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An application of intuitionistic fuzzy information for handwritten Arabic word recognition

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Abstract
The main objectives of this paper are to use intuitionistic fuzzy information to characterize handwritten Arabic words for recognition, using an extract of the IFN/ENIT data set and to compare them with an intuitionistic fuzzy similarity measure.

Key words fuzzy set, intuitionistic fuzzy set (IFS), intuitionistic fuzzy similarity measure, word recognition

1 Introduction

The concept of Intuitionistic fuzzy sets (IFSs) introduced by Atanassov [1,4] constitute a generalization of fuzzy set theory [13], and has been successfully applied in different areas such as; logic programming [2,3], decision making problems [10], medical diagnosis [9] etc.
Handwritten Arabic words present many difficulties for recognition because of the variations in information between different writers and the overlapping between the words characters. So, features representing the words cannot be exact, they only contain imprecision. This last grows when the words are not normalized. In our work we use an extract of the IFN/ENIT data set [8] constituted of different names of Tunisian towns written by many writers. So, the use of intuitionistic fuzzy information is very suitable to characterize these words. Thus, the use of an intuitionistic fuzzy similarity measure to match between them is necessary.
In section 2, we present an overview of intuitionistic fuzzy similarity measures followed by the description of words data set and the feature extraction. Therefore, we present obtained results by applying an intuitionistic fuzzy similarity measure from literature.

2 Overview of intuitionistic fuzzy similarity measures

Many intuitionistic fuzzy similarity measures are presented in literature in the following, we present some of them.

Let X={x_1,x_2,...,x_n} a discourse universe, *A* and *B* two intuitionistic fuzzy sets in X defined as follow:

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle | x \in X\},$$
$$B = \{\langle x, \mu_B(x), \nu_B(x)\rangle | x \in X\}$$

Where $\mu_A(x) \in [0,1], \nu_A(x) \in [0,1]$ with the condition $0 \le \mu_A(x) + \nu_A(x) \le 1, \forall x \in X$. This is similar to $\mu_B(x)$ and $\nu_B(x)$.

- Measures proposed in [7]

$$S_e^p(A,B) = 1 - \frac{1}{\sqrt[p]{n}} \sqrt[p]{\sum_{i=1}^{n} \left(\rho_{\mu_{AB}}(x) - \rho_{\nu_{AB}}(x)\right)^p} . \tag{1}$$

where $\rho_{\mu_{AB}}(x) = \frac{|\mu_A(x) - \mu_B(x)|}{2}$ and $\rho_{\nu_{AB}}(x) = \left|\frac{1-\nu_A(x)}{2} - \frac{1-\nu_B(x)}{2}\right|$

$$S_s^p(A,B) = 1 - \frac{1}{\sqrt[p]{n}} \sqrt[p]{\sum_{i=1}^{n} \left(\rho_{s_1}(x_i) + \rho_{s_2}(x_i)\right)^p} . \tag{2}$$

With $\rho_{s_1}(x_i) = \frac{|m_{A_1}(x_i) - m_{B_1}(x_i)|}{2}$ and $\rho_{s_2}(x_i) = \frac{|m_{A_2}(x_i) - m_{B_2}(x_i)|}{2}$

Where A_1 and A_2 are the subintervals from *A* divided by the median value denoted $m_A(x) = \frac{\mu_A(x) + 1 - \nu_A(x)}{2}$ of the interval $[\mu_A(x), 1 - \nu_A(x)]$. The two subintervals are defined as: $[\mu_A(x), m_A(x)]$ and $[m_A(x), 1 - \nu_A(x)]$. The median values of the subintervals A_1 and A_2 are denoted m_{A_1} and m_{A_2} and have the values $m_{A_1} = \frac{m_A(x) + \mu_A(x)}{2}$ and $m_{A_2} = \frac{m_A(x) + 1 - \nu_A(x)}{2}$

Proceeding similarly for B_1 and B_2 to compute $m_B(x)$, $m_{B_1}(x)$ and $m_{B_2}(x)$

- Measures proposed in [11]

The measures proposed here are distance measures.

$$d_1(A,B) = \frac{1}{n} \sum_{i=1}^{n} \left[\frac{|\mu_A(x_i) - \mu_B(x_i)| + |\nu_A(x_i) - \nu_B(x_i)|}{4}\right] + \frac{1}{n} \sum_{i=1}^{n} \frac{\max(|\mu_A(x_i) - \mu_B(x_i)|, |\nu_A(x_i) - \nu_B(x_i)|}{2} . \tag{3}$$

$$d_2^p(A,B) = \frac{1}{\sqrt[p]{n}} \sqrt[p]{\sum_{i=1}^{n} \left[\rho_\mu(x_i) + \rho_\nu(x_i)\right]^p} . \tag{4}$$

where $\rho_\mu(x_i) = \frac{|\mu_A(x_i) - \mu_B(x_i)|}{2}$, $\rho_\nu(x_i) = \frac{|\nu_A(x_i) - \nu_B(x_i)|}{2}$ and p is a positive integer.

- Measures proposed in [12]

Let x, y elements in A with $x = |\mu(x), 1 - \nu(x)|$, $y = |\mu(y), 1 - \nu(y)|$ then:

- $T(x) = 1 - \mu(x) - \nu(x)$ is called the indeterminacy degree of $x \in A$
- $\delta(x) = \mu(x) + T(x)\mu(x)$ is called the favor degree of $x \in A$

- $\alpha(x) = \nu(x) + T(x)\nu(x)$ is called the against degree of $x \in A$

The similarity between two elements x and y is evaluated by the function M:

$$M(x,y) = 1 - \frac{1}{2}\left(\delta_{xy} + \alpha_{xy}\right). \tag{5}$$

Where $\delta_{xy} = \left|\delta(x) - \delta(y)\right|$ and $\alpha_{xy} = \left|\alpha(x) - \alpha(y)\right|$

The similarity between two IFSs is evaluated as:

$$S(A,B) = \frac{1}{n}\sum_{i=1}^{n} M\left(V_A(x_i, V_B(x_i)\right) = 1 - \frac{1}{2n}\sum_{i=1}^{n}\left(\left|\delta_A(x_i) - \delta_B(x_i\right| + \left|\alpha_A(x_i) - \alpha_B(x_i)\right|\right). \tag{6}$$

3 Data set words presentation

We use 6537 images of 824 handwritten Tunisian town/village names extracted from the IFN/ENIT data set [8]. The data set images are written by different writers and undergo some preprocessing like noise reduction but are not normalized. In this data set, every image is described by some information like the number of characters and the number of connected compounds.

We divide data set on two data sets: the first serves as training data set constituted of 4357 word images and the second serves as test data set constituted of 2180 word images. Our recognition process is done on two steps:

- description of images by features using intuitionistic fuzzy sets
- comparison between test data set and training data set using an intuitionistic fuzzy similarity measure

In the following subsections, we describe these processes with more details.

4 Features extraction

We extract features based on some information incorporated in the IFN/ENIT data set and without any normalization of images. The information already exists in the data set are:

- number of word characters
- number of word connected compounds
- the coordinates of the top line and those of the base line of the word
- the description of each word connected compound edge with Freeman chain code

We are interesting to extract features from word connected compounds, so we delete diacritic signs from images because they can be misplaced and cause noise for recognition. The extracted features from the word connected compounds are:

- normalized sum of pixel distances from the base or the top lines
- higher black pixel coordinates
- direction frequency of freeman chain code.

4.1 Normalized sum of pixel distances from the base or the top lines

The image Top line and the image base line are considered as lines in a plane having the equation: y=ax+b. Each pixel in image is considered as a point in the plane. So, the distance of a pixel to the image baseline or to the image top line is computed as mathematical distance of a point to a line.

For each black pixel in the edge of connected compounds three mathematical distances are computed as:

- d_1: the sum of distances of each pixel from the top line if the pixel is upper the top line (figure 1 A)
- d_2: the sum of distances of each pixel from the baseline if the pixel is under top line and upper the baseline (figure 1 B)
- d_3: the sum of distances of each pixel from the baseline if the pixel is under this last (figure 1 C).

Figure 1 shows a word composed by six connected compounds, and the positions that can take a pixel in the second connected compound of the word.

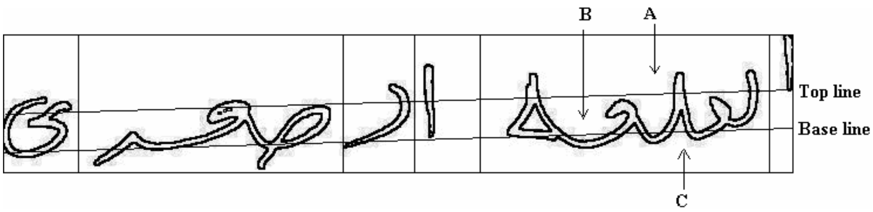

Figure 1 Pixels Positions of the second word connected compound

Each distance is divided by the sum of all black pixels of connected compound edge denoted as S. So, we normalize the distance sums as: $d_1=d_1/s$, $d_2=d_2/s$ and $d_3=d_3/s$.
These results are fuzzified by computing the membership degree of each of them to a trapezoidal function.
Inspired of the work of Ioannis and al. [6] who proposed membership and non-membership functions given by:

$$\mu_A(x)=\lambda\mu_{\tilde{A}}(x) \text{ and } \nu_A(x)=\left(1-\mu_{\tilde{A}}(x)\right)^{\lambda}$$

where $\lambda\in[0,1]$ and $\tilde{A}$ an ordinary fuzzy set.
We compute membership and non-membership degrees for each normalized sum distances.

4.2 Higher black pixel coordinates

Finding the coordinate of the higher black pixel in a connected compound can indicate the presence of a stroke. This information can be determinative to differentiate between connected compounds and for consequence can differentiate between words. The searched pixel can be in the beginning, in the middle or at the end of the connected compound.
The abscise of the higher black pixel can indicate its position in the connected compound and the ordinate comparing with its position on top line can indicate a degree of membership to a triangular fuzzy set to be a stroke.
The non-membership degree is computed as: 1 - membership degree.
For every connected compound, we retain six degrees of belongingness and non-belongingness. The two first degrees represent the membership degrees of a pixel in the beginning of connected compound, the two second degrees represent the membership degrees of a pixel in the middle of connected compound, and the two last degrees represent the membership degrees of a pixel at the end of connected compound.

4.3 Direction frequency of freeman chain code

Every connected compound is described by a chain code of freeman which is constituted by a succession of numbers from zero to seven. The numbers indicate directions of a pixel

constructing the connected compound edge. This directions can be vertical, horizontal or representing a curvature.
We compute the number (N) of each direction in the chain code, and we divide it by the total number (T) of directions of chain code. So, we obtain eight information. It is obvious that all obtained information is in the interval [0, 1] (N is less than T).
We are interested to the pixels indicating the curvature direction because of their importance. So, we consider the results obtained for these pixels as their degree of belongingness to curvature and zero as degree of non-belongingness to curvature. The others direction information are considered as degree of non-belongingness to curvature. So, their degree of belongingness to curvature is zero and their degree of non belongingness is N/T. As a result, we obtain a vector of sixteen numbers representing degree of belonging and non-belonging of freeman chain code numbers.

5. Experimental results

We trial similarity measure d_2^p (4) to match between dataset test and dataset training. The recognition results are presented in table 1.

Training set	Test set	1-best	2-best	10-best
4357 words	2180 words	66.78%	75.18%	89.17%

Table 1. Recognition results using intuitionistic fuzzy similarity measure

A loss in the recognition rate is about 10.82%.
The results obtained are acceptable. May be they are modest in the first best words founds but they are good in the ten best words founds. These results can be explained by:
- The method of similarity computation: we computed the mean of similarity between each feature similarity degree of two words matched. May be aggregation operators between similarity degrees can improve results [5].
- The insufficiency of the used features.

6. Conclusion

In this paper we have presented handwritten Arabic word with features based on intuitionistic fuzzy sets. We used an intuitionistic fuzzy similarity to compare between test set and training set. The experimental results show that intuitionistic fuzzy sets can be used for word recognition. To improve results, other features based on intuitionistic fuzzy sets can be used.

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