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Zoning methods for handwritten character recognition: A survey

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ABSTRACT

This paper presents a survey on zoning methods for handwritten character recognition. Through the analysis of the relevant literature in the field, the most valuable zoning methods are presented in terms of both topologies and membership functions. Throughout the paper, diverse zoning topologies are presented based on both static and adaptive approaches. Concerning static approaches, uniform and non-uniform zoning strategies are discussed. When adaptive zonings are considered, manual and automatic strategies for optimal zoning design are illustrated as well as the most appropriate zoning representation techniques. In addition, the role of membership functions for zoning-based classification is highlighted and the diverse approaches to membership function selection are presented. Concerning global membership functions, the paper introduces order-based approaches as well as fuzzy approaches using border-based and ranked-based fuzzy membership values. Concerning local membership functions, the recent parameter-based approaches are described, in which the optimal membership-function is selected for each zone of the zoning method. Finally, a comparative analysis on the performance of zoning methods is presented and the most interesting approaches are focused on in terms of topology design and membership function selection. A list of selected references is provided as a useful tool for interested researchers working in the field.

1. Introduction

Handwriting characters recognition is a very complex task since different writing styles and handwriting variability can produce extreme differences in characters [38,60]. Additionally, the need to develop multilingual systems means coping with the specificities of a large variety of alphabets with different characteristics and degrees of complexity, as is the case of English, Latin, Arabic, Chinese and Indian scripts discussed in the comprehensive surveys of Plamondon and Srihari [45], Arica and Yarman-Vudal [2], Lorigo and Govindaraju [37], Nagy [40], Pal and Chauduri [43], respectively.

No matter what alphabet is considered, the feature extraction process plays a fundamental role in handwritten character recognition. Thousands of different features have been considered, such as features based on coefficients derived from mathematical transforms, moment-based features, graph-based features, geometrical features, projection, histograms, intersections, contour-based features, gradient-based features and so on. The outstanding survey by Trier et al. [64] offers an overview on the large variety of different types of features that have been considered in literature.

Whatever feature type is used, zoning methods have been widely adopted to derive useful information on the local characteristics of patterns. In general, by letting B be a pattern image, a zoning method Z_M can be generally considered as a partition of B into M sub-images (M integer, $M>1$), named zones (i.e. $Z_M=\{z_1, z_2,\ldots, z_M\}$), each one providing local information on patterns [35,64].

In the past, zoning methods were widely implemented for both analysis and recognition of handwritten characters. When zoning is used for pattern analysis, the main goal is to investigate the mechanism of human perception. In this case, the pattern image is partitioned into zones and the relevance of the information carried out from each zone is evaluated, in the context of human recognition processes [61,62]. When zoning is used for the synthesis of recognition systems, the main goal of a zoning method is to derive useful information on the local characteristics of patterns. This approach, which has also been exploited in many commercial OCR systems specifically devoted to the recognition of machine-printed characters [5], is widely used in the context of handwritten character recognition. This is due to its ability to extract useful information for recognition aims, reducing the effects of variability of handwritten characters [56]. Static zoning methods use standard partitions of the pattern image, obtained using both regular and non-regular grids. More recently, zoning design has been considered as an optimization problem and adaptive zoning design techniques have been proposed, in which zoning topology

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is obtained as the result of optimization problems [14,20,50]. Along with the developments in the design of zoning topologies, several advances have also been registered in membership function design. Standard membership functions use the winner-takes-all strategy. In this case, each feature has influence only on the zone in which it is has been found. Other membership functions have also been defined, according to global or local strategies [21,27]. Recently, Impedovo et al. [16] presented and discussed some of the most important advancements in the field.

This paper presents a complete survey on zoning techniques for handwritten character recognition. Through the paper, the main aspects of zoning design are addressed, based on zoning topology and membership function selection. The paper is organized as follows. Section 2 discusses the topologies of zoning methods. Both static and adaptive topologies are considered, and the most valuable zoning representation techniques are highlighted. Section 3 deals with the membership function selection for zoning-based classification. Global and local membership functions are discussed in this Section, as well as new membership functions based on fuzzy strategies and parameter-based approaches. Section 4 presents a comparative analysis of the zoning methods, based on the most valuable results published in the literature. Section 5 reports the conclusion of this paper.

2. Topologies

The taxonomy of zoning methods is shown in Fig. 1, when topologies are considered. Zoning topologies can be classified into two main categories: Static and Adaptive. Static topologies are designed without using priori information on feature distribution in pattern classes. In this case, zoning design is performed according to experimental evidences or on the basis of intuition and experience of the designer. Conversely, adaptive topologies can be considered as the results of optimization procedures for zoning design. In this case, a variety of information can be used to design the topology most profitable for the specific classification problem.

2.1. Static topologies

Zoning methods based on static topologies use simple grids that are superimposed on the pattern image. In the simplest case, they use $u \times v$ regular grids, determining uniform partitions of the pattern image into regions of identical shape.

Fig. 2 shows some examples of uniform topologies, based on regular grids 2×2 (Fig. 2a), 3×2 (Fig. 2b), 3×3 (Fig. 2c), 4×4 (Fig. 2d), 5×5 (Fig. 2e). For example, Suen et al. [61,62] use 2×2, 3×2, 1×2 and 2×1 grids for zoning design and present a model to evaluate the distinctive parts of handwritten characters. A uniform topology obtained by a 3×2 regular grid is used by Blumenstain et al. [4] for handwritten character recognition and by Morita et al. [39], who derive contour-based features for digit recognition. Oliveira et al. [42] adopt a 3×2 grid and extract contour-based features from each zone. Koerich [30] and Koerich and Kalva [31] examined the input image dividing the handwritten character according to a 3×2 regular grid. The same grid is used by Verma et al. [68] for character recognition using a back-propagation neural network. A 3×3 regular grid for zoning design is used by Baptista and Kulkarni [3] who extract geometrical feature distribution from each zone, and by Singh and Hewitt

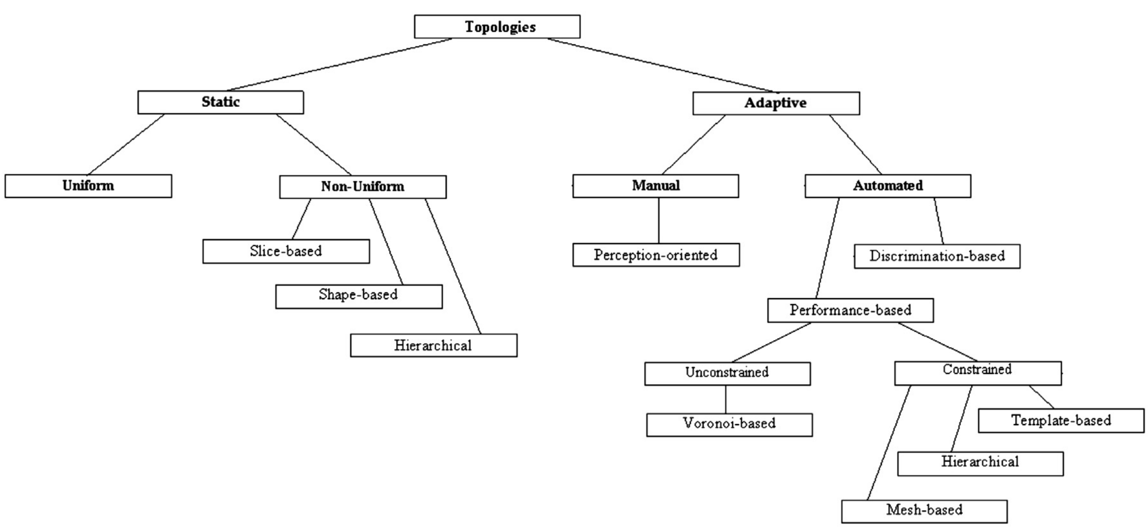

Fig. 1. Zoning methods: topologies.

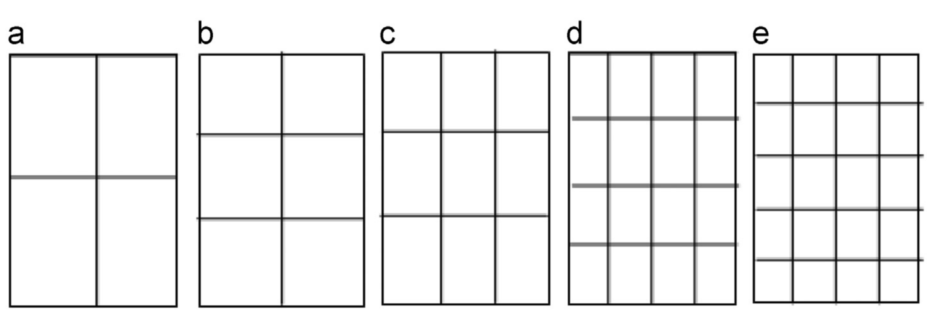

Fig. 2. Uniform zonings.

[59] that use a modified Hough transform method to extract features for handwritten digit and character recognition. Phokharatkul et al. [49] present a system for handwritten Thai character recognition based on Ant-minor algorithm. They use a 4×3 regular grid for zoning design in order to extract closed-loop and end-point features from the pattern image. A 4×4 regular grid is used by Cha et al. [8] to extract gradient, structural and concavity information from the pattern image, and by Negi et al. [41] to derive the density of pixels in the different zones. Kimura and Shridhar [28] use a zoning topology based on a 4×4 regular grid to detect information from contour profiles of the patterns. In each zone the number of segments on the contour of the pattern with the same orientation is counted. Four basic orientations are considered: 0°,90°,$+45^\circ$,-45°.

The same grid is used by Liu et al. [36] to recognize Chinese characters by a directional decomposition approach. Camastra and Vinciarelli [7] use a 4×4 regular grid for recognizing isolated cursive characters extracted from word images. In this case, two sets of operators are applied to each zone. The operators of the first set measure the percentage of foreground pixels in the zone with respect to the total number of foreground pixels in the character image. The operators of the second set estimate to what extent the black pixels in the cell are aligned along some directions. Xiang et al. [70] apply zoning to the recognition of car plates. They extract pixel density features dividing the character input image from car plates using a 4×4 regular grid. Sharma and Gupta [60] use 4×4, 6×6 and 8×8 regular grids to extract pixel density from the pattern image. Impedovo et al. [17] presented an optimized clustering technique for handwritten digit recognition and use a 5×5 regular grid for extracting gradient-based features. Rajashekararadhya and Ranjan [52–55] use a 5×5 regular grid for zoning design. For each zone, the average distances from the character centroid to the pixels in each row/column are considered as features. A 5×5 regular grid is also used by Vamvakas et al. [66,67] to compute local density in the character image, whereas 1×10 and 10×1 grids are considered for extracting profile projection features in the vertical and horizontal directions, respectively.

Jin and Wei [26] extract directional features for Chinese character recognition by using 4×4, 8×8, 10×10, 4×9 and 4×16 regular grids. Impedovo et al. [18,19] perform handwritten numeral recognition by using uniform zoning methods with M zones, for $M=2$ (1×2, 2×1 grids), $M=4$ (1×4, 4×1, 2×2 grids), $M=6$ (3×2, 6×1 grids), $M=9$ (3×3 grid), $M=16$ (4×4 grid). They use a genetic algorithm to determine the optimal weight vector to balance local decisions by using M zones.

In other cases the pattern image is non-uniformly partitioned into regions of different shape. This is the case of slice-based, shape-based and hierarchical zoning methods. For instance, Takahaski [63] uses vertical, horizontal and diagonal grids to split the pattern images into slice-zones and determines for each zone the orientation histograms detected from pattern contours. Vertical zoning is obtained by a 1×4 grid (Fig. 3a), horizontal zoning is obtained by a 6×1 grid (Fig. 3b) and two oriented 6×1 grids are used for diagonal zonings: $+45^\circ$ (Fig. 3c) and -45° (Fig. 3d). Two slice-based zonings obtained by 1×3 and 4×1 regular grids are also considered in the work of Phokharatkul et al. [49] to extract features according to a histogram-based approach for the recognition of handwritten Thai characters.

More recently, Roy et al. [56,57] propose novel shape-based zoning techniques using circular ring and convex hull ring partitioning criteria. In this case, a set of circular rings is defined as concentric circles whose center is the center of the minimum enclosing circle of the character. Similarly, convex hull rings are also constructed from the convex hull shape of the character. The radii of the rings of the sets are defined according to an arithmetic progression. In this case, to make the system rotation invariant, the features are mainly based on angular information of the external and internal contour pixels of the character.

Hierarchical zoning methods are generally used for multi-resolution feature extraction strategies. For instance, Park et al. [44] present a character recognition methodology (named Hierarchical OCR) based on a multiresolution and hierarchical feature space. Features at different resolutions, from coarse to fine-grained, are implemented by means of a recursive classification scheme (Fig. 4).

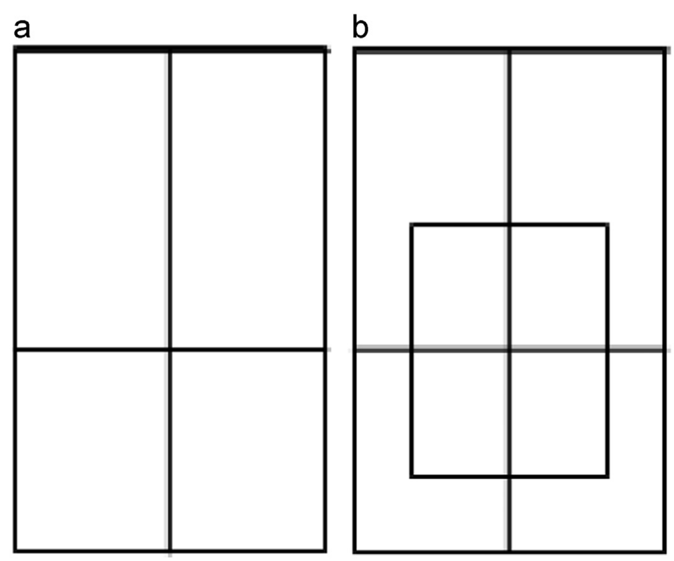

Fig. 4. Hierarchical zoning.

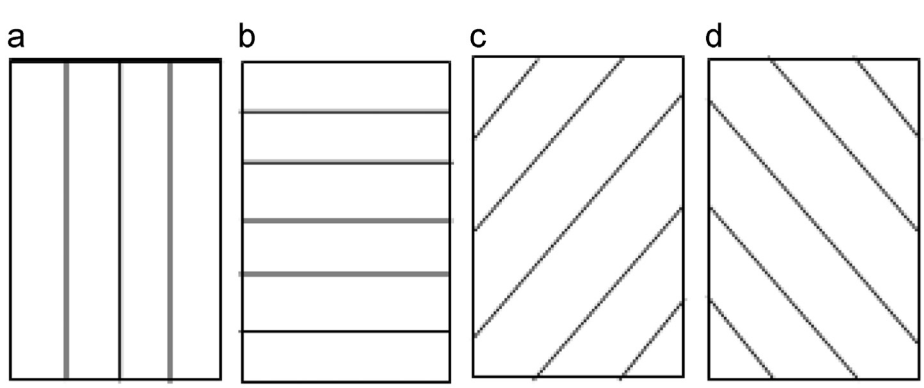

Fig. 3. Slice-based zoning methods.

In this case a variable size rectangular grid is used to define sub-images for the quin (quad) tree. The bounding box of a character image is divided into four rectangular regions (Fig. 4a). After the center of the mass of the contour has been determined, a vertical and horizontal line through the center of the mass will delineate the four regions. The quin tree structure is similar with an additional fifth subregion which is located in the central area formed by joining the centers of the other four subregions (Fig. 4b). Subsequent layers are successively constructed using the same method.

2.2. Adaptive topologies

Adaptive zoning topologies are designed according to the result of optimization procedures. In the past, manual approaches used perception-oriented strategies to support human experts in the process of zoning design. More recently, automated approaches have been proposed, based on the optimization of well-defined cost functions and zoning representation techniques.

The perception-oriented approach proposed by Aires et al. [1] and Freitas et al. [12,13] is based on non-regular grids for zoning design, resulting in a non-uniform splitting of the pattern image. The authors consider concavity/convexity features derived from the analysis of background pixels of the input image. In order to make the zoning design process less empirical, they define the zoning grid by using the confusion matrices looking for the relation between the zones. Fig. 5 shows two examples of non-uniform zonings obtained with a perception-oriented approach. In Fig. 5a, the pattern image is partitioned into five zones, according to a non-symmetrical criterion. In Fig. 5b, the pattern image is symmetrically partitioned into seven zones.

When automated zoning design is used, zoning topology is designed according to the result of an optimization process. So far, two kinds of optimal functions have been considered in literature: discrimination-based and performance-based. Functions of the first category consider the discrimination capability of the zoning topology; functions of the second category consider the classification performance associated to the topology.

Valveny and Lopez [65] use a zoning method and divide the pattern image into five rows and three columns. The size of each row and column is determined in such a way to maximize the discriminating capabilities of the diverse zones of the pattern image. In the work of Impedovo et al. [10] zoning design is performed according to the analysis of discriminating capability of each zone, estimated by means of the statistical variance of feature distributions. Di Lecce et al. [9] designed the zoning problem as an optimization problem in which the discrimination capability of each zone is estimated by the Shannon Entropy (E) defined as:

$$E=\sum_{i=1}^{n} p_i \cdot \log_2 \frac{1}{p_i} \tag{1}$$

where n being the number of classes and p_i the probability that a feature (i.e. an end-point, a cross-point etc.) occurs in that zone for the patterns of the i-th class. In this case, the zoning design process starts from the analysis of the most discriminative points of the pattern image and continues according to a region-growing process. Fig. 6 shows two examples of zoning methods, with $M=6$ (Fig. 6a) and $M=7$ (Fig. 6b), obtained by Shannon Entropy estimation.

In the adaptive approach proposed by Gatos et al. [15], features are extracted after adjusting the position of every zone based on local pattern information. This adjustment is achieved by moving every zone towards the pattern body. The offset that is used for adjusting zone position is calculated by maximizing the local pixel density around the zone.

More recently, zoning has been designed by considering classification performance. Impedovo et al. [20] define the optimal zoning as the zoning for which the Cost Function (CF) associated to the classification is minimum, with

$$CF(Z)=a \times Sub(Z)+Rej(Z) \tag{2}$$

where $Sub(Z)$ and $Rej(Z)$ are, respectively, the substitution rate and the rejection rate when the zoning Z is considered, and coefficient a is the cost value associated to the treatment of substitutions with respect to rejections. The authors use Voronoi Tessellation for zoning description since it provides, given a set of points (named Voronoi points) in continuous space, a means of naturally partitioning the space into zones, according to proximity relationships among the set of points.

Fig. 7 shows two Voronoi-based zoning methods of the $M=6$ (Fig. 7a) and $M=9$ (Fig. 7b) zones, respectively. In addition, changing the position of the Voronoi points corresponds to the modification of the zoning method. Therefore, zoning description with Voronoi Tessellation offers the possibility to easily adapt the zoning to the specific characteristics of the classification problem. Impedovo et al. [20] also propose a genetic algorithm for zoning

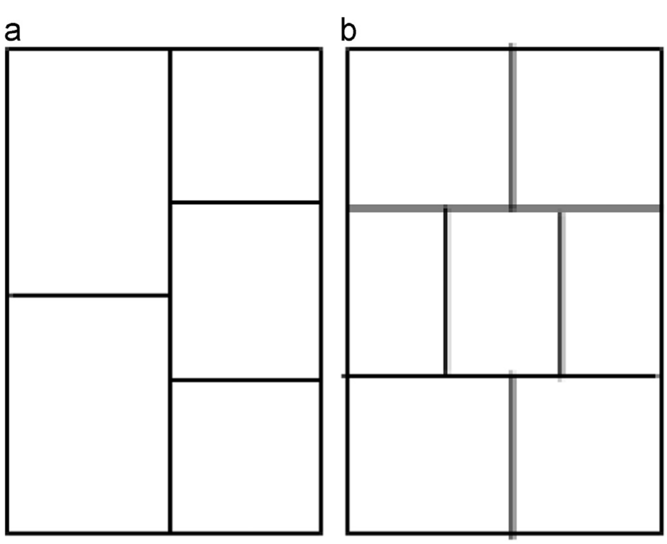

Fig. 5. Perception-oriented zoning methods.

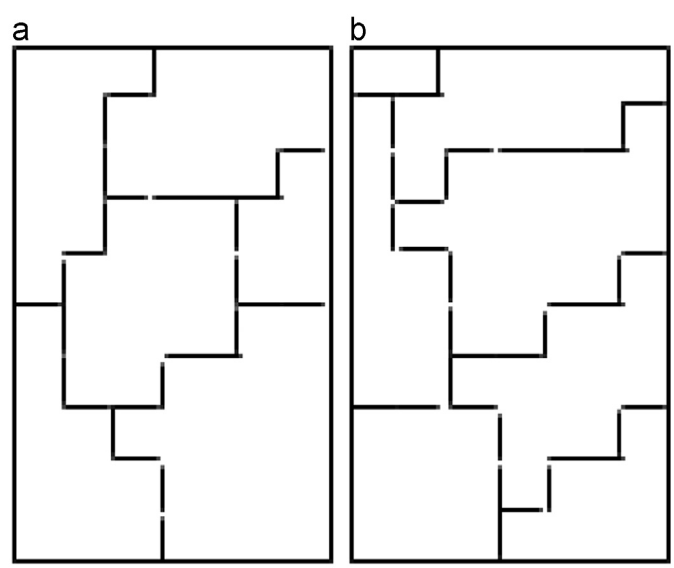

Fig. 6. Discrimination-based zoning methods.

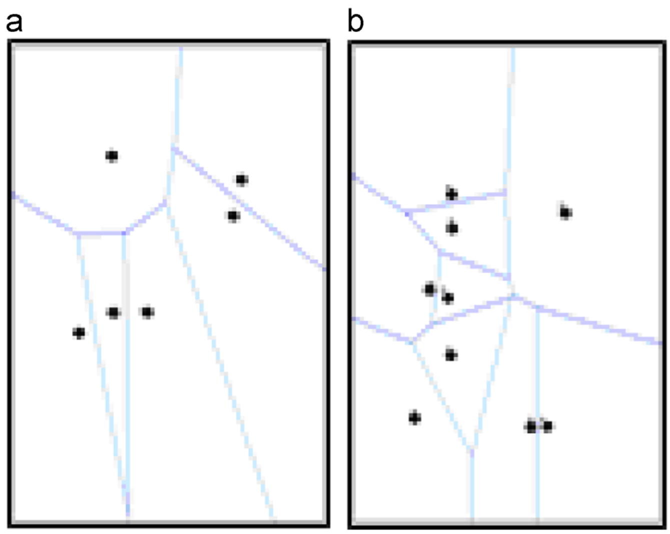

Fig. 7. Performance-based zoning methods (Voronoi-based).

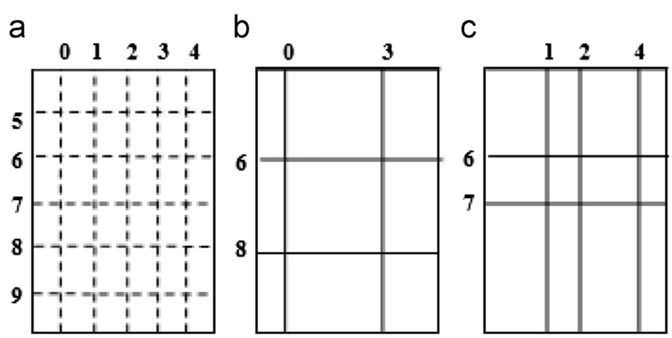

Fig. 8. Performance-based zoning methods (Template-based).

design, in which each individual of the genetic population is a set of Voronoi points (corresponding to a zoning method) and the cost function associated to the classification is considered as a fitness function.

Ferrante et al. [11] perform an analysis of Voronoi-based zoning and estimate the optimal number of zones, depending on the characteristics of the classification problem. More recently, a new technique has been proposed to define, in a unique process, the optimal number of zones of the zoning method along with the optimal zones, defined through Voronoi diagrams [25]. For the purpose a new formulation of the zoning design problem has been considered and a multi-objective genetic algorithm was used for optimal zoning design [25,47].

Radtke et al. [50,51] present an automatic approach to define zoning using Multi-Objective Evolutionary Algorithms (MOEAs). Using the template in Fig. 8a, they define the zones based on fixed position divisions (dotted lines) that can be turned on and off. Since each division has two states, it can be controlled by a single bit indicating whether the division is on or off. The idea is to provide a self adaptive methodology to define the best zoning method according to two diverse optimality criteria: an error rate as low as possible (Eq. 3.1) and a minimal number of non-overlapping zones (Eq. 3.2):

$$f_{\text{error}} = 1 - \frac{n_{\text{correct}}}{n_{\text{validation}}} \tag{3.1}$$

$$f_{\text{zones}} = (1 + \sum_{i=0}^{4} div_i) \times (1 + \sum_{j=5}^{9} div_j) \tag{3.2}$$

where, in Eq. (3.1), n_{correct} is the number of correct classification and $n_{\text{validation}}$ is the size of the validation database; whereas, in Eq. (3.2), div_x is a bit from the coding string ($x = 1,2,\ldots,9$), determining the zones turned on and off. A NSGA-II multi-objective selection operator is used for the optimization procedure. Fig. 8b,c shows two zoning methods of $M = 9$ and $M = 12$ zones, respectively. Lazzerini and Marcelloni [33] apply a method for fuzzy classification and recognition of two-dimensional shapes to handwritten characters. The character image is partitioned horizontally and vertically into stripes. For each dimension, a set of weights is determined that define the importance of each stripe in the classification process and a genetic algorithm is used to optimize stripe dimension with respect to the recognition rate.

Lemieux et al. [34] present a hierarchical zoning method in which floating zones are determined by a genetic programming approach. Inspired by the approach of Park et al. [44], Gagné and Parizeau [14] use a tree-based hierarchical zoning for handwritten character classification. They present a genetic programming approach for optimizing the feature extraction step of a handwritten character recognizer. Their recognizer operates on a hierarchical feature space of orientation, curvature, and center of mass primitives. The nodes of the hierarchy represent rectangular zones of their parent node whereas the tree root corresponds to the entire image. Genetic programming is used to simultaneously learn the best hierarchy and the best combination of fuzzy features. For this purpose, they use population-based multi-objective optimization techniques based on the concept of Pareto optimality, where solutions are ranked according to a dominance criterion. Further improvements have led them to use a data-driven hierarchical topology where zones are recursively defined around the center of mass of strokes, instead of the absolute center of a parent region.

Wu and Ma [69] use a 7×7 partitioning criterion and propose an elastic mesh-based approach in which the overlapped zones are dynamically defined through mapping the input image to a virtual normalized image. Non-linear shape normalization based on weighted dot density is used to absorb pattern variability. Also the recognition system of Kato and Suzuki [27] for Chinese and Japanese handwritten characters uses a 7×7 zoning topology with overlapping zones. A similar approach which uses overlapped zones to reduce border effects has been proposed by Kimura et al. [29].

3. Membership functions

Whatever zoning topology is considered, pattern description should be able to absorb as much as possible intra-class variability while maintaining inter-class differences. For this reason, the feature-zone membership function is very important since it determines the way in which a feature can influence the different zones of a zoning method [23,32]. As Fig. 9 shows, two categories of membership functions have been considered in the literature: global and local. Traditional zoning-based classification approaches use global membership functions. In this case a single membership function is adopted globally, i.e. for all zones of the zoning method. More recently, the use of local membership functions has been proposed. In this case, a family of membership functions is considered and for each zone of the zoning method a specific membership function of the family is used.

3.1. Global membership functions

Two types of global membership functions can be found in the literature: order-based and fuzzy-based. In both cases, the functions are defined according to the proximity criterion of features to

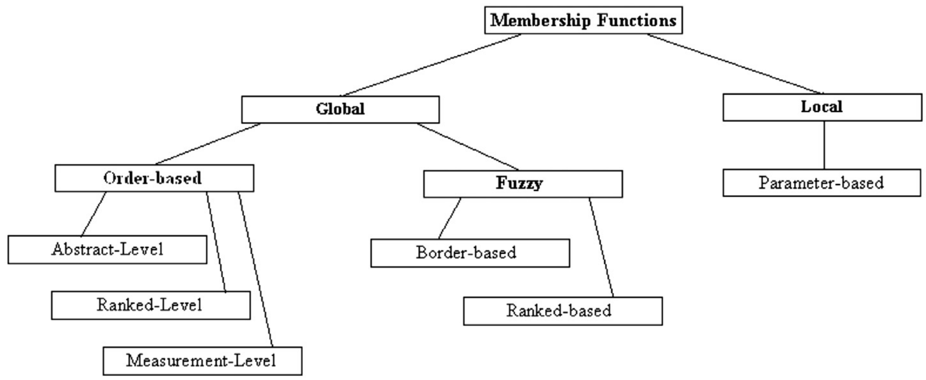

Fig. 9. Zoning methods: membership functions.

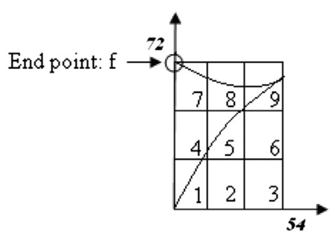

Fig. 10. Feature extraction using regular 3 × 3 zoning.

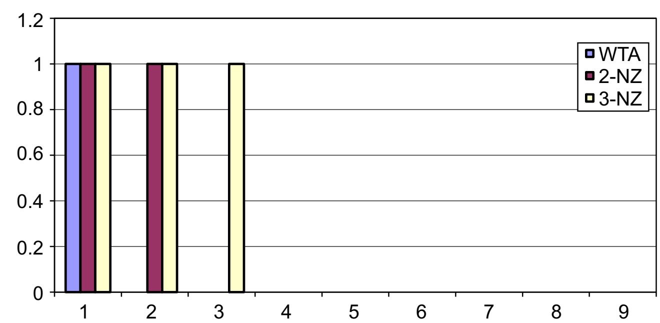

Fig. 11. Abstract-level membership functions.

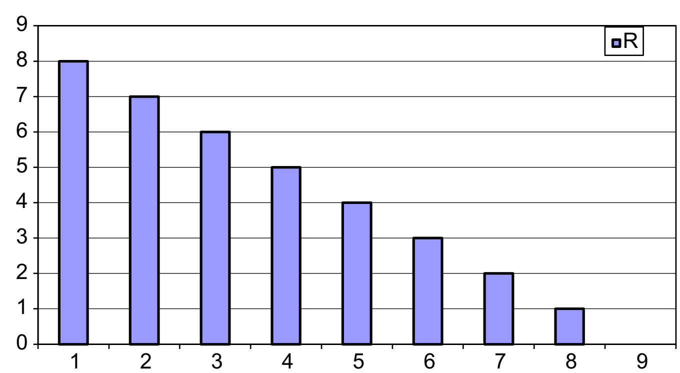

Fig. 12. Ranked-level membership function.

the diverse zones. When order-based membership functions are considered, the membership values are assigned on the basis of the values of specific proximity-based functions. In other cases, fuzzy-based membership functions are utilized, in which fuzzy membership values are adopted to define the influence of a feature in each zone. More precisely, let $Z_M=\{z_1, z_2,\ldots, z_M\}$ be a zoning method and let f be a feature extracted from the pattern image. A membership function gives the set of weights w_j that define the influence of feature f on zone j, for $j=1,2,\ldots,M$. According to the type of values used to define influence weights w_j, $j=1,2,\ldots,M$, three classes of order-based membership functions can be defined [21,22]: abstract-level, ranked-level and measurement-level. When abstract-level membership functions are considered, the influence values are given in the form of Boolean values. When ranked-level membership functions are used, the influence values are integers. When measurement-level membership functions are used the influence values are real numbers. Let $d_j=dist(pf, pz_j)$ be the distance between position pf in which feature f is located and center pz_j of zone z_j, $j=1,2,\ldots,M$. In order to formally define the order-based membership functions, let.

$$\langle j_1, j_2, \ldots, j_m, j_{m+1}, \ldots j_M \rangle \tag{4}$$

be a sequence of indexes so that

- $j_m \in \{1,2,\ldots,M\}$, $\forall m=1,2,\ldots, M$;
- $j_{m1} \neq j_{m2}$, $\forall \mathrm{m}_1,\mathrm{m}_2=1,2,\ldots M$, $m_1 \neq m_2$;

and for which it results

$$d_{jm1} \le d_{jm2,} \forall m_1, m_2 = 1, 2, \ldots, M. \tag{5}$$

The sequence of zones $\langle j_1 j_2,\ldots j_m j_{m+1},\ldots j_M\rangle$ are arranged according to the increasing order of the distances between the feature and the centers of the zones. For example, Fig. 10 shows a uniform zoning based on a regular grid 3 × 3 of a pattern image of size 54 × 72. In this case, $P=\{pz_1, pz_2,\ldots, pz_M\}=\{(9, 12), (27, 12), (45, 12), (9, 36), (27, 36), (45, 36), (9, 60), (27,60), (45, 60)\}$ is the set of centers of the zones and pf=(1,72) is the position in which feature f (an end-point, in the example in Fig. 10) is detected. In this case the list of indexes is $\langle j_1 j_2,\ldots j_m j_{m+1},\ldots j_M\rangle=\langle 7, 8, 4, 9, 5, 6, 1, 2, 3\rangle$. Now, when abstract-level membership functions are used, the influence of f to each zone z_j is defined using Boolean values. Two main functions can then be considered [21]:

- *The Winner-takes-all* (*WTA*) membership function:

$$w_j = 1 \quad \text{if } j = j_1, w_j = 0 \quad \text{otherwise} \tag{6}$$

It is worth noting that the WTA membership function is the standard membership function used in the literature.

- *The k-Nearest Zone* (*k-NZ*) membership function:

$$w_j = 1 \quad \text{if } j \in \{j_1, j_2, \ldots, j_k\}, w_j = 0 \quad \text{otherwise} \tag{7}$$

Fig. 11 reports an example of abstract-level membership functions WTA, 2-NZ and 3-NZ.

When ranked-level membership functions are used, the influence of f to each zone z_j is defined using integer values:

- *The Ranked-based* (R) membership function:

$$w_j = M - m \quad \text{if } j = j_m, w_j = 0 \quad \text{otherwise} \tag{8}$$

Fig. 12 shows an example of ranked-level membership function.

When measurement-level membership functions are used, the influence of f to each zone z_j is defined using real values:

- *Linear Weighting Model* (L):

$$w_j = 1/d_j \tag{9}$$

- *Quadratic Weighting Model* (Q):

$$w_j = 1/d_j^2 \tag{10}$$

- *Exponential Weighting Model* (E):

$$w_j = 1/\alpha^{\beta \times dj} (\text{with } \alpha, \beta \text{ parameters}) \tag{11}$$

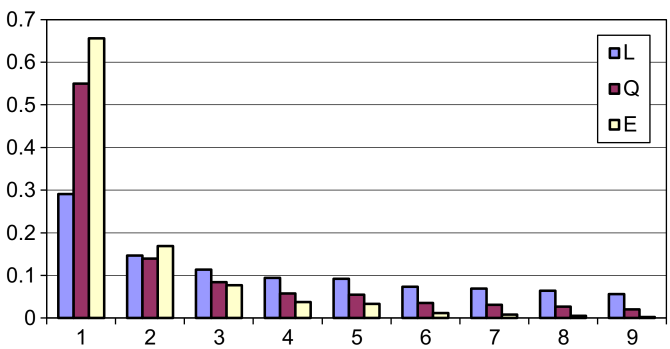

Fig. 13. Measurement-level membership functions.

Fig. 13 shows an example of measurement-level membership functions (L, Q and E with $\alpha = 1.2$ and $\beta = 1$). Please note that in Fig. 13 the weights are normalized so that $w_{1+} w_{2+\ldots} w_M = 1$, for the sake of clarity.

A different type of global membership functions uses fuzzy values. Cao et al. [6] use a 3×3 regular grid for zoning design and consider contour-based feature for character recognition. They observe that when the contour curve is close to zone borders, small variations in the contour curve can lead to large variations in the extracted features. Therefore, they try to compensate for this by using a fuzzy border. Features detected near the zone borders are given fuzzy membership values to two or four zones.

A similar approach is proposed by Lajish [32] who uses a non-overlapped zoning method based on a 3×3 regular grid. For each zone, see Fig. 14, he considers three boundary regions of different size ("A": smaller region, "B": average region, "C": larger region) and set the membership values of a feature according to the degree of inclusion in the zone or within its boundaries. Fig. 14 shows the zoning based on the 3×3 regular grid and the fuzzy regions for each zone type: corner zones (zones 1,3,7,9), peripheral zones (zones 2,4,6,8) and central zone (zone 5). Membership values for each feature, extracted from the pattern contour, are set according to their degree of inclusion in that zone. A feature that is in a zone is assigned a membership value 1. All features in the fuzzy regions of type "A" are assigned a membership value 0.75; features in the fuzzy regions of type "B" are assigned a membership value 0.5; features in the fuzzy region of type "C" are assigned a membership value 0.25. A similar membership function is presented by Kato et al. [27]. They split the pattern image of 64×64 pixels into 7×7 equal subareas of 16×16 pixels, where each subarea overlaps eight pixels of the adjacent subareas, as Fig. 15a shows. Furthermore, each subarea is divided into four areas A,B,C,D (Fig. 15b): A is a 4×4 area in the center, B is a 8×8 area exclusive of area A, C is a 12×12 area exclusive of areas A and B, D is a 16×16 area exclusive of A,B,C, and D. In this case, the weights are 4,3,2,1 for the areas A,B,C,D, respectively (Fig. 15c).

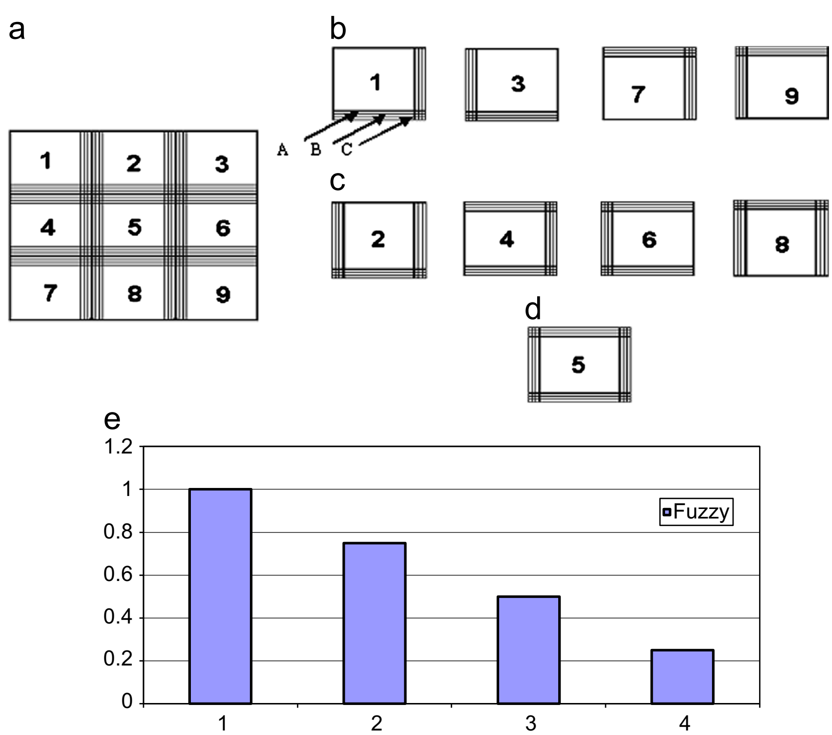

Fig. 14. Border-based fuzzy membership function in non-overlapped zoning.

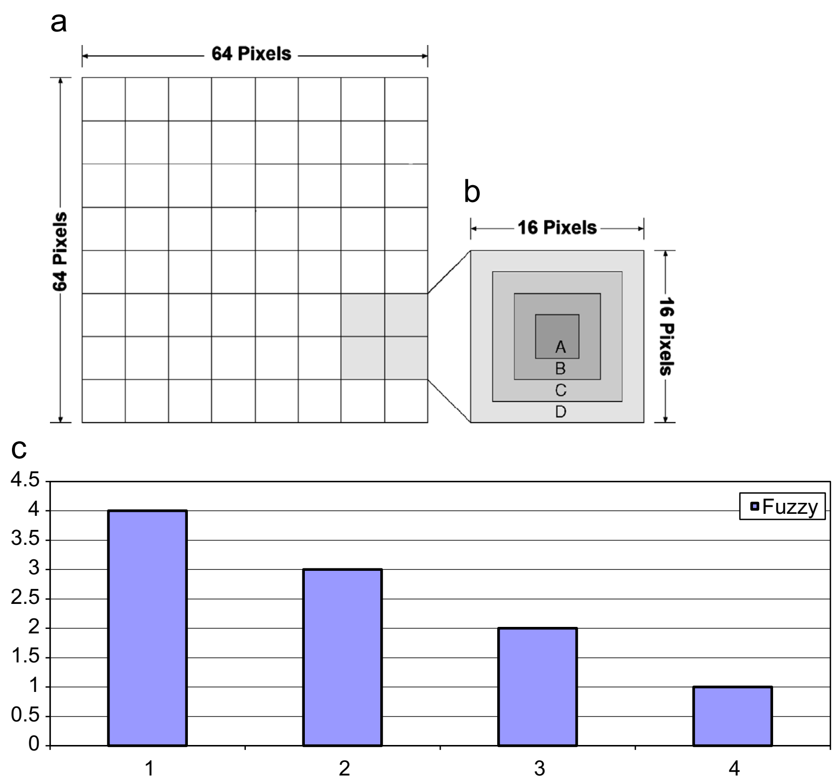

Fig. 15. Border-based fuzzy membership function in an overlapped zoning.

Pirlo et al. [46] use ranked-based fuzzy membership. In this case the fuzzy membership function is any weighting function defined through a set of weights FM={μ_1, $\mu_{2,\ldots}$, μ_m,…,μ_M}, μ_m being the weight for the zone corresponding to the m-th position of the sequence in (4) (and therefore the m-zone closest to the feature) and for which it follows that:

$$\mu_m \geq 0, \quad m=1,2,\ldots,M \tag{12a}$$

$$\mu_m \geq \mu_{m+1}, \quad m=1,2,\ldots,M-1 \tag{12b}$$

$$\mu_1+\mu_2+\cdots+\mu_m+\cdots+\mu_M=1 \tag{12c}$$

The selection of the best suited fuzzy membership for a given zoning-based classification problem most certainly involves detecting optimal weights μ_m, m=1,2,…M, which maximize the classification performance. For this purpose, a real-coded genetic algorithm has been proposed to find, in a single optimization procedure, the optimal fuzzy membership function together with the optimal zoning described by Voronoi Tessellation. Fig. 16 shows an example of optimal zoning (Fig. 16a) and optimal fuzzy membership function (Fig. 16b) for handwritten digit recognition.

3.2. Local membership functions

The use of local membership functions derives from the consideration that different parts of the character can exhibit features with diverse statistical distributions. Therefore, each zone of the character requires a specific membership function. Impedovo and Pirlo [24,48] present a new class of parameter-based membership functions, based on exponential models, and select the most profitable set of parameters for each zone of the zoning method. When parameter-based membership functions are used, a set of specialized functions is considered, one for each zone of the zoning method. The influence of feature f on zone z_j is defined using real values as follows:

$$w_j = 1/\alpha_j^{\beta j \times dj}(\alpha_j, \beta_j \text{ parameters}) \tag{13}$$

Therefore, as Fig. 17 shows, in this case the problem of optimal zoning design is faced by defining both the optimal topology (Voronoi Diagrams are considered for this purpose) (Fig. 17a) and the optimal parameters of the membership functions for each zone (Fig. 17b).

4. Zoning methods: a comparative analysis

The comparison of zoning method performance for handwritten character recognition is a difficult task since there are differences in experimental methodology and settings, as well as differences in the databases used. In order to attempt such a comparison, an analysis of some of the most valuable zoning methods was carried out in two separate steps, considering topologies and membership functions. Concerning zoning topologies, Table 1 reports some of the most relevant results presented in the literature. All examples in Table 1 used the standard WTA membership function (see Eq. (6)). Blumenstein et al. [4] used two feature sets based on direction-based features and transition-based features, respectively. In addition, they used a Back-Propagation Network (BPN) and a Radial Basis Functions Network (RBFN) for classification. Patterns from the CEDAR database were considered for their tests. More precisely, the first dataset (DS-1) consists of characters automatically segmented from words in the CEDAR database (CITIES/BD directory). DS-1 contains 18,655 lower case (LC) and 7175 upper case (UC) training patterns; 2240 LC and 939 UC testing patterns. When DS-1 was considered the best result was achieved by direction-based features. In this case, BPN

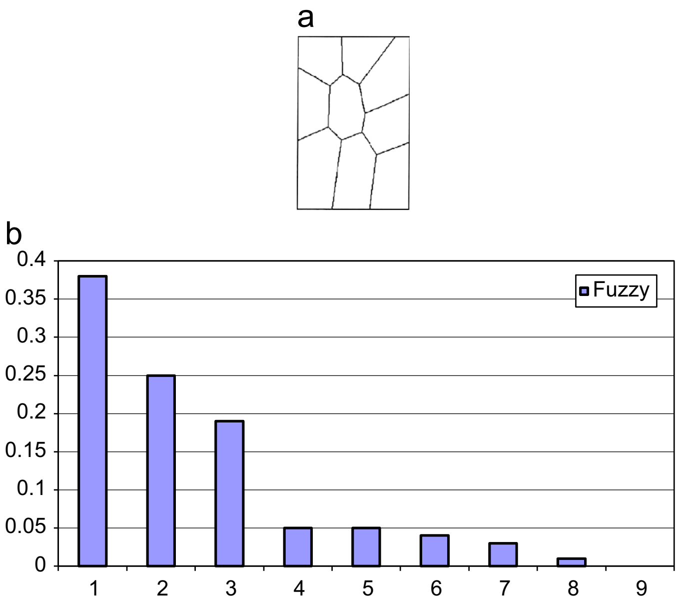

Fig. 16. Rank-based fuzzy membership function in Voronoi-based optimal zoning.

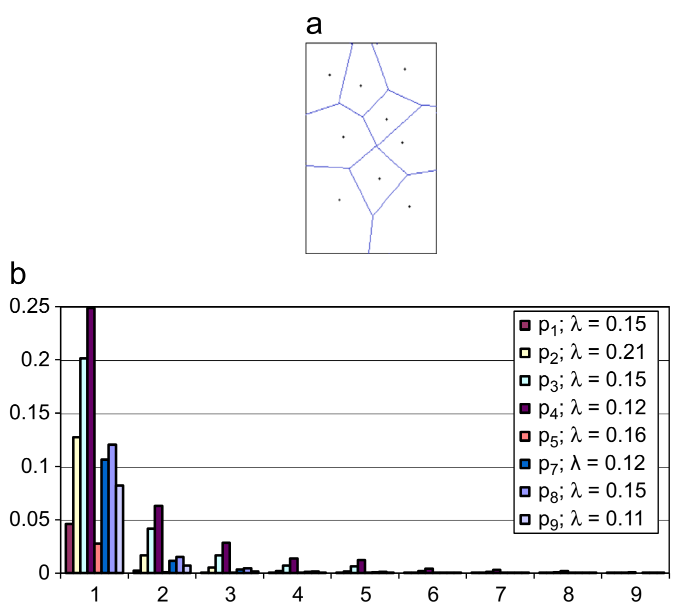

Fig. 17. Optimal zoning topology and optimal parameter-based membership functions.

provided a recognition rate of 69.78% and 80.62% for LC and UC characters, respectively; RBFN provided a recognition rate of 70.63% for LC characters and 79.98% for UC characters. The second dataset (DS-2) consists of pre-segmented characters from the CEDAR database (BINANUMS/BD & BL directories). DS-2 contains 19,145 characters for training and 2183 characters for testing. When DS-2 was used, the best recognition rate, equal to 85.48%, occurred when RBFN and transition features were considered. Conversely, the best recognition rate was 83.65% when BNP and direction-based features were used.

Singh and Hewitt [59] used a Linear Discriminant Analysis (LDA) technique and a Nearest Neighbor (NN) classifier to recognize numerals and characters of the CEDAR database. They used feature information related to oriented segments, extracted through the Hough Transform. The best results were obtained by the uniform 3×3 zoning topology. When numerals are considered the recognition rate is 93.9% by LDA and 88.3% by NN. Conversely, when characters were used, the best recognition rate was 76.3% by LDA and 62.7% by NN.

Sharma and Gupta [58] used pixel density information as features whereas classification was performed by a k-nn technique ($k=1$). 10,000 training patterns and 5400 test patterns were used for the experimental test. The best results were achieved with a uniform 4×4 zoning, for which a 99.89% recognition rate was registered.

Rajashekararadhya and Ranjan [53] used a uniform 5×5 zoning for handwritten character recognition. A distance-based feature set was considered and a k-nn classifier, a feed-forward backpropagation neural network classifier and support vector machine classifiers were used. The approach, applied to the MNIST database, using 5000 training digits and 1000 testing digits, led to a recognition rate of 97.2% using the SVM classifier. When 12,000 training samples and 3000 testing samples of the ISI Bangla digit database were considered, the authors achieved a recognition rate of 95.47%.

Impedovo et al. [23] used uniform zonings based on 2×2, 3×3, 4×4, 5×5 regular grids for handwritten digit classification. For the experimental tests, they considered a set of geometrical feature and a k-nn classifier ($k=1$). 18,468 numerals from the BR directory of the CEDAR database were used for learning and 2213 numerals from the BS directory for the test. At the best, a recognition rate of 87.8% was achieved, when the uniform 5×5 zoning was used.

Roy et al. [57] used contour-based angular information as features and considered two shape-based zoning techniques. The first one used seven circular hull rings, the second one used seven convex hull rings. Classification was performed by a Support Vector Machine (SVM). For the experimental tests, carried out in the domain of touching characters, a suitable dataset of 8250 characters was considered. The recognition rate was equal to 98.44% using k-fold cross validation ($k=5$).

Freitas et al. [13] used a perception-oriented approach to zoning design. They considered a set of concavity/convexities features, obtained by labeling the background pixels of the input image, and a feed-forward Multi-Layer Perceptron (MLP) for class-modular classification. The experiments were carried out using the IRONOFF database of handwritten characters, which was composed of 26 classes of uppercase characters. The database, which consisted of 10,510 images, was divided into the training, validation and testing sets, containing 60%, 20% and 20% of the images, respectively. Using non-symmetrical zoning topologies and a metaclass strategy, they achieved a recognition rate of 90.4%.

Impedovo et al. [10] used a discriminate-based criterion for zoning design. They considered a set of geometrical features for numeral recognition and a Statistical Classifier (STC). The experimental results were carried out on the CEDAR database. In particular, they used 18,468 numerals of the BR directory for learning and 2213 numerals of the BS directory for testing. When $M=9$ zones were considered the recognition rate was equal to 82.5%.

Di Lecce et al. [9] optimized zoning topology in order to define zones with maximum discrimination capability estimated with Shannon entropy. A STC was used and a set of nine geometric features has been considered. In the experimental test, in which 18,468 numerals for testing (CEDAR database, BR directory) and 2671 numerals for test (CEDAR database, BS directory) were used, a recognition rate of 84.4% was registered.

Impedovo et al. [20] used a Voronoi-based optimal zoning topology and a statistical classification technique for the recognition of handwritten digits and characters. They considered two geometrical feature sets containing nine and 57 types of features, respectively. For the experimental test, they considered the CEDAR database of handwritten digits and the ETL database of handwritten characters. In particular, concerning handwritten digits,

Table 1
Performance vs zoning topologies.

	Topology	Features	Classification	Performances	CEDAR	MNIST	ISI	IRONOFF	UNIPEN	Proprietary	Notes
Static	3×2 Uniform (Blumenstein et al. [4])	Direction-based, transition-based	BPN, RBFN	DS-1: RR=69.78% (LC), 80.62% (UC) (BPN); RR=70.63% (LC), 79.78 (UC) (RBFN)DS-2: RR=83.65 (BPN), RR=85.48 (RBFN)	*						DB: CEDAR:DS-1: LS: 18,655 (LC), 7175 (UC); TS: 2240 (LC), 939 (UC) DS-2: LS: 19,145, TS: 2183
	3×3 Uniform (Singh and Hewitt [59])	Oriented segments (Angle threshold: $\pm20°$)	NN, LDA	DS-1: RR=93.9% (LDA), 88.3% (NN) DS-2: RR=76.3% (LDA), 62.7% (NN)	*						DB: CEDARDS-1: numeralDS-2: characters
	4×4 Uniform (Sharma and Gupta [58])	Density features	k-NN	RR= 99.89%						*	LS: 10,000 digits TS: 5400 digits
	5×5 Uniform (Rajashekararadhya and Ranjan [53])	Distance-based features	SVM	DS-1: RR=97.2% DS-2: RR=95.47%		*	*				DS-1: DB: MNIST, LS: 5000 digits; TS: 1000 digitsDS-2: ISI Database: LS: 12,000 digits; TS: 3000 digits
	2×2, 3×2; 3×3, 4×4, 5×5 Uniform (Impedovo et al. [23])	Geometrical features	k-NN	RR=76.5% (2×2), RR=77.9% (3×2), RR=79.8% (3×3), RR=76.4% (4×4), RR=87.8% (5×5)	*						DB: CEDAR LS: 18,468 digits (BR Directory), TS: 2213 digits (BS Directory)
	Non-uniform: shape-based (Roy et al. [57])	Contour-based Feature	SVM	RR=98.44%						*	DB: 8250 characters
Dynamic	Manual: perception-oriented (Freitas et al. [13])	Concavities/ convexities	MLP	RR=90.4%				*			DB: IRONOFF, 10,510 characters
	Automated: discriminant-based (Impedovo et al. [10])	Geometric Features	STC	RR=82.5%	*						DB: CEDAR, LS: 18,468 digits (BR Directory), TS: 2213 digits (BS Directory)
	Automated: discriminant-based (Di Lecce et al. [9])	Geometric features	STC	RR=84.4%	*						DB: CEDAR, LS: 18,468 digits (BR Directory), TS: 2671 digits (BS Directory)
	Automated: Voronoi-based (Impedovo et al. [20])	FS1: 9 Geometric features FS2: 57 Geometric features	STC	DS-1: RR=96% (FS1, M=9), 91% (FS2, M=9) DS-2: RR=85% (FS1, M=25), 92% (FS2, M=25)	*						DS-1: DB: CEDAR, LS: 18,467 digits (BR Directory), TS: 2189 digits (BS Directory) DS-2: DB: ETL, LS: 29,770 characters, TS: 7800 characters.
	Automated: template-based (Radtke et al. [51])	Concavities/ Contour/ pixel distribution	NN	RR=95%		*					DB: NIST – SD19_hsf-0123: LS: 50,000 digits, TS: 10,000 digits
	Automated: hierarchical (Gagnè and Parizeau [14])	Orientation- and curvature-based features	MLP	RR=96.37%					*		DB: UNIPEN LS: 15,953 characters (Train R01/ V07), TS : 8598 characters (DevTest-R02/V02)

The asterisks indicate the database (Cedar, Mnist, ISI, etc..) to which the results reported in table are referred.

18,467 patterns for learning (BR directory) and 2189 patterns for the test (BS directory) were used. In this case, the most profitable Voronoi-based zoning was $M=9$ which led to a 96% recognition rate by the first feature set and 91% by the second feature set. Concerning handwritten characters, 29,770 patterns for learning (1145 samples for each class) and 7800 patterns for the test (300 samples for each class) were used. At the best, the recognition rate was 85% and 92% for the first and the second feature set, respectively, when $M=25$ zones were used.

Radke et al. [51] used a template-based adaptive zoning and considered features to be a set of concavities, contour-based information and pixed distribution. For the experimental results, they considered a Nearest Neighbor (NN) classifier and a database of 50,000 training patterns and 10,000 test patterns, extracted from the NIST SD-19 hsf-0123 handwritten digit database. At the best, a recognition rate of 95% was achieved, using a zoning method based on $M=6$ zones.

Gagné and Parizeau [14] used genetic programming for optimizing simultaneously the best hierarchical topology and the best set of fuzzy features. The recognizer used a back-propogation Multi-Layer Perceptron (MLP) as a classifier and operated in a hierarchical feature space. They used orientation and curvature-based primitives that included three randomly generated parameters (center, core and boundary) specifying a symmetric trapezium fuzzy set. Experiments were conducted on the dataset of isolated digits of the UNIPEN database. The training data were from UNIPEN Train-R01/V07, consisting of 15,953 characters; the testing data were from DevTest-R02/V02, consisting of 8598 characters. At the best, they obtained an average recognition rate equal to 96.37%, using k-fold cross validation ($k=10$).

In conclusion, Table 1 shows that adaptive topologies usually lead to superior recognition rates with respect to static approaches. This result has also been confirmed by some papers in the literature that compare in detail static vs adaptive zonings using the same experimental context. Ferrante et al. [11] and Impedovo et al. [20] have shown that, no matter how many zones are considered, the Voronoi-based optimal zoning will outperform uniform zoning methods. Radke et al. [50] have shown that an adaptive zoning method can provide the best trade-off between zone number and error rate. Also Gagné and Parizeau [14] have demonstrated that an adaptive approach can outperform human-designed hierarchical zonings.

Table 2 compares some relevant results obtained using different membership functions for zoning-based classification. Impedovo et al. [23] analyzed the performance of order-based membership functions in the context of handwritten digit recognition. To this purpose, they considered uniform zoning topologies and a set of geometrical features. For the experimental tests, they used 18,467 learning patterns and 2189 testing patterns from the CEDAR database. The results, obtained by a Distance-based Classifier (DBC), demonstrated that the performance of a zoning method strongly depends on the membership function used. More precisely, the best recognition rate was achieved using the uniform zoning method based on a 5×5 regular grid. In this case, the classification rates were equal to 87.8%, 85.4%, 85%, 85% 86.7% and 87.8%, when the WTA (Eq. (6)), 2-NZ, (Eq. (7)), R (Eq. (8)), L (Eq. (9)), Q (Eq. (10)) and E (Eq. (11)), with $\alpha=1.1$, $\beta=1$) were considered, respectively. They also showed that, in general, exponential membership function E (with $\alpha=1.1$, $\beta=1$) provided the best recognition results, equal to 87.8%, on average.

Lajish [32] used fuzzy-zoning technique and a normalized vector distance measure. Class-modular Back-propagation Neural Networks (BNN) were used for classification together with a region-based fuzzy membership function. The experiments were conducted on 44 basic Malayalam handwritten characters. Two datasets of 15,752 samples were used for training and testing and a recognition rate of 78.87% was obtained.

Kato and Suzuki [27] used a hierarchical partitioning topology based on a 7×7 regular grid and direction-based features along with a region-based fuzzy membership function. Two Distance Based Classifiers (DBC) using a city block distance and an asymmetric Mahalanobis distance were used for rough and fine classification, respectively. The experimental tests were carried out on the ETL9B database that contained 3036 kinds of characters (2965 Chinese character classes (Kanji) and 71 Japanese character classes (Kana)). In this case, a 99.42% recognition rate was obtained.

Lazzerini and Marcelloni [33] used a region-based fuzzy membership function along with a stripe-based fuzzy partitioning of the pattern image. A Similarity Based Classifier (SBC) was considered for pattern classification and a genetic algorithm was used to optimize the partitions with respect to the recognition rate. The experimental results were performed on the dataset of characters of the NIST database hsf_4 (containing the segmented handprinted characters of 500 writers), that was a partition of the NIST SD19 database. An average recognition rate of 79.57% and 75.86% was obtained, respectively, on the training set and on the test set, when k-fold cross validation was considered ($k=10$).

Wu and Ma [69] used direction-based features extracted from the contour of the pattern image. They adopted a fuzzy border-based membership function and a hierarchical overlapped elastic meshing, based on a 7×7 sub-division of the pattern image. For the experiments, they used the ETL9B database. For each character feature in training, vectors were extracted from training patterns and their mean vector was stored as a reference for classification. An average recognition rate equal to 96.42% was obtained when a minimum Euclidean Distance-based Classifier (DBC) was used for classification. Pirlo et al. [46] used a ranked-based fuzzy membership function for the recognition of handwritten numerals and characters. The recognizer adopted a statistical-based classifier (SBC) and used a set of geometrical features along with a Voronoi-based optimal zoning topology. For the experimental test, they used 18,468 digits from the CEDAR database and 29,770 characters from the ETL database. The k-fold cross validation ($k=10$) led, at the best, to a recognition rate equal to 95% for digits and 93% for characters, respectively, for $M=9$ and $M=25$.

Impedovo et al. [24] used parameter-based membership functions and Voronoi-based topology for the recognition of handwritten numerals extracted from the CEDAR database. Digit classification was performed by a Nearest Neighbor (NN) classifier and used a set of geometric features. The best results occurred for $M=9$ (being M the number of zones). In this case, using a k-fold cross validation technique (with $k=10$), the recognition rate was

Table 2
Performance vs membership functions.

Membership function	Features	Classification	Performances	CEDAR	NIST	ETL	Proprietary	Notes
Abstract-level ranked-level measurement-level (Impedovo et al. [23])	Geometric features	DBC	RR=87.8% (WTA), 85.4% (2-NZ), 85% (R), 85% (L), 86.7% (Q), 87.8% (E)	*				DB: CEDAR LS: 18,467 digits, TS: 2213 digits
Fuzzy : border-based (Lajish [32])	Fuzzy distance features	BNN	RR= 78.87%				*	LS: 15,752 characters, TS: 15,752 characters
Fuzzy: Border-based (Kato et al. [27])	Fuzzy direction -based features	DBC (City-Block Dist., Asymmetric Mahalanobis Dist.)	RR=99.42%			*		DB: ETL9B 607,200 characters
Fuzzy: border-based (Lazzerini and Marcelloni [33])	Fuzzy distribution-based features	SBC	RR=79.57% (learning set), 75.86% (test set)		*			DB: NIST 19 – SD19 – hsf_4
Fuzzy: border-based (Wu and Ma [69])	Projection-based features	DBC	RR=96.42%	*		*		DB: ETL9B 607,200 characters
Fuzzy: ranked-based (Pirlo et al. [46])	Geometric features	STC	DS-1: RR=95% DS-2: RR=93%	*				DS-1: DB: CEDAR, 18,468 digits, DS-2: DB: ETL, 29,770 characters
parameter-based (Impedovo et al. [24])	Geometric features	NN	RR=92%					DB: CEDAR, 18,468 digits

DB, Database; LS, Learning Set; TS, Test set; RR, Recognition rate.
The asterisks indicate the database (Cedar, Mnist, ISI, etc..) to which the results reported in table are referred.

equal to 92% and the improvement with respect to standard order-based membership functions was up to 77%.

In conclusion, Table 2 shows that membership functions plays a fundamental role in zoning-based classification. When order-based membership functions were considered, WTA and Measurement-level functions based on the exponential model provided the best result [23]. Better results were also achieved by new fuzzy membership functions, both region-based [27,69] and ranked-based [46].

5. Conclusion

This paper has presented an overview on zoning methods. In the first part of the paper, the problem of zoning topologies has been addressed. Starting from the description of standard topologies, based on static partitioning criteria, the most sophisticated techniques for adaptive topology design have been illustrated. In the second part, aspects concerning membership function selection have been discussed and overviews of the most valuable membership functions proposed in the literature have been presented. Successively, a comparative analysis has been presented in terms of both topologies and membership functions. The results demonstrated that recent zoning approaches, based on adaptive topologies and fuzzy membership functions, could significantly outperform standard zoning methods. In addition, automated techniques for zoning design based on the optimization of cost functions associated to classification has been shown to offer the possibility of designing the best zoning for the requirements of a specific application.

Conflict of interest statement

None declared.

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