strokes can appear differently in the same characters and can be placed in different positions, which may change the characters meaning. For this reason, defining the spatial relation is necessary. In spite of the advantages, relationships have not been actively modeled in many online handwritten character recognition systems. They were tackled in many offline task (Clément et al., 2018). As a matter of fact, in order to infer the relationship within handwriting stroke, we should first invest strokes' topological properties i.e centroid and bounding boxes.

Bounding Box: A stroke bounding box is defined as the smallest rectangle that firmly encloses the stroke. Bounding box of stroke 'S' is represented by four coordinates: $x_1^S = min(x_i^S)$, $x_2^S = max(x_i^S)$, $y_1^S = min(y_i^S)$ and $y_2^S = max(y_i^S)$ as depicted in the figure 4.

Centroid: The most common technique to check the position of stroke within a region or not is to ana-

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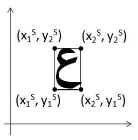


Figure 4: Bounding box of an Arabic stroke.

lyze the coordinates of its centroid. We define the x-coordinate of the centroid of a stroke s as $x_c = (x_2^S - x_1^S)/2$ and the y-coordinate as $y_c = (y_2^S - y_1^S)/2$. At this level, the consideration of two successive handwritten strokes S and S_1 and the use of the center of their bounding boxes and the centroids of both strokes enable us to identify the following geometrical features.

i) The angle of the line passes through the two centroids of strokes with respect to the horizontal line as expressed in the equation below:

$$\theta = \tan^{-1}\left(\frac{y_c^{S_1} - y_c^S}{x_x^{S_1} - x_p^S}\right) \tag{2}$$

ii) The intersection points

$$S \cap S_1 = \begin{cases} 1 \text{ if } (S \cap S_1 \neq \varnothing) \Rightarrow \textit{intersect} \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

iii) The distance between the y-coordinates of the centroids, denoted by $dist_y(S, S_1) = y_c^{S_1} - y_c^S$

iv) The distance between the x-coordinates of the centroids, denoted by $dist_x(S, S_1) = x_c^{S_1} - x_c^S$

v) The distances between the x-coordinates of the bottom right boundaries, denoted by $dist_{bt}(S, S_1) = x_2^{S_1} - x_2^S$

vi) The distances between the x-coordinates of the Top left boundaries, denoted by $dist_{top}(S, S_1) = x_1^{S1} - x_1^S$

An illustrative example is presented in figure 5 with the different calculated metrics.

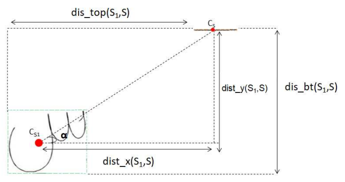
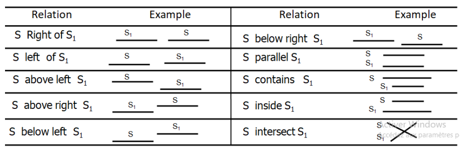


Figure 5: Geometrical features between two handwritten strokes S and S_1 of Latin character.

The different features serve as input to a fuzzy controller whose outputs are a spatial relation type. Therefore a set of ten spatial relations are identified as illustrated in figure 6.



Relation	Example	Relation	Example
S Right of S_1	S_1 S	S below right S_1	S_1 S
S left of S_1	S S_1	S parallel S_1	S S_1
S above left S_1	S S_1	S contains S_1	S S_1
S above right S_1	S_1 S	S inside S_1	S S_1
S below left S_1	S S_1	S intersect S_1	S S_1

Figure 6: Strokes relationships.

3.5 Matching Handwritten Graphs and Recognition

The comparison of two handwritten graphs can be formulated as a problem of inexact graph matching. For thus, we adopted an algorithm based a tree search of the node mappings. The following sections describe the main parts of this algorithm in detail.

3.5.1 Proposed Algorithm

Given two FARGs G_1 which denotes the template handwritten graph and G_2 the test one. The graph G_1 has N nodes, which are represented as $n_{x^i}(i \in 1, 2 \cdots N)$ while graph G_2 has N' nodes, which are represented as $n_{y^i}(i \in 1, 2 \cdots N')$. Assume that any n_{x^i} or n_{y^i} can be expressed by a vector of μ_{x^i} and μ_{y^i} respectively:

$$\mu_x^i = \mu_x^{(i)}[1], \mu_x^{(i)}[2], ..., \mu_x^{(i)}[a], ..., \mu_x^{(i)}[A], a \in \{1, 2, ...A\} \tag{4}$$

$$\mu_y^i = \mu_y^{(i)}[1], \mu_y^{(i)}[2], ..., \mu_y^{(i)}[a'], ..., \mu_y^{(i)}[A], a' \in \{1, 2, ...A\} \tag{5}$$

A is the total number of membership degree associated with nodes regardless of n_x^i. Different weights are assigned to each node features according to their relative importance to describe the node characteristics. We denote by $W_{n_x^i}$ the weight of node n_{x^i} and $W_{n_y^i}$ the weight of node n_{y^i}. G_1 and G_2 are represented in the weight space as a weight vector of W_N and $W_{N'}$ respectively :

$$W_N = \left[W_{n_x^1}, W_{n_x^2}, ..., W_{x^N}\right], i \in \{1, 2, ...N\} and \textstyle\sum_{i=1}^{N} W_{n_x^i} = 1 \tag{6}$$

$$W_{N'} = \left[W_{n_y^1}, W_{n_y^2}, ..., W_{y^{N'}}\right], i \in \{1, 2, ...N'\} and \textstyle\sum_{i=1}^{N'} W_{n_y^i} = 1 \tag{7}$$

node n_x^i and node n_y^i with the highest value of W_N and W_N' respectively are considered the most important nodes during the nodes matching.

The edge between every node n_x^i and n_x^j in G_1 is represented by a vector of $e_x^{(i,j)}$ while the edge between every node n_y^i and n_y^j in G_2 is represented by a vector of $e_y^{(i,j)}$. Similarly, both edges $e_x^{(i,j)}$ and $e_y^{(i,j)}$ are represented by a set of vectors denoted below :

$$e_x^{(i,j)} = e_x^{(i,j)}[1], e_x^{(i,j)}[2], ..., e_x^{(i,j)}[b], ..., e_x^{(i,j)}[B], b \in \{1, 2, ...B\} \tag{8}$$

$$e_y^{(i,j)} = e_y^{(i,j)}[1], e_y^{(i,j)}[2], ..., e_y^{(i,j)}[b'], ..., e_y^{(i,j)}[B], b' \in \{1, 2, ...B\} \tag{9}$$

Where B is the total number of membership associated with edges regardless of $e_x^{(i,j)}$ or $e_y^{(i,j)}$ respectively. If we denote by $W_{e_x^i}$ the weight of edge $e_x^{(i,j)}$ and $W_{e_y^i}$ the weight of edge $e_y^{(i,j)}$. G_1 and G_2 are represented in the weight space as a weight vector W_T and $W_{T'}$ respectively :

$$W_T = \left[W_{e_x^1}, W_{e_x^2}, ..., W_{e_x^T}\right], i \in \{1,2,...T\} and \sum_{i=1}^{T} W_{e_x^i} = 1 \quad (10)$$

$$W_{T'} = \left[W_{e_y^1}, W_{e_y^2}, ..., W_{e_y^{T'}}\right], i \in \{1,2,...T'\} and \sum_{i=1}^{T'} W_{e_y^j} = 1 \quad (11)$$

With T and T' are the total number of edges in template and test character respectively.
The graph matching is carried out by means of a tree search algorithm provided in **algorithm 1**.

Algorithm 1: Tree-based search algorithm.

```
Input: Template graph $G_1$ and test graph $G_2$
Output: The lowest cost match between $G_1$ and $G_2$
Matching($G_1$,$G_2$)
  $Dist_{min} = \infty$
  P = $\emptyset$
  $N_{min}$=NULL
  N= $\emptyset$
  N'= $\emptyset$
  N $\leftarrow extract_{nodes}(G_1)$
  N' $\leftarrow extract_{nodes}(G_2)$
  for each node $n \in N$ do
      for each node $n' \in N'$ do
          Compute Dist($n$,$n'$) using Eq(10)
          if (Dist($n$,$n'$) $\prec$ $Dist_{min}$) then
              $Dist_{min}$=Dist($n$,$n'$)
              $N_{min}$=$n'$
          end if
      end for
      $P \leftarrow P \cup \{(n,N_{min})\}$
      $N \leftarrow N$ - $\{(n)\}$
      $N' \leftarrow N'$ - $\{(N_{min})\}$
  end for
  Return P
```

In order to identify the similarity between two entities a distance metric is needed. From this perspective, the weighted euclidean distance metrics opts for the fuzzy attributes. Given a node n_x^i in G_1 and its pair node in G_2 is n_y^j, a distance between the two nodes is measured using weighted Euclidean metric (WED) as portrayed below:

$$Dist_1 = [\sum_{i=1}^{A} W_{n_i} \times (\mu_x^i - \mu_y^i)^2]^{\frac{1}{2}} \quad (12)$$

The weights W_{N_i} are proposed as:

$$W_{N_i} = max(max(\mu_x^i), max(\mu_y^i)) \quad (13)$$

It is noticeable that a distance between two paired edges is computed by the equation below:

$$Dist_2 = [\sum_{i=1}^{B} W_{e_i} \times (e_x^{(i,j)} - e_y^{(i,j)})^2]^{\frac{1}{2}} \quad (14)$$

The weights W_{e_i} are proposed as:

$$W_{e_i} = max(max(e_x^{(i,j)}), e_y^{(i,j)})) \quad (15)$$

A synthesis distance caused by all nodes is then expressed by:

$$Dist_{nodes} = \sum_{i=1}^{L_1} Dist_1 \quad (16)$$

A synthesis distance caused by all edges is then expressed by:

$$Dist_{edges} = \sum_{i=1}^{L_2} Dist_2 \quad (17)$$

Where L_1 and L_2 are the number of matched node pairs and the number of matched edge pairs, respectively. Thus a similarity measure between a pair of FARG r can be defined directly with

$$Sim(G_1, G_2) = W_{G_1} \times Dist_{nodes} + W_{G_2} \times Dist_{edges} \quad (18)$$

Where W_{G_1} and W_{G_2} are properly selected weights of G_1 and G_2. The procedure of computation of similarity is summarized below (**algorithm 2**).

Algorithm 2: The proposed FARG matching algorithm.

```
Input: Template graph $G_1$ and test graph $G_2$
Output: Matching similarity measure $Sim$
  $Dist_1 = \emptyset$
  $Dist_2 = \emptyset$
  $Dist_{nodes} = \emptyset$
  $Dist_{edges} = \emptyset$
  $P_1 = \emptyset$
  $P_1$=matching( $G_1$, $G_2$)
  for each successor pairs of nodes $\{(n,n'),(n_1,n'_1)\} \in P1$ do
      $E_1$=$extract_{edge}(n,n_1) \in G_1$
      $E_2$=$extract_{edge}(n',n'_1) \in G_2$
      $Dist_2$=Compute Dist($E_1$,$E_2$) using Eq(12)
      $Dist_{edges} \leftarrow Dist_{edges} \cup \{(Dist_2)\}$
  end for
  for each pair of nodes $(n,n') \in P1$ do
      $Dist_1$=Compute Dist($n$,$n'$) using Eq(10)
      $Dist_{nodes} \leftarrow Dist_{nodes} \cup \{(Dist_1)\}$
  end for
  $Dist_{nodes} \leftarrow Dist_{nodes} \cup \{(Dist_1)\}$
  Compute Sim using Eq(16)
```

3.6 Recognition

The proposed approach uses a fuzzy graph matching algorithm to recognize online handwritten characters.

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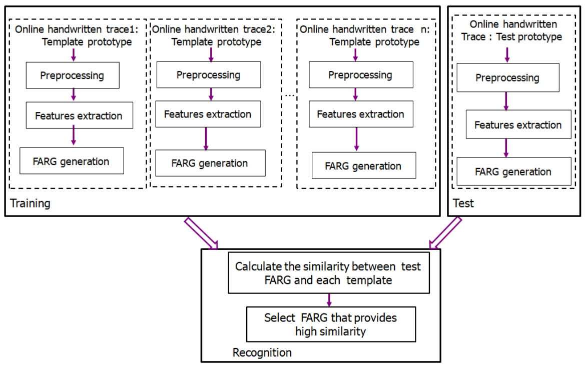
Online handwritten trace1: Template prototype
Preprocessing
Features extraction
FARG generation
Online handwritten trace2: Template prototype
Preprocessing
Features extraction
FARG generation
Online handwritten trace n: Template prototype
Preprocessing
Features extraction
FARG generation
Training
Online handwritten Trace : Test prototype
Preprocessing
Features extraction
FARG generation
Test
Calculate the similarity between test FARG and each template
Select FARG that provides high similarity
Recognition

Figure 7: Flowchart of the proposed algorithm for handwritten recognition characters.

Figure7 illustrates an overview of the framework and rests upon a set of phases as described below.
In the first phase, the FARG of handwritten characters for both template and test are extracted as explained in section 3. In the second phase the similarity of nodes $Sim(nodes)_{ij}$ as well as $Sim(edges)_{ij}$ between a graph $FARG_i$ of the i^{th} test graph and a graph $FARG_j$ of the j^{th} template graph is calculated as mentioned in algorithm 2. Then the similarity S_j between the two graphs is computed by summing up the nodes and edges similarities. Therefore, the class corresponding to the graph which provides the best match (maximum degree of similarity) constituent the recognized handwritten character.

$$C = argmax_j\{Sim_j\} \tag{19}$$

4 EXPERIMENTAL RESULTS

At this stage of analysis, we shall address the obtained results, discuss them and evaluate them in order to assess the effectiveness and feasibility of our approach.

4.1 Datasets

ADAB Data Base: The data base ADAB (El Abed et al., 2011) was developed in cooperation between the Institut fuer Nachrichtentechnik (IfN) and Research Groups in Intelligent Machines,Tunisia at University of Sfax. It was collected by using digital tablets connected to computers,more than 130 different writers mainly of Tunisian nationality. This database contains 21575 online Tunisian town and village names in Arabic languages. **IRONOFF database:** The database IRONOFF (Viard-Gaudin et al., 1999) is created using the mechanism Pen Tablet which was of a tablet type A4Wacom Ultra Pad sampling speed of 100 points per second since 1999. The prototype is recorded in the format UNIPEN. IRONOFF database is characterized by the dominance of isolated symbols, French and English words as well as digits.
A set of 1135 handwritten characters are randomly selected from these data bases to perform fuzzy graph matching and therefore to carry out the recognition task. First, each handwritten words is converted into graphs by representing strokes by nodes and spatial relationships between them by edges. Table 1 portrays the graph and its distribution degree. We denote the ex, tr and tes as the size of examples, training and testing of both datasets respectively. Minimum and maximum of nodes N and edge E degrees for graphs are also presented. The size varies from small graphs with under 5 nodes and edges and up to 15 nodes and edges in both datasets.

Table 1: Graph and their degree distribution.

	Size			Min		Max	
Dataset	ex	tr	tes	$\|N\|$	$\|E\|$	$\|N\|$	$\|E\|$
IRONOFF	634	381	253	2	1	10	45
ADAB	519	312	207	2	1	15	105

4.1.1 Experimental Results

In order to explain why the FARG has such an excellent performance, time complexity should be analyzed.

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4.1.2 Execution Time

The different experiments were performed on PC with Intel Core i7-7500, 8 GB RAM. Table 2 displays the required time of each input character for generating (building) its corresponding graph related to the nodes number.

Table 2: Computational time for graph generation.

Number of nodes	Graph generation times
$\prec 5$	$\prec$ 10s
5-10	10-25 s
$\succ 10$	$\succ$ 25s

It can be observed that the method requires less execution time for a smaller number of nodes. Table 3 introduces the running time for some handwritten drawing. For each entry we would illustrate the drawn characters property number of nodes of template and test graph (N_G, N'_G, respectively) ,the time for generating both graphs(GG) N_G and N'_G , the time for graph matching between graphs(M) (section 3) and finally the total computational time. Note that the largest computational times are required for generation (building) graphs mainly due to the pre-processing step which was performed to reduce the noise and step needed for calculating nodes/edges attributes.

Table 3: Computational time.

Scripts	$\|N_G\|$	$\|N'_G\|$	Computational time		
			GG	M	Total
”البقالطة”	11	11	56	22	78
”بومهل”	4	4	18	7	25
”نشيو”	7	7	30	9	39
”بزمة”	6	6	24	8	32
”مغراوة”	7	7	40	17	57
”أريانة”	10	10	46	18	64
”A”	3	3	14	6	20
”B”	2	2	12	4	16
”Money”	2	2	14	5	19
”Quiz”	5	5	18	6	24
”quelqu’un”	8	8	42	19	61
”Neptune”	8	8	48	15	63

4.2 Recognition Accuracy

For both dataset, the training and testing sets contain 60% and 40% of graphs respectively, and serve as the dataset graphs. Referring to table 4 and table 5, we get an impressive recognition rate which exceeds 98% for both dataset. Next, our ultimate objective is to evaluate our approach which is based on graph matching with related works. It is worth noting, a large variety of recognition algorithms has been tested on these datasets and some of the best results are outlined.

Table 4: Best reported recognition results for the ADAB dataset.

Systems	Recognition rate
HMM (Khlif et al., 2016)	93.33%
MLP-HMM (Elleuch et al., 2016)	96.45%
CNN (Tagougui et al., 2013)	91.8%
AUC-HMM1 (El Abed et al., 2011)	98.45%
FARG matching (present work)	98.62 %

In table 4, we compared our results with results conducted on ADAB dataset by (Khlif et al., 2016),(Elleuch et al., 2016), (Tagougui et al., 2013) and (El Abed et al., 2011) and based on HMM, MLP-HMM, CNN networks and AUC-HMM1 respectively. The recognition rate provided by our algorithm exhibits an improvement that varies between 6.82% and 0.17% over the four participating systems.
Table 5 reports also the performance of our recognition systems on IRONOFF dataset. We achieved a very competitive rate with respect to other two published result (Akouaydi et al., 2019) based on ConvLSTM and BCP+LSTM. We exhibited an improvement that varies between 6.24% and 1.24% over related systems. This finding which based on the use of an efficient WED metric jointly with a tree search process guides the matching solutions and therefore contributes to a high-rate recognition.

Table 5: Best reported recognition results for the IRONOFF dataset.

Systems	Recognition rate
ConvLSTM(Akouaydi et al., 2019)	93%
BCP+LSTM(Akouaydi et al., 2019)	98%
FARG matching (present work)	99.24%

5 CONCLUSIONS

In this paper, we aimed at setting forward a new approach to perform an online handwritten recognition. The nodes and edges of the graph are labeled using fuzzy logic attributes. The graphs are matched using a WED as the similarity function and based on a tree search process. The approach is tested on ADAB and IRONOFF datasets. This approach helps to recognize the handwritten character and achieve recognition rates of 98.62 % and 99.24% respectively. Our work is an initial step that can be further developed as it opens new perspectives and offers different horizons for future works in the domain of handwritten recognition includes the investigation of a graph embedding method with a new classification schemes such as deep learning.

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