Pattern Anal Applic
DOI 10.1007/s10044-015-0500-4

THEORETICAL ADVANCES

A novel fuzzy approach for handwritten Arabic character recognition

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Received: 22 December 2013 / Accepted: 25 June 2015

Abstract The aim of our work is to present a new method based on structural characteristics and a fuzzy classifier for off-line recognition of handwritten Arabic characters in all their forms (beginning, end, middle and isolated). The proposed method can be integrated in any handwritten Arabic words recognition system based on an explicit segmentation process. First, three preprocessing operations are applied on character images: thinning, contour tracing and connected components detection. These operations extract structural characteristics used to divide the set of characters into five subsets. Next, features are extracted using invariant pseudo-Zernike moments. Classification was done using the Fuzzy ARTMAP neural network, which is very fast in training and supports incremental learning. Five Fuzzy ARTMAP neural networks were employed; each one is designed to recognize one subset of characters. The recognition process is achieved in two steps: in the first one, a clustering method affects characters to one of the five character subsets. In the second one, the pseudo-Zernike features are used by the appropriate Fuzzy ARTMAP classifier to identify the character. Training process and tests were performed on a set of character images manually extracted from the IFN/ENIT database. A height recognition rate was reported.

Keywords Off-line character recognition · Handwritten Arabic · Pseudo-Zernike moments · Fuzzy ARTMAP

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1 Introduction

Automatic recognition of handwritten scripts is an area of pattern recognition that is extremely useful in numerous fields, including documentation analysis, mailing address interpretation, bank check processing and more recently the reconstruction and recognition of historical manuscripts.

Although substantial progress has been recently achieved, the recognition of Arabic handwritten character remains far away from human performances. The major difficulties come from the similarity of some character forms, the existence of ligatures, and the infinite variety of writing styles produced by different writers. Therefore, Arabic handwriting recognition is still an open and interesting area for research and novel ideas.

Arabic script is written from right to left. Each word may consist of several separated sub-words. A sub-word is either a single character or a set of connected characters. Although, seven Arabic characters out of 28 do not join to their left neighbours, others join to the neighbouring characters to make a word or a sub-word. Each character may take up to four different shapes, depending on its position in the word. The neighbouring characters, separated or connected, may overlap vertically. There are similar characters that only differ by their dots number and/ or position. Figure 1 shows all printed Arabic characters

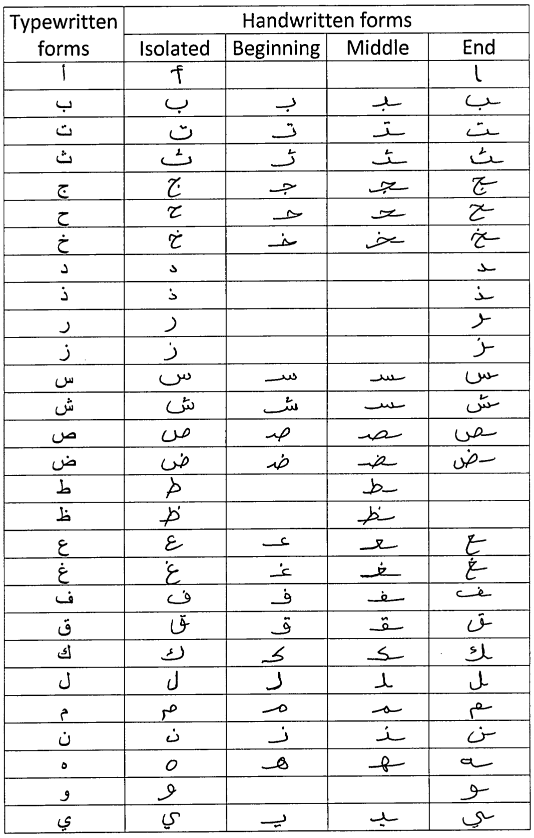


Fig. 1 Different forms of Arabic characters

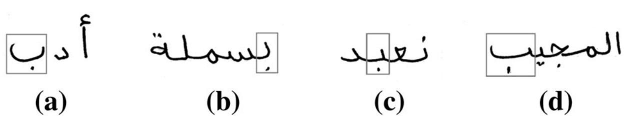


Fig. 2 The four forms of the character 'ب' used in some words: **a** isolated, **b** beginning, **c** middle and **d** end form

and their various handwritten forms (isolated, beginning, middle, and end form), while Fig. 2 presents some examples using these forms in some Arabic handwritten words.

Artificial neural networks have been widely used for classification and pattern recognition tasks. Neural network classifiers exhibit powerful discriminating properties and they have been successfully used in handwriting recognition particularly with digits, isolated characters, and words in small vocabularies [27]. The most commonly used family of neural networks for handwritten characters recognition task is the feed-forward network, which includes multilayer perceptron (MLP) and radial-basis function (RBF) networks [22]. MLP networks are widely used in handwritten character recognition systems because they are very easy to train and very fast in the classification decision process.

In this paper, we have chosen to use the Fuzzy ARTMAP neural network. Lately, this network [19] has been considered one of the most important pattern classifiers. It has certain advantages over many other neural network models: it is faster to train (a small number of training epochs are required), and can even incrementally learn novel patterns without retraining the network.

The present work is an attempt to develop a robust Arabic handwriting characters recognition system. We aim at designing a new and fast recognizer which classifies handwritten Arabic characters in all their forms. The remainder of this paper is divided into six sections. The next section resumes several works done in isolated handwritten Arabic character recognition field. Section 3 describes data preprocessing and Sect. 4 expounds features extraction. Section 5 introduces the character recognition technique using fuzzy artificial neural networks. Section 6 presents the experimental results registered with the IFN/ENIT Arabic handwritten words database and our new database. Finally, some concluding remarks end the paper.

2 Related works

Arabic script recognition approaches can be classified into two main categories according to script nature. The first category is based on printed (typewriting) script [13, 16, 33, 45, 51, 54]. Under the second category fall all approaches that are based on handwriting script (on-line [4, 6, 26, 30, 56] or off-line [2, 12, 32, 39, 43, 47] with or without segmentation).

Handwritten Arabic character recognition systems were extensively studied and developed for many years. However, consistent comparison of different proposed solutions remains difficult; because in practice, diverse private unpublished databases are used, where different number of handwritten words and characters are stored [1, 7, 11, 49].

Usually, a characters recognition system is based on three main steps: preprocessing, features extraction, and recognition (classification).

Preprocessing step is typically used to reduce noise and increase features discrimination capacity. The most used operations are: filtering and smoothing, normalization, binarization, slant correction, baseline detection, contour tracing and thinning. The last two preprocessing methods were intensively used in Arabic optical character recognition systems (OCRS) [9, 21, 25, 42, 55].

In the second step, character images are analysed and one or more sets of features are then extracted. Features extraction is a very important process in every OCR system; a lot of techniques have been adopted by searchers [8, 9, 21, 37, 55], some of which are: geometrical features (moments, histograms, and direction features), structural features (line element features, Fourier descriptors, topological features) and transformation methods [principal component analysis (PCA), linear discriminant analysis (LDA), kernel PCA].

The last phase of a OCRS is building a recognizer. This stage is achieved in two steps. The first one builds a representative model for each character form to recognize (learning). The second one classifies new forms which have never been presented to the recognizer (classification).

The most common approaches are: neural networks (NN), support vector machine (SVM), hidden Markov models (HMM), decision tree, and more recently combined classifiers approaches [8, 37, 40–42].

Next paragraphs summarize some pertinent works done in the field of off-line handwritten Arabic characters recognition.

Aburas and Rehiel [3] implemented an algorithm based on the property that the wavelet compressed image is a decomposition vector which can uniquely represent the input image to be correctly reconstructed later at decompression stage. This property can be effectively used to recognize the character's image. The level three of detail of the wavelet transform has been selected because it does support enough details about the image information required to generate a unique vector and minimized errors on detection (recognition) stage. After the character's image is scanned in the system the 'COMPOVECTOR CODE' will produce a decomposition vector. This vector is assumed to uniquely represent input image. Then Euclidean distance between this vector and each vector in the codebook is computed. The results achieved on a dataset of 41 sets for the twenty-eight Arabic alphabets where each set was written by 48 writers were promising in terms of accuracy (98 %).

Shanbehzadeh et al. [52] introduced a new set of features representing handwritten Farsi letters. This set is a combination of two sets of features to distinguish similarity in letters. The first set of three features explains the general structure of a letter including the number of components. These features are employed to find the best match for a letter. The second set includes seventy-five features. These features are extracted from partitioning a letter into smaller parts. Such smaller parts are generated by dividing the letters into smaller frames. The database used in the experiment consists of 3000 letters. Each letter is normalized to 50×50 pixels. After normalization, the feature vectors are classified by Vector quantization. Authors achieved a recognition rate of 87 %.

Rachidi et al. [49] presented an approach based on a criterion constructed from a pre-topological pseudo-distance that allows measuring the degree of dissimilarity between the characters. Authors have applied three preprocessing operations; binaring, filtering and centring. Training was applied on a database of 6188 handwritten isolated Arabic characters using the crossing distances in each character class. The experimental results achieved a recognition rate of 90 %.

The system of Abandah and Younis [1] had explored best sets of feature extraction techniques and studied the accuracy of well-known classifiers for Arabic letters. The principal component analysis technique is used to select best subset of features out of a large number of extracted features (secondary components features, main body features, skeleton features, and boundary features). Authors used parametric and non-parametric classifiers and found out that a subset of 25 features is needed to get 84 % recognition rate using a linear discriminant classifier, and using more features does not substantially improve this accuracy. However, for features fewer than 25 features, a quadratic discriminant classifier is more accurate than the linear classifier. For training and testing, authors have implemented a database of 440 letters. The highest registered recognition rate was 87 %.

Amrouch et al. [11] proposed a new system based on HMMs where the Hough accumulator of the character image is partitioned into equal horizontal bands that will be used to extract directional information. For experiments the authors used 42 Arabic handwritten isolated characters. Encouraging results appear with a rate of 85.71 % of good recognition.

Aljuaid et al. [7] presented a system for off-line Arabic character recognition including a preprocessing and segmentation steps. The system used a thinning process and found vertical and horizontal projection profiles. The recognition phase is managed by genetic algorithm. The genetic algorithm stands on feature extraction algorithm that defines six features for each segment. Registered recognition rate was 90.46 %.

In the system of Niya and Sajedi [44], Farsi handwritten letters were recognized by a combination of decision-tree methods. First, the preprocessing operation is done on the letters' images including normalization, thinning, reduction and noise reduction, and then the letters feature vector is extracted using the forth momentums from the second level of wavelet and contour transforms. The database used in this study is the "Hoda" handwritten letter collection. The mean recognition rate was 97.89 %.

It is a fact that intensive researches have been done to resolve the problem of handwritten Arabic character recognition, where different systems have been designed to deal with this problem. Nevertheless, a lot of work remain to be done to reach a high accuracy and efficiency.

In this work, we tried to reduce and simplify as much as possible the number of preprocessing methods to speed up the recognition process. So only one form of primitives was used (pseudo-Zernike moments) which are calculated from a compact representation of the characters' images (skeleton). Also, a set of Fuzzy ARTMAP neural networks were used as classifiers, this kind of networks have been proved to overcome the main disadvantage of neural recognizers which is time consuming [17].

3 Preprocessing

In this section, we will describe the used preprocessing steps. The aim of preprocessing phase is the removal of all noisy pixels in the words images. It includes: thinning, contour tracing and connected components detection.

3.1 Zhang-Suen thinning algorithm

The skeleton of a form shows the general shape of a pattern, and many important features can be extracted from it. In this work, the thinning process is used to simplify the character shape and the stroke thickness which is variable from character to character according to pen size, pressure while writing, ink and paper type. Also, features extraction and connected components detection will be done faster on the character skeleton (fewer pixels to treat).

We choose to use the algorithm proposed by Zhang and Suen [66] which produces a perfect 8 connected skeletons. The algorithm operates in two steps successively applied to the image. Each step identifies contour points that can be deleted.

Step 1 of the algorithm flags a contour point P1 (Fig. 3) for deletion if the following conditions are satisfied:

1. $2 \leq B(P1) \leq 6$;
2. $A(P1) = 1$;
3. $P2 * P4 * P6 = 0$;
4. $P4 * P6 * P8 = 0$.

Step 2 flags a contour point P1 for deletion if the following conditions are satisfied:

1. $2 \leq B(P1) \leq 6$;
2. $A(P1) = 1$;
3. $P2 * P4 * P8 = 0$;
4. $P2 * P6 * P8 = 0$.

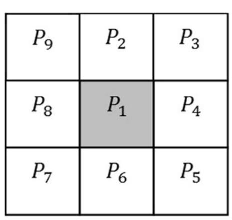


Fig. 3 A 3 by 3 filter mask showing the target pixel P1 and its 8 neighbouring pixels

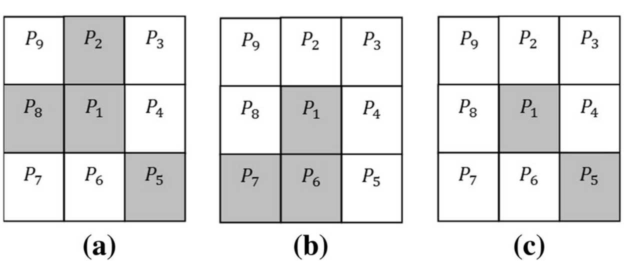


Fig. 4 Examples of functions computations of A(P1) and B(P1): in **a** A(P1) = 3, B(P1) = 3, in **b** A(P1) = 1, B(P1) = 2 and in **c** A(P1) = 1, B(P1) = 1

Figure 4 shows examples of calculation of both functions A(P1) and B(P1).

In this algorithm, step 1 is applied to all image pixels. If all the conditions of this step are satisfied, the point will be flagged to be removed. After Step 1 has been applied to all pixels of the image, the flagged pixels will be removed. Then Step 2 is applied to the image exactly like Step 1. This process will be repeated, until no further changes occur in the image.

3.2 Connected components detection

Connected component detection is a fundamental feature of many computer vision systems, usually considered in binary images. A connected component is a region of connected pixels which have the same value. Many effective algorithms for extracting connected components have been published through several works [28, 29, 35, 50, 53]. Some methods employ a simple recursive algorithm, while others were designed for larger images and work on only one part of the image at a time.

The proposed character recognition system uses connected components number of each character (and if needed it's contour) to divide the characters' set into five subsets. For example, if the character contains more than one connected component then it will have diacritics.

3.3 Contour tracing

We have used a quick and simple algorithm to extract the contour of each character. In brief, the algorithm scans character image and keeps all black pixels having at least a white pixel as neighbour.

In our work, the contour is used to detect holes in characters shape. Firstly the body of the character is separated from its diacritics; afterwards its contour is extracted and finally the number of connected components is counted. If the contour of the character body contains more than one connected component then the character will have at least one hole.

Figure 5 shows examples of preprocessing steps applied to some Arabic letters.

4 Features extraction

Zernike [34] defined a complete orthogonal set of complex polynomials over the polar coordinate space inside the unit circle (i.e. $x^2 + y^2 = 1$). The Zernike function of order p and a repetition q is defined in the polar coordinate system (ρ, θ) as:

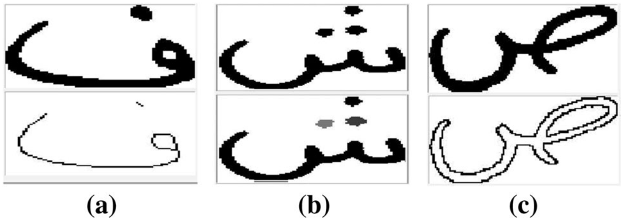


Fig. 5 Preprocessing operations applied on some Arabic characters: **a** thinning, **b** connected components detection and **c** contour tracing

$$V_{pq}(x,y) = V_{pq}(\rho,\theta) = R_{pq}(\rho)e^{jq\theta} \quad (1)$$

where $j = \sqrt{-1}$, $p \geq 0$, q is a positive or negative integer, $q \leq p$, $p - |q|$ is even, ρ is the distance from the origin to (x, y) pixel, θ is the angle between vector ρ and x-axis in counter-clockwise direction, and $R_{pq}(\rho)$ is the orthogonal radial polynomial given by:

$$R_{pq}(\rho) = \sum_{s=0}^{\frac{p-|q|}{2}} (-1)^s \frac{(p-s)!}{s!\left[\frac{p+|q|}{2} - s\right]!\left[\frac{p-|q|}{2} - s\right)!}\rho^{p-2s} \quad (2)$$

For a digital image, Zernike moments are given by:

$$Z_{pq} = \frac{p+1}{\pi}\sum_x\sum_y f(x,y)V^*_{pq}(\rho,\theta), \quad x^2+y^2 \leq 1 \quad (3)$$

where $V^*_{pq}(\rho,\theta)$ is the complex conjugate of the previously defined Zernike polynomial $V_{pq}(\rho,\theta)$.

The magnitude of the Zernike moments is invariant to rotations and translation. However, scaling invariance is achieved by dividing them by the mass of the image.

$$Z'_{pq} = \frac{|Z_{pq}|}{M} \quad (4)$$

Where $|Z_{pq}|$ is the magnitude of the moment and M the mass of the image.

Bhatia and Wolf [14] derived pseudo-Zernike moments from Zernike moments. They redefined the radial polynomial as follow:

$$R_{pq}(\rho) = \sum_{s=0}^{p-|q|}(-1)^s \frac{(2p+1-s)!}{s!(p-|q|-s)!(p+|q|+1-s)!}\rho^{p-s} \quad (5)$$

where $p \geq 0$ and q is a positive or negative integer subject to $|q| \leq p$.

Pseudo-Zernike moments offer more feature representation capabilities and robustness than Zernike moments and perform better on noisy images [60].

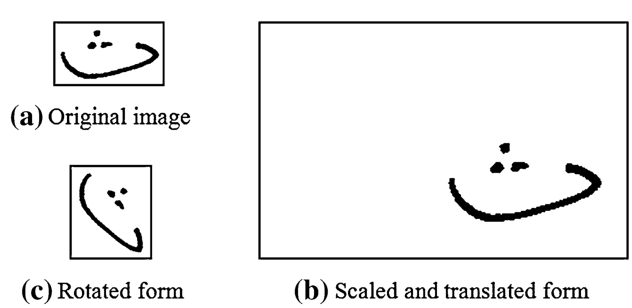
In this work, we have used feature vectors containing pseudo-Zernike moments up to order 15. These moments provide translation, rotation and scaling invariance. Figure 6 provides an example of computed pseudo-Zernike moments for a character image and its rotated, translated and scaled forms.

5 Classification

Having extracted the primitives, it is now required to store them in some forms and associate them with a character. Each pattern should identify only one character, and each character may be represented by several distinct patterns. These primitives are fed to a classifier. The classifier is then trained to identify each form. After this, if the pattern for an unknown character is presented to the classifier, it would be able to classify the character based on the identical pattern (or that which matches closely) to which it has been trained.

Variety of classification methods can be applied. We used the Fuzzy ARTMAP neural network, which is an incremental supervised learning classifier. It has the ability to learn new knowledges (plasticity) and maintain the previously acquired ones (stability).

Fuzzy ARTMAP network is composed of two Fuzzy ART networks. Fuzzy ART [20] is an unsupervised self-



	Form (a)	Form (b)	Form (c)
Z'_{10}	0,467956	0,472403	0,378030
Z'_{20}	0,047055	0,039978	0,132084
Z'_{21}	0,030225	0,029788	0,037632
Z'_{22}	0,138591	0,136692	0,170552
Z'_{30}	0,296485	0,298537	0,207600
Z'_{31}	0,110975	0,109789	0,122408
…	…	…	…

Fig. 6 Pseudo-Zernike moments of a character image and its rotated, translated and scaled form

organizing neural network; it consists of two layers: comparison layer and output layer. It is similar to many iterative clustering algorithms where each pattern is processed by finding the nearest cluster and then updating that cluster to be closer to the pattern.

Fuzzy ART (Fig. 7) is controlled by a selection parameter α ($\alpha > 0$), a vigilance parameter ρ ($0 \le \rho \le 1$) and a learning parameter β ($0 \le \beta \le 1$).

Fuzzy ARTMAP neural network [19] consists of two Fuzzy ART modules ($FuzzyART_a$ and $FuzzyART_b$) which are linked by a map field module, F^{ab} (Fig. 8).

During the learning phase, the input vector I, is presented to the $FuzzyART_a$ module and the desired output vector O, is presented to the $FuzzyART_b$ module. The categories produced by both modules are then compared by the map field module (F^{ab}). If $FuzzyART_a$ predicts a category which is dis-confirmed by the $FuzzyART_b$ module then a mismatch event is triggered and constraint the $FuzzyART_a$ module to search for a better category by increasing temporarily its vigilance parameter ρ_a, otherwise to commit a new node.

The map field module, F^{ab}, is activated if either of the Fuzzy ART modules are active, and its output vector X^{ab} is calculated as follow:

- If both $FuzzyART_a$ and $FuzzyART_b$ are active, then F^{ab} only becomes active if both predict the same category: $X^{ab} = Y^b \wedge W^{ab}$.
- If the winning category output of $FuzzyART_a$ is chosen (and $FuzzyART_b$ is inactive), then its weight activates F^{ab}: $X^{ab} = W^{ab}$.
- If a node in $FuzzyART_b$ is active (and $FuzzyART_a$ is inactive), then the corresponding node in F^{ab} is activated: $X^{ab} = Y^b$.

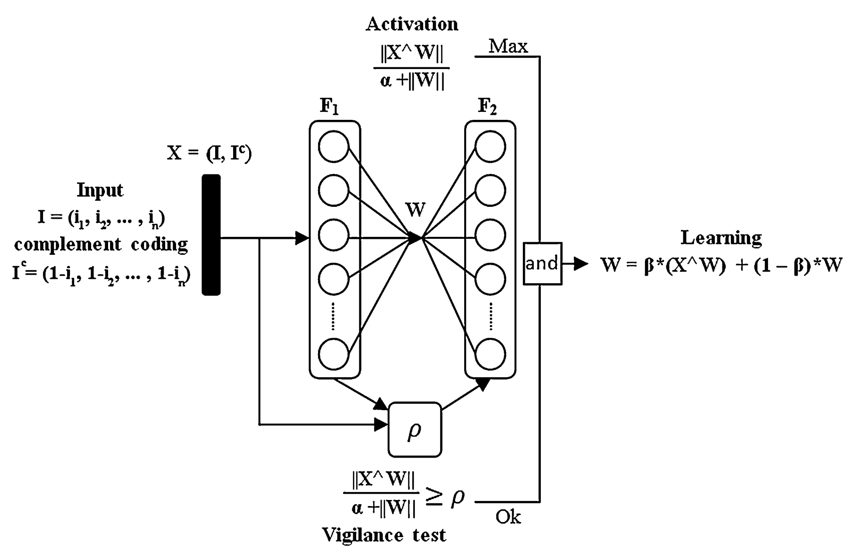


Fig. 7 Fuzzy ART architecture

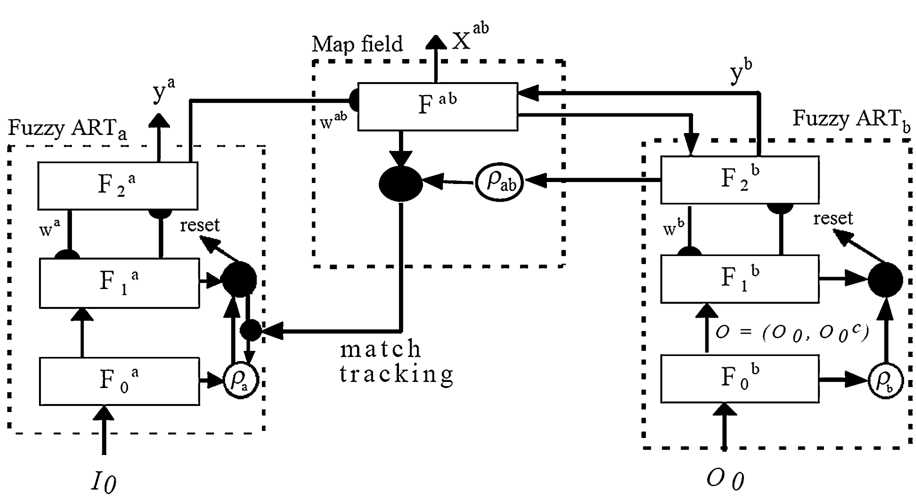


Fig. 8 Fuzzy ARTMAP architecture

– Otherwise (both *Fuzzy ART* module are inactive): $X^{ab} = 0$.

During tests, the $FuzzyART_b$ module remains inactive. Input is then propagated over the $FuzzyART_a$ module and the produced category is used to select the corresponding vector in the F^{ab} module.

A detailed description of the architectures and dynamics of the both neural networks (Fuzzy ART and Fuzzy ARTMAP) are given here [19, 20].

As mentioned above, the Fuzzy ARTMAP is a fusion of two Fuzzy ART networks working like combined classifiers, which is an undeniable advantage. In addition, The Fuzzy ARTMAP network is very easy to parametrize and converges quickly. It has a fast and incremental learning algorithm [19], and it is proven to be noise tolerant [18]. Also, this network has been successfully applied to solve different problems in pattern classification domain [24, 38, 57, 58, 61, 63, 65] and optical character recognition [10, 15, 17, 31, 48, 59, 62].

In our proposed approach, the novelty lies in the way and the number of the used Fuzzy ARTMAP networks, where five independent networks were exploited, each one is designed to recognize one subset of characters classes (10, 16, 18, 21 and 31 characters classes). This implementation improves and speeds up the learning process and leads to reach a high correct recognition rate (since there is less classes to be learned and classified for each network).

Also, until now, the Fuzzy ARTMAP network was never used in published works achieved in the field of Arabic handwriting. This paper presents to us an opportunity to test for the first time this network and report its performances towards the specific problems of Arabic script.

6 Experimental results

The proposed classification system pre-classifies the 96 possible forms of handwritten characters (Fig. 1) in five subsets created automatically by a grouping method based on characters' structural characteristics. This method leads to dispatch several characters having the same main body into different sets classified by different classifiers, which reduces confusion during the recognition process (Fig. 9).

Our system uses five Fuzzy ARTMAP neural networks to classify characters; each classifier is intended to one forms set. The used Fuzzy ARTMAP networks differ by the number of neurons in their output layers (F2).

Unlike some systems such as Yalniz et al. [64] and Lawgali et al. [36] in which four different back-propagation neural networks were designed for recognizing a particular form of the characters, in our proposed approach, isolated, beginning, medial, and end forms of different characters may belong to the same class and be recognized by the same Fuzzy ARTMAP neural network. Also, the proposed automatic grouping method leads to activate only one Fuzzy ARTMAP network at a time during classification.

The recognition process starts by thinning the target image and if necessary traces its contour. These preprocessing steps will be coupled to connected components detection algorithm (Sect. 3) to extract additional structural characteristics used to establish the main set of the processed images. Figure 10 resumes our system architecture.

The number of connected components is easy to find since each connected component has a different colour fixed by the connected components detection algorithm. Also, the character main body can be considered as the connected component having the highest number of pixels. Note here, that the connected components detection algorithm is always applied on a thinned character image to make it faster.

Character images were scanned bottom upwards to detect the position of diacritics; if the first detected connected component does not represent the character main body, diacritics will be positioned below the main body. Otherwise, diacritics are considered above the main body, even if they are localized inside the main body of some characters.

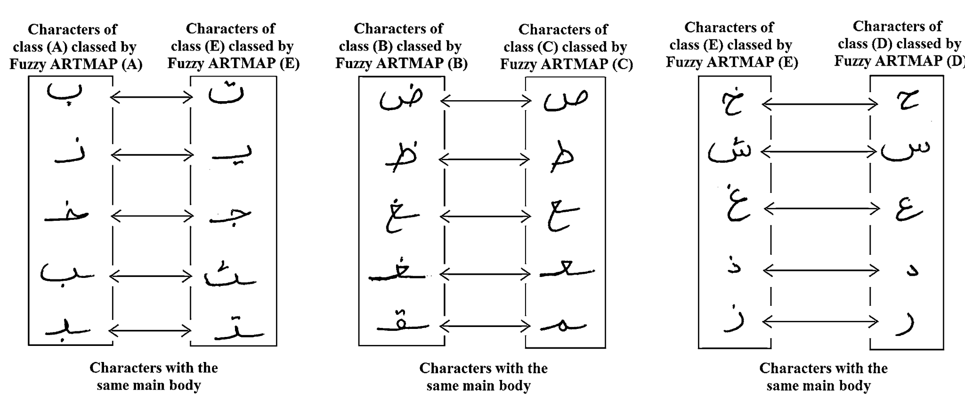


Fig. 9 Characters with the same main body allocated to different subsets

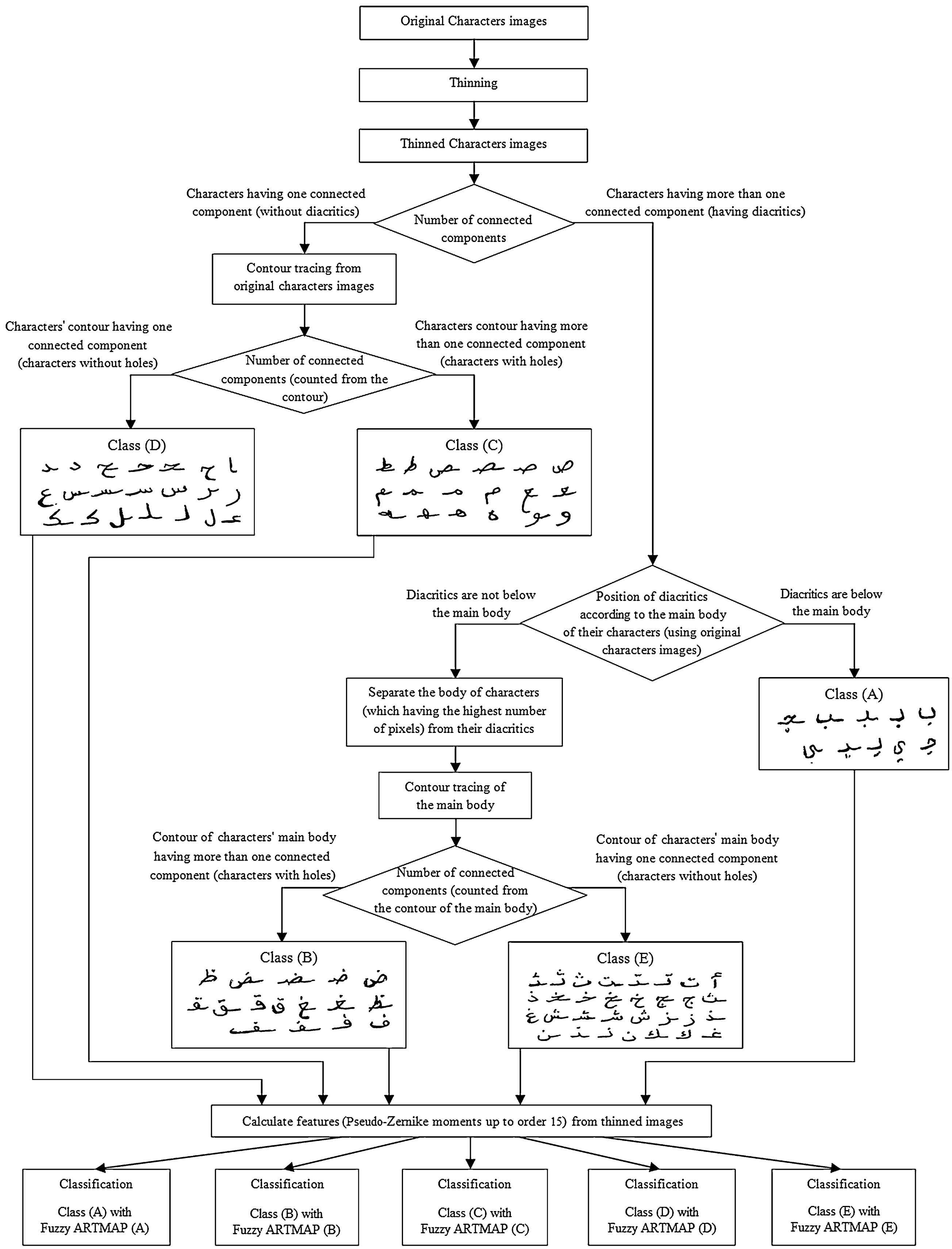


Fig. 10 Architecture and dynamics of the proposed system

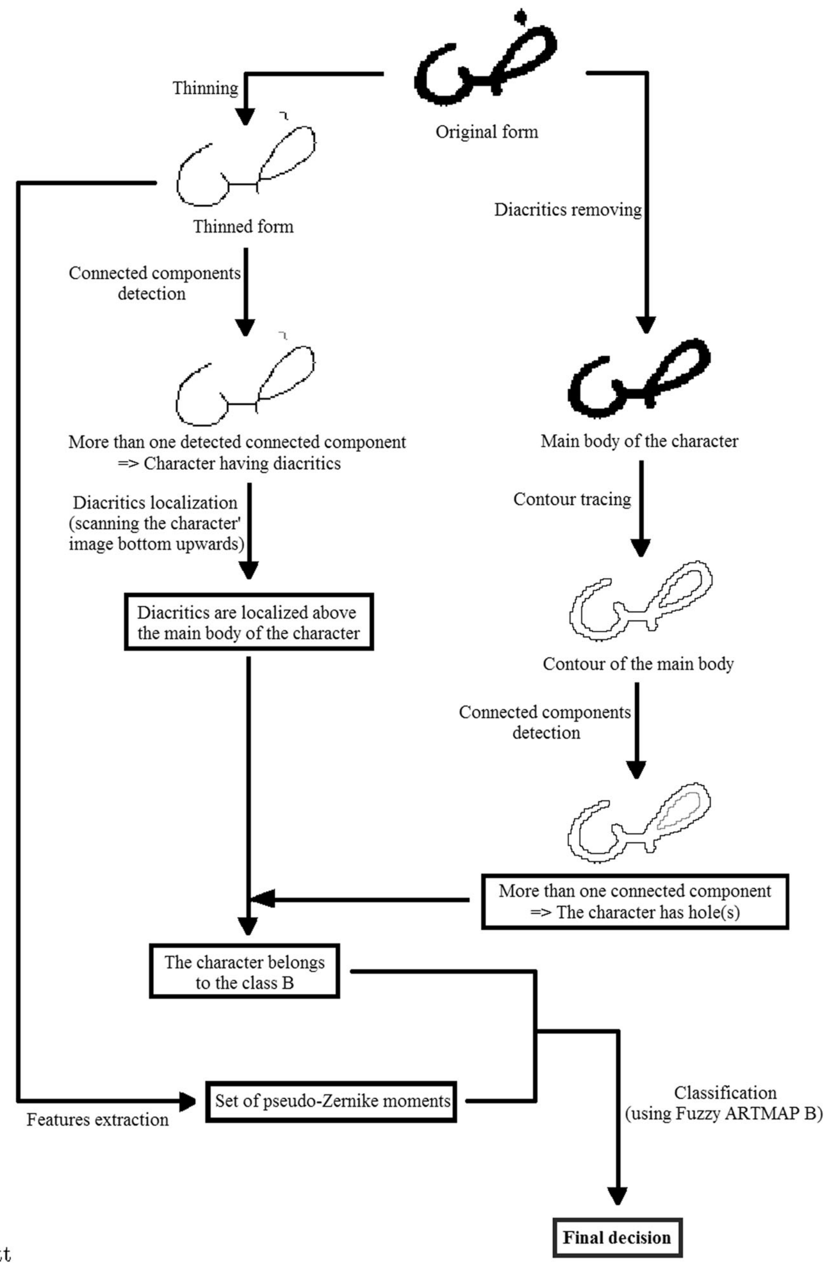


Fig. 11 Recognition process of a given character

Note here, that the number of diacritics does not represent a pertinent information to distinguish between characters; usually, in Arabic handwriting, diacritics represented by one, two or three points are mostly written as one stroke. Figure 11 explains the character recognition process.

To evaluate performances of OCRS, they should be compared objectively on the same database. Unfortunately, a few free databases are available for Arabic handwriting recognition. The well-known one is the IFN/ENIT database [46].

The IFN/ENIT database was produced by the Institute for Communications Technology at the Technical University of Braunschweig (IFN) and the Ecole Nationale d'Ingenieurs de Tunis (ENIT). The total number of binary images of handwritten Tunisian town/village names is 26459. Those names were written by 411 writers, and they were labelled according to 946 name classes.

To train and test the proposed model, a subset of the IFN/ENIT Arabic handwritten words was manually segmented producing a database of 3840 handwritten character images (40 samples for each character); all of them were in binary format and saved as a BMP (Bitmap) files (Fig. 12).

The extracted character images are a reasonable representation of the types of variations found across a set of

100 writers; the objective is to collect the most representative character set, so we have worked on the mainly factors responsible for variations in handwriting styles like the age, the sex, the education level, the profession and the residence town, etc. We have also considered characters with various stroke widths. Badly written characters and those containing overlappings were not taken (Fig. 13).

The extracted dataset was split into two subsets; training subset and test subset in the ratio 60/40, respectively. The training images were extracted from sets ‘a’, ‘b’, ‘c’ and ‘d’ of the IFN/ENIT database, while the test images was picked from the set ‘e’ (Table 1).

The proposed method was implemented in Delphi programming language. The system was developed under Microsoft Windows 7 (Ultimate edition) environment and the hardware platform was an *Intel*Core™i5 2.3 GHz with 4 gigabytes (GB) of random access memory (RAM). Tests were performed for different configurations of parameters to find the best values giving the best recognition rate. Table 2 lists the optimal parameters which recorded the highest recognition rates; used to configure the five networks of the proposed model.

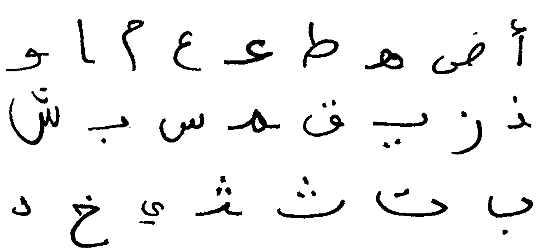


Fig. 12 Characters samples extracted from the IFN/ENIT database

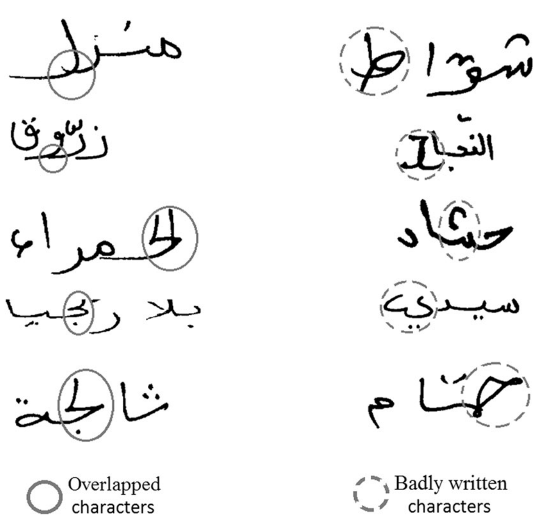


Fig. 13 Examples of badly written words extracted from the IFN/ENIT database

Table 1 Training and test subsets extracted from the IFN/ENIT database

IFN/ENIT database sets	a	b	c	d	e
Training subset	547	618	492	647	
Test subset					1536

The choice parameter α and the training rate β for both Fuzzy ART networks of each Fuzzy ARTMAP were fixed, respectively, to 0.001 and 1 (for fast learning).

The architecture, training times and recognition rates registered by the proposed system are listed in Table 3.

The value attributed to the vigilance parameter ρ_{ab} of the map field module is vital because it influences directly the learning process of the Fuzzy ARTMAP network. If ρ_{ab} tends towards 1, the network will lose its generalization capacity.

Figure 14 shows that the recognition rate recorded on the test set decreases when ρ_{ab} overtakes a threshold value, even if the accuracy registered on the learning set continues to increase.

Characters with a not-null false accepted rate (FAR) and/or false rejected rate (FRR) are listed in Table 4. The lowest values reported for FARs are a good indicator for the system’s performances.

We have examined the FAR and FRR of each character. The worst rates were reported by the Fuzzy ARTMAP (D) where we find many characters having the same main body (such as ت ث, ـت, ـث ـتـ ـثـ and ـتـ ـثـ). Also, there are some letters with loops (such as ـغـ, ـفـ, ـقـ and ـصـ, ـمـ, ـعـ, ـهـ) which have a slight difference in the way the loop is drawn.

When writing a character, variations can occur in different ways, like in the number and position of dots and strokes. As mentioned before the number of dotes is not a conclusive characteristic to distinguish between characters; since in Arabic handwriting, diacritics represented by points are mostly written as one stroke.

We tried to fix the problem using additional models for characters registering the highest FRRs but this affects the generalization capacity of the Fuzzy ARTMAP classifier, which leads to an unsuitable classification.

To show the efficiency of the proposed clustering method, another system using only one Fuzzy ARTMAP

Table 2 Optimal parameters of different Fuzzy ARTMAP networks

	α	β	ρ_a	ρ_b	ρ_{ab}
Fuzzy ARTMAP (A)	0.001	1	0.9	0.9	0.95
Fuzzy ARTMAP (B)			0.88	0.88	0.92
Fuzzy ARTMAP (C)			0.86	0.86	0.92
Fuzzy ARTMAP (D)			0.82	0.82	0.87
Fuzzy ARTMAP (E)			0.78	0.78	0.8

Table 3 Individual performances of the Fuzzy ARTMAP classifiers

	Inputs	Outputs	Training eochs	Training time (s)	Recognition rate (%) (IFN/ENIT)
Fuzzy ARTMAP (A)	136	10	2	0.56	99.3
Fuzzy ARTMAP (B)		16	2	1.05	97.2
Fuzzy ARTMAP (C)		18	2	1.18	93.4
Fuzzy ARTMAP (D)		21	3	1.99	90.7
Fuzzy ARTMAP (E)		31	5	5.74	88.7
Average					93.8

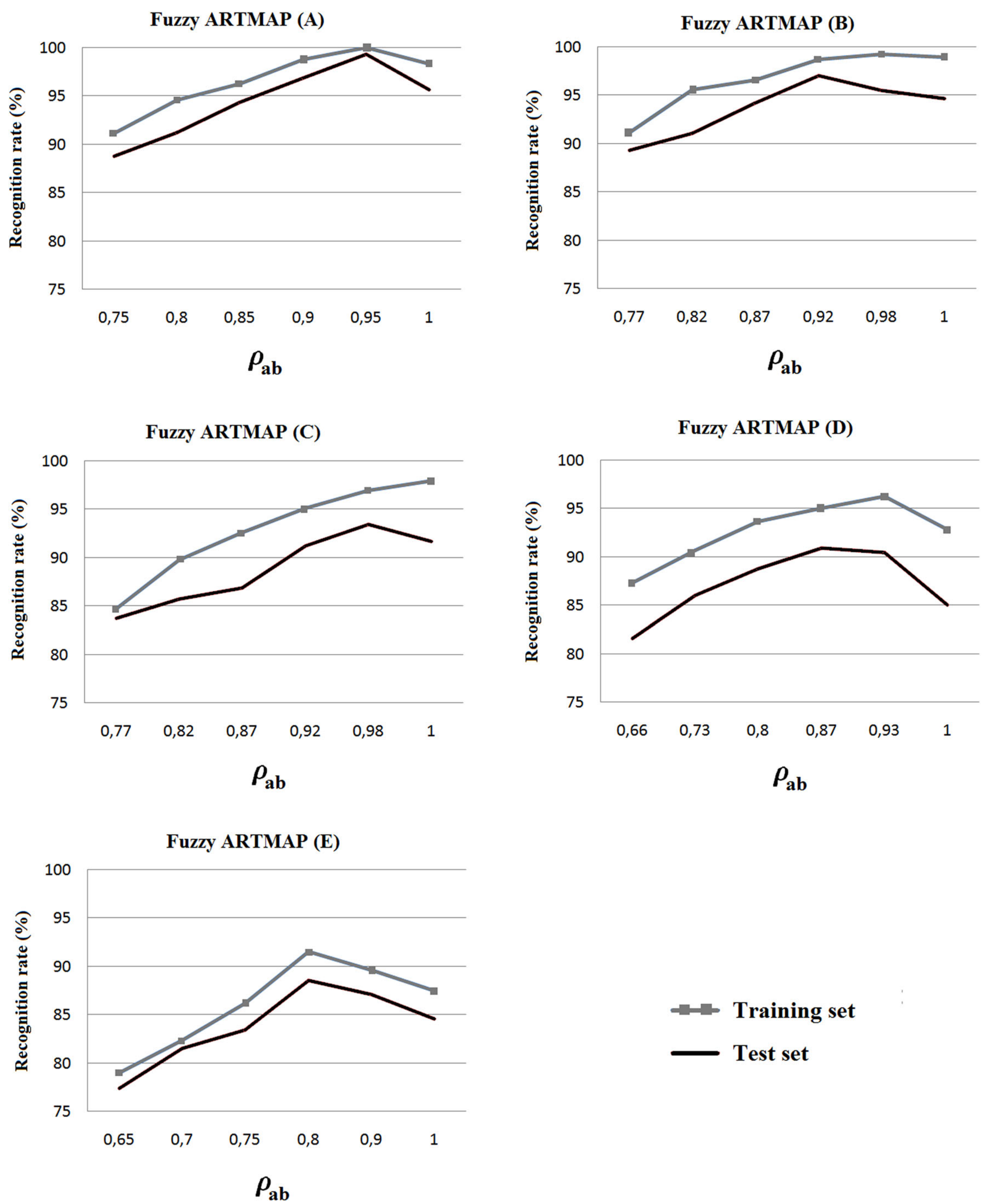


Fig. 14 Character recognition rates of Fuzzy ARTMAP classifiers according to the vigilance parameter of the map field module

Table 4 Characters recognition performances

Classifier	Character	Genuine	Forgery	FAR (%)	FRR (%)	Often taken as
Fuzzy ARTMAP (A)	بـ	16	144	0	6.25	
	يـ			0.69	0	بـ
Fuzzy ARTMAP (B)	ـغـ	16	240	0.83	6.25	ـفـ
	ـفـ			0.83	12.5	ـغـ ـقـ
	ـقـ			0.41	12.5	ـغـ ـفـ
	فـ			0.41	6.25	قـ
	قـ			0.41	6.25	فـ
Fuzzy ARTMAP (C)	ـصـ	16	272	1.1	18.75	ـهـ ـعـ
	ـمـ			1.1	18.75	ـصـ ـعـ
	ـعـ			1.1	18.75	ـمـ ـهـ
	ـهـ			1.1	18.75	ـصـ ـمـ ـعـ
	هـ			0.7	18.75	مـ
	مـ			1.8	12.5	هـ
	صـ			0	12.5	مـ
Fuzzy ARTMAP (D)	حـ	16	320	0.31	25	د
	ـحـ			0.62	18.75	ـد ـلـ
	د			1.56	18.75	حـ ر
	ـد			3.43	25	ـحـ ـلـ ـر
	عـ			0.93	25	كـ
	ـلـ			0.62	25	ـد
	كـ			1.25	18.75	عـ
	ر			0.62	25	د
	ـر			0.31	12.5	ـد
Fuzzy ARTMAP (E)	ت	16	480	0.83	25	ث
	تـ			0.83	25	ثـ
	ـتـ			0.62	18.75	ـثـ
	ـت			0.62	18.75	ـث
	ث			0.83	25	ت
	ثـ			0.83	25	تـ
	ـثـ			0.62	18.75	ـتـ
	ـث			0.62	18.75	ـت
	خـ			0.41	25	ذ نـ
	ذ			1.25	25	خـ ز نـ
	ـذ			1.04	25	ـز ـنـ
	ز			0.83	25	ذ نـ
	ـز			0.41	25	ـذ ـنـ
	نـ			0.83	25	خـ ز
	ـنـ			1.04	25	ـذ ـز

Table 5 Character recognition rate using one Fuzzy ARTMAP

Inputs	Outputs	Training epochs	Training time (s)	Recognition rate (%) (IFN/ENIT)
136	96	5	25.20	84.7

Table 6 Character recognition rate using one MLP

Inputs	Hidden layer	Units	Outputs	Transfer function	Training epochs	Training time (s)	Recognition rate (%) (IFN/ENIT)
136	1	100	96	Hyperbolic tangent sigmoid	10000	865	80.5

Table 7 Individual performances of the MLP classifiers

	Inputs	Hidden layer	Units	Outputs	Transfer function	Training epochs	Training time (s)	Recognition rate (%) (IFN/ENIT)
MLP (A)	136	1	20	10		1000	7	92.5
MLP (B)			30	16	Hyperbolic	2000	15	87.1
MLP (C)			40	18	tangent	2000	18	85
MLP (D)			50	21	sigmoid	5000	55	82.4
MLP (E)			60	31		8000	126	81
Average								85.6

Table 8 Recognition rates of tested architectures

Tested architecture	Recognition rate (%)	
	IFN/ENIT	Our database
5 Fuzzy ARTMAP	93.8	92.2
5 MLP	85.6	83.9
1 Fuzzy ARTMAP	84.7	82.2
1 MLP	80.5	80

neural network has been developed and tested on the same set of images (Table 5).

To show the effectiveness of the proposed recognition model, more experiments have been conducted using the most commonly used neural network [17]; the multilayer perceptron (MLP) [23]. Tests using one multilayer perceptron and also five multilayer perceptrons trained with a typical back-propagation algorithm (BP) [27] have been achieved. The architecture of the used MLPs and the obtained results are summarized in Tables 6 and 7.

The Fuzzy ARTMAP neural network gives superior performance in training with few epochs compared to the large number of training epochs needed for a multilayer perceptron neural network (MLP).

Results show that the best correct recognition rate for the system using a single Fuzzy ARTMAP network and the system using five MLPs are almost equivalent. The proposed model using five Fuzzy ARTMAP networks and based on the new clustering method generates the best recognition rate.

We noticed that a large number of works related to Arabic handwriting recognition were tested on private and

Table 9 Comparison results

Systems	Features	Classifiers (recognition techniques)	Number of classes	Number of characters	Number of writers	Used database	Recognition rate (%)
Aburas and Rehiel [3]	Based on wavelet decomposition	Euclidean distance	28	1968	48	Private	98
Shanbehzadeh et al. [52]	Number of components and 75 statistical features	Vector quantization	32	3000	–	Private	87
Rachidi et al. [49]	Pre-topological operators (adherency, interior, frontier, border)	Pre-topological pseudo-distance	17	6188	26	Private	90
Abandah and Younis [1]	Structural characteristics, statistical characteristics and Fourier descriptors	LDA classifier QDA classifier DLDA classifier DQDA classifier 3 k-nearest neighbours	104	4992	48	Private	87
Amrouchet al. [11]	Hough directional primitives	Hidden Markov	17	6188	26	Private	85.71
Aljuaid et al. [7]	Structural features	Genetic algorithm	–	–	–	–	90.46
Niya and Sajedi [44]	Wavelet transform and contour's features	Combined decision trees	36	–	–	Hoda database	97.89
Lawgali et al. [36]	DCT	4 MLP (BP algorithm)	–	6033	–	IFN/ENIT	90.73
Alabodi and Li [5]	Structural features	Regression algorithm	–	240	–	IFN/ENIT	90.3
Our system	Pseudo-Zernike moments	5 Fuzzy ARTMAP	96	3840	100	IFN/ENIT	93.8

unavailable databases developed for this purpose. For this reason we have designed a new large database of Arabic handwritten words which will be soon available freely for research and academic use. The proposed system has been also tested on our new database for comparison, where 1536 images were used.

Table 8 summarizes the obtained results of the presented architectures tested on both databases (IFN/ENIT and our new database).

To have an idea on the registered performances, we compared our system to some recent works (Table 9). It is observed that the proposed system achieves a decent recognition rate compared to the available systems in the literature.

It has to be noticed that the two systems which reported the highest recognition rates, were tested on a restricted number of classes (28 classes for the system of Aburas and Rehiel [3], and 36 classes for the system proposed by Niya and Sajedi [44]).

7 Conclusion

The objective of this work is to implement a new and fast method for off-line character recognition covering all possible shapes of Arabic letters. The goal was achieved through a clustering technique based on a structural characteristics; followed by a classification process using five Fuzzy ARTMAP neural networks. The proposed method can be integrated in any handwritten Arabic words recognition system based on an explicit segmentation process.

The proposed clustering technique employed structural characteristics extracted from character images using preprocessing procedures. This makes the recognition process much efficient, since each Fuzzy classifier has to learn and recognize a few characters' forms. Also, some characters having the same main body but different number of connected components and/or position of diacritics have been grouped into different sets and classified by a distinct Fuzzy ARTMAP network which leads to increase the recognition rate.

Finally, the thinned character images have been used in features extraction step. The preprocessed images were represented by a set of pseudo-Zernike moments vectors and passed to the corresponding Fuzzy ARTMAP network to be classified. A height recognition rate was reported.

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