New Advancements in Zoning-Based Recognition of Handwritten Characters

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***Abstract* — In handwritten character recognition, zoning is one of the most effective approaches for features extraction. When a zoning method is considered, the pattern image is subdivided into zones each one providing regional information related to a specific part of the pattern.**

The design of a zoning method concerns the definition of zoning topology and membership function. Both aspects have been recently investigated and new solutions have been proposed, able to increase adaptability of the zoning method to different application requirements.

In this paper some of the most recent results in the field of zoning method design are presented and some valuable directions of research are highlighted.

Keywords- Handwritten Character Recognition, Feature Extraction, Zoning Methods, Zoning Topologies, Membership Functions

I. INTRODUCTION

Let B be a pattern image, a zoning method Z_M can be considered as a partition of B into M sub-images (M integer, M>1), named zones (i.e. $Z_M=\{z_1, z_2, ..., z_M\}$), each one providing information related to a specific part of the pattern [1, 2].

In the past, zoning has been successfully applied to hand-written character recognition, since it has been found that region-based feature extraction is able to absorb variability of handwritten patterns. Thus, several zoning methods have been proposed so far, based on diverse zoning topologies and membership functions [3, 4].

Concerning zoning topologies, traditional approaches used static partitioning criteria of the pattern image, obtained according to standard grids superimposed on the pattern image. In this case zoning design was performed without using any a priori information on feature distribution, but only on the basis of the personal experience of the designer. More recently, the problem of zoning design has been considered as an optimization problem. In this case a priori information on feature distribution is used to determine the optimal zoning topology for a given classification problem. Both manual and automated processes were considered for designing the optical zoning topology.

Membership function selection is another field of growing interest when zoning methods are considered. A membership function determines the way in which a feature has influences on the diverse zones of a zoning method. Membership functions can be classified into two main categories: global and local. Global membership functions are unique for all zones of the zoning method. More recently, local membership functions have been introduced, that can be adapted to each zone of the zoning methods, according to the local characteristics of feature distributions.

In this paper, starting from the analysis of the zoning methods in the literature, some of the most relevant advancements are presented. In particular, Section II addresses the problem of topology design. In Section III the problem of membership function selection is presented. Some of the most valuable applications of zoning methods in the field of handwritten digit and character recognition are discussed in Section IV. The conclusions of this paper are reported in Section V.

II. TOPOLOGIES

Zoning topologies can be classified in two main categories: static and dynamic.

Static topologies are designed according to pre-defined standard models, defined on the basis of intuition or personal experience of the designer. When static topologies are considered, they are generally based on simple grids that are superimposed on the pattern image [1]. Uniform and non-uniform grids can be considered for the purpose. When uniform u×v regular grids are used, they determine partitions of the pattern image into regions of equal size. Suen et al. [5] use 2×2, 3×2, 1×2 and 2×1 grids for zoning design. Blumenstain et al. [6] use a 3x2 regular grid for handwritten character recognition. Oliveira et al. [7] adopt a 3×2 grid and extract contour-based features from each zone. Baptista and Kulkarni [8] use a 3×3 regular grid to extract geometrical feature from each zone. Phokharatkul et al. [9] 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. [10] to extract gradient, structural and concavity information from the

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pattern image. Liu et al. [11] use a 4×4 regular grid to recognize Chinese characters by a directional decomposition approach. Rajashekararadhya and Ranjan [12, 13] use a 5x5 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.

Zoning topologies can be classified in: slice-based, shape-based and hierarchical. A slice-based topology is proposed by Takahaski [14], which uses vertical, horizontal and diagonal grids to split the pattern images. More recently, P.P. Roy et al. [15, 16] propose a novel shape-based topology 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. Finally, Park et al. [17] present a hierarchical topology based on a multi-resolution approach. Features at different resolutions, from coarse to fine-grained, are extracted by means of a recursive splitting scheme.

Dynamic topologies are designed according to some kind of optimization carried out on the basis of a-priori information. Freitas et al. [18] use the confusion matrices to analyze the relation between the regions and use this information to make the zoning design process less empirical. More recently, zoning optimization has been carried out in an automated manner on the basis of the discrimination capability of the zones or considering the classification performance. Dimauro et al. [19] and Di Lecce et al. [20] presented two discriminant-based approaches using respectively the standard deviation and the Shannon Entropy as estimators of the discrimination capability of the zones.

More recently, Impedovo et al. [21] define the optimal zoning topology as the topology for which the Cost Function (CF) associated to the classification is minimum. In this case Voronoi Tessellation was considered 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. In this approach, a genetic algorithm is used for topology optimization, in which each individual of the genetic population is a set of Voronoi points (corresponding to a zoning topology) and the cost function associated to the classification is considered as a fitness function. Following this approach, Ferrante et al. [22] perform the analysis of Voronoi-based zoning and estimate the optimal number of zones, depending on the characteristics of the classification problem. Radtke et al. [23, 24] present an automatic approach to define zoning using Multi-Objective Evolutionary Algorithms (MOEAs). 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 and a minimal number of non-overlapping zones. Gagné and Parizeau [25] use a tree-based hierarchical zoning topology for handwritten character classification.

III. MEMBERSHIP FUNCTIONS

Whatever zoning topology is used, its performance strongly depends on the membership function considered to describe the way in which a feature of a pattern has influences on the different zones [26].

Global membership functions can be categorized into order-based and fuzzy. When order-based functions are used, the influence of a feature on each zone is defined by a weight that depends on the distance between the position in which the feature is detected and the zone. Depending on the type of weight that is considered three types of order-based functions were proposed: abstract-level functions, in this case the weights are Boolean values; ranked-level functions, in this case the weights are integer values; measurement-level functions, in this case the weights are real values [27, 28].

Other global membership functions use fuzzy values that can be defined according to border-based and ranked-based criteria. Cao et al. [29] 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. Pirlo et al. use ranked-based fuzzy membership. In this case the fuzzy membership function is any weighting function defined according to the positivity, monotonicity and standard energy criteria. The selection of the best suited fuzzy membership function for a given zoning-based classification problem most certainly involves detecting optimal function weights 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 topology described by Voronoi Tessellation.

Local membership functions derives from the consideration that different parts of the character can exhibit features with diverse statistical distributions. Impedovo et al. [30] present a new class of parameter-based membership functions and select the most profitable set of parameters for each zone of the zoning method. Therefore, when parameter-based membership functions are used, a set of specialized functions is considered, one for each zone of the zoning method.

IV. ZONING METHODS: A COMPARISON

This section presents a comparison among some of the most valuable zoning methods. Concerning zoning topologies, Table I reports some of the most relevant results

TABLE I: PERFORMANCE VS ZONING TOPOLOGIES

	Topology	Features	Classification	Performances	Dataset
STATIC	3x2 Uniform (Blumenstein et al [6])	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: 18655 (LC), 7175 (UC); TS: 2240 (LC), 939 (UC) - DS-2: LS: 19145, TS: 2183
	2x2, 3x2; 3x3, 4x4, 5x5 Uniform (Impedovo et al. [26])	Geometrical Features	k-NN	RR: 76.5% (2x2), RR: 77.9% (3x2), RR: 79.8% (3x3), RR: 76.4% (4x4), RR: 87.8% (5x5)	DB: CEDAR LS: 18468 digits (BR Directory), TS: 2213 digits (BS Directory)
	Non-Uniform: Shape-based (Roy et al. [16])	Contour-based Feature	SVM	RR: 98.44%	DB: 8250 characters
DYNAMIC	Manual: Perception-oriented (Freitas et al. [18])	Concavities/convexities	MLP	RR: 90.4%	DB: IRONOFF, 10510 characters
	Automated: Voronoi-based (Impedovo et al. [31])	FS1: 9 Geometric Feaures FS2: 57 Geometric Fetures	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: 2,189 digits (BS Directory) DS-2: DB: ETL, LS: 29,770 characters, TS: 7,800 characters.
	Automated: Template-based (Radtke et al. [24])	Concavities / Contour / Pixel Distribution	NN	RR: 95%	DB: NIST - SD19_hsf-0123: LS: 50000 digits, TS: 10000 digits

(DB=Database; LS=Learning Set; TS=Test Set; RR=Recognition Rate)

presented in the literature. Blumenstein et al. [6] 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. Impedovo et al. [26] used uniform zonings based on 2x2, 3x3, 4x4, 5x5 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 2,213 numerals from the BS directory for the test. At the best, a recognition rate of 87.8% was achieved, when the uniform 5x5 zoning was used. Roy et al. [16] used contour-based angular information as features and considered two shape-based zoning techniques. The first one used 7 circular hull rings, the second one used 7 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. [18] used a perception-oriented approach to zoning design. They considered a set of concavity/convexities features, obtained by labelling 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.

Impedovo et al. [31] 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 9 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. Radke et al. [24] used a template-based dynamic zoning and considered features to be a set of concavities, contour-based information and pixed distribution. For the experimental results, they considered a Nearest Neighbour (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.

Table II compares some relevant results obtained using different membership functions for zoning-based classification. Impedovo et al. [26] 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 2,189 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 results demonstrate that, in general, exponential membership function E (with α=1.1,

TABLE II. PERFORMANCE VS. MEMBERSHIP FUNCTIONS

Membership Function	Features	Classification	Performances	Data
Abstract-level Ranked-level Measurement-level (Impedovo et al. [26])	Geometric Features	DBC	RR: 87.8% (WTA), 85.4% (2-NZ), 85% (R), 85% (L), 86.7% (Q), 87.8% (E)	DB: CEDAR LS: 18467 digits, TS: 2213 digits
Fuzzy: Border-based (Kato et al. [32])	Fuzzy Direction - based Features	DBC (City-Block Dist., Asymmetric Mahalanobis Dist.)	RR=99.42%	DB: ETL9B LS: 303600 characters, TS: 303600 characters
Fuzzy: Border-based (Wu and Ma [33])	Projection-based Features	DBC	RR: 96.42%	DB: ETL9B LS: 303600 characters, TS: 303600 characters
Fuzzy: Ranked-based (Pirlo et al. [34])	Geometric Features	STC	DS-1: RR: 95% DS-2: RR= 93%	DS-1: DB: CEDAR, 18468 digits, DS-2: DB: ETL, 29770 characters
Parameter-based (Impedovo et al. [30])	Geometric Features	NN	RR: 92%	DB: CEDAR, 18468 digits

(DB=Database; LS=Learning Set; TS=Test Set; RR=Recognition Rate)

β=1) provided the best recognition results. Kato and Suzuki [32] used a hierarchical partitioning topology based on a 7x7 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 3,036 characters (2965 kinds of Chinese characters (Kanji) and 71 kinds of Japanese characters (Kana)) and, for each character, 100 samples were used for training and 100 for testing. In this case, a 99.42% recognition rate was obtained. Wu and Ma [33] used direction-based features ex-tracted from the contour of the pattern image. They adopted a fuzzy border-based membership function and a hierarchical overlapped elastic meshing, based on a 7x7 sub-division of the pattern image. For the experiments, they used the ETL9B database, that had 3,036 characters and each character had 200 sample images. One hundred sets with odd number order were used in training and 100 sets with even number order are used in testing. 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. [34] 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. [30] used parameter-based member-ship functions and Voronoi-based topology for the recognition of handwritten numeral extracted from the CEDAR database. Digit classification was performed by a Nearest Neighbour (NN) classifier and used a set of geometric features.

V. CONCLUSIONS

This paper presents an overview of zoning methods and highlights some advancements in the field of topology design and membership function selection. Finally, some of the most interesting techniques in the literature are presented. The comparative analysis shows that dynamic topologies usually lead to superior performances with respect to static approaches, as well as the use of adaptive and fuzzy membership functions.

REFERENCES

[1] S. Impedovo, A. Ferrante, R. Modugno, G. Pirlo, "*Zoning Methods for Hand-written Character Recognition: An Overview*", Proc. 12th International Conference on Frontiers in Handwriting Recognition (ICFHR-12), Nov. 16-18, 2010, Kolkata, India, IEEE Computer Society Press, pp. 329-334.

[2] O.D.Trier, A.K.Jain , T.Taxt, "Feature Extraction Methods For Character Recognition – A Survey", *Pattern Recognition*, Vol. 29, n.4, pp. 641-662, 1996.

[3] C.Y.Suen, C. Nadal , R.Legault, T.A.Mai, L.Lam, "Computer Recognition of unconstrained handwritten numerals", Proc. IEEE, Vol. 80, pp. 1162-1180, 1992.

[4] S. Mori, C.Y.Suen, K.Yamamoto, "Historical Review of OCR research and development", Proc. IEEE, Vol. 80, pp. 1029-1058, 1992.

[5] C.Y.Suen, J.Guo, Z.C.Li , "Analysis and Recognition of Alphanumeric Handprints by Parts", IEEE T- SMC, Vol. 24, n. 4, pp. 614-630, 1994.

[6] M. Blumenstein, B. Verma and H. Basli, "A novel feature extraction technique for the recognition of segmented handwritten characters",

Proc. 7th Int. Conf. Document Analysis and Recognition (ICDAR'03), 2003, pp. 137–141.

[7] L.S. Oliveira, R. Sobourin, F. Bartolozzi, C.Y. Suen, "Automatic Recognition of Handwritten Numeral Strings: A Recognition and Verification Strategy", IEEE T-PAMI, Vol. 24, n.11, pp. 1438-1454, 2002.

[8] G. Baptista, K.M.Kulkarni, "A high accuracy algorithm for recognition of hand-written numerals", Pattern Recognition, Vol. 4, pp. 287 291, 1988.

[9] P.Phokharatkul, K.Sankhuangaw, S.Phaiboon, S.Somkuarnpanit, and C.Kimpan "Off-Line Hand Written Thai Character Recognition Using Ant-Miner Algorithm," Transactions on ENFORMATIKA on Systems Sciences and Engineering, vol. 8, pp. 276-281, October 2005.

[10] S.-H.Cha, C.C. Tappert, S.N. Srihari, "Optimizing Binary Feature Vector Similarity using Genetic Algorithm and Handwritten Character Recognition", Proc. ICDAR 2003, pp. 662-665, Edinburgh, UK, Aug. 2003.

[11] C.L. Liu, I.J. Eim, and J.H. Kim, "High Accuracy Handwritten Chinese Character Recognition by Improved Feature Matching Method". Proc. 4th ICDAR, pp. 1033-1037, 1997.

[12] S.V. Rajashekararadhya, P.V. Ranjan, V.N. Manjunath Aradhya, "Isolated Handwritten Kannada and Tamil Numeral Recognition: A Novel Approach", First Int. Conf. on Emerging Trends in Engineering and Technology, 2008. pp. 1192–1195.

[13] S.V. Rajashekararadhya, P.V. Ranjan, "Handwritten Numeral/Mixed Numerals Recognition of South-Indian Script: the Zone-Based Feature Extraction Method", Journal of Theoretical and Applied Information Technology (JATIT), 2005-2009, Vol. 7, No. 1, pp. 63-79.

[14] H. Takahashi, "A Neural Net OCR Using Geometrical and Zonal Pattern Features", Proc. ICDAR, 1991, pp. 821-828, Saint-Malo, France.

[15] P.P. Roy, U. Pal, J. Llados, F. Kimura, "Convex hull based approach for multi-oriented character recognition from graphical documents", Proc. ICPR, 2008.

[16] P.P. Roy, U. Pal, J. Llados, M. Delalandre, "Multi-Oriented and Multi-Sized Touching Character Segmentation using Dynamic Programming", Proc. ICDAR 2009, 2009, pp. 11-15.

[17] J. Park, V. Govindaraju and S. N. Srihari, ""OCR in a Hierarchical Feature Space", IEEE T-PAMI, Vol. 22, No. 4, 2000, pp. 400-407.

[18] C. O.A. Freitas, L.S. Oliveira and F. Bortolozzi, "Handwritten Character Recognition using nonsymmetrical perceptual zoning", IJPRAI, Vol. 21, N. 1, 2007 pp. 1-21.

[19] G. Dimauro, S.Impedovo, G. Pirlo, A.Salzo, "Zoning Design for Handwritten Numeral Recognition", in *Lecture Notes in Computer Sciences*, Vol. 1311, Ed. by A. Del Bimbo, Springer Verlag, Berlin, 1997, pp. 592-599.

[20] V. Di Lecce, G. Dimauro , A. Guerriero , S. Impedovo , G. Pirlo, A.Salzo, "Zoning Design for Handwritten Numeral Recognition", Proc. of Seventh International Workshop on Frontiers in Handwirting Recognition (IWFHR-7), pp. 583-588, 2000.

[21] S. Impedovo, M.G. Lucchese, G. Pirlo, "Optimal Zoning Design by Genetic Algorithms", IEEE Transactions on Systems, Man and Cybernetics - Part A: Systems and Humans, Vol. 36, n. 5, pp. 833-846, Sept. 2006.

[22] A. Ferrante, S. Impedovo, G. Pirlo, C. Trullo "On the Design of Optimal Zoning for Pattern Classification", *Proc. of the 11th IAPR Conference on Frontiers in Handwriting Recognition*, August 19-21, 2008, Concordia University, Montreal, Quebec, Canada, CENPARMI Press, pp. 130-134.

[23] P.V.W. Radtke, T. Wong and R. Sabourin, "A Multi-objective Memetic Algorithm for Intelligent Feature Extraction", Lecture Notes in Computer Science, 2005, Volume 3410, pp. 767-781.

[24] P. V. W. Radtke, L.S. Oliveira, R. Sabourin, T. Wong, "Intelligent Zoning Design Using Multi-Objective Evolutionary +Algorithms", in Proc. 7th International Conference on Document Analysis and Recognition (ICDAR2003), p.824-828, 2003.

[25] C. Gagné and M. Parizeau, "Genetic engineering of hierarchical fuzzy regional representations for handwritten character recognition", *International Journal of Document Analysis*, 2006, Vol. 8, n. 4, pp. 223-231.

[26] S. Impedovo, R. Modugno, G. Pirlo, "Membership Functions for Zoning-based Recognition of Handwritten Digits", *Proc. International Conference on Pattern Recognition*, Istanbul, Turkey, August 2010, pp. 1876 – 1879.

[27] S. Impedovo, G. Pirlo, "Class-oriented Recognizer Design by Weighting Local Decisions", Proc. 12th International Conference on Image Analysis and Processing ICIAP '03, Mantova (Italy), Sept. 2003, pp. 676-681.

[28] S. Impedovo, A. Ferrante, R. Modugno, G. Pirlo, "Feature Membership Functions in Voronoi-based Zoning", Emergent Perspectives in Artificial Intelligence, Eds. R. Serra and R. Cucchiara, Lecture Notes in Artificial Intelligence, Vol. 5883, 2009, ISSN: 0302-9743, Springer Publ., pp. 202-211.

[29] J.Cao, M.Ahmadi, M.Shridhar, "Handwritten Numeral Recognition with Multiple Features and Multistage Classifiers", IEEE Int. Symp.Circ.Syst., pp.323-326, London, 1994.

[30] S. Impedovo, G. Pirlo, "Tuning between Exponential Functions and Zones for Membership Functions Selection in Voronoi-based Zoning for Handwritten Character Recognition", Proc. ICDAR 2011, Bejing, China, 2011, pp. 997-1001.

[31] S. Impedovo, R. Modugno, G. Pirlo, "Analysis of membership Functions for Voronoi-based Classification", *Proc. International Conference on Frontiers in Handwriting Recognition 2010*, Kolkata, India, 2010, pp. 220-225.

[32] N. Kato, M. Suzuki, "A Handwritten Character Recognition Using Directional Element Feature and Asymmetric Mahalanobis Distance", IEEE Trans. PAMI, 21, pp. 258-262, 1999.

[33] T. Wu, S. Ma, "Feature extraction by hierarchical overlapped elastic meshing for handwritten Chinese character recognition", Proc. 7th Int. Conf. on Document Analysis and Recognition (ICDAR), 2003, pp. 529-533.

[34] G. Pirlo, D. Impedovo, "Fuzzy Zoning-based Classification for Handwritten Characters", IEEE Transactions on Fuzzy Systems, Vol. 19, No. 2, 2011, pp. 780-784.