HANDWRITTEN CHARACTER RECOGNITION WITH OPTIMAL ZONING USING GA

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ABSTRACT

The pattern recognition process is intelligent activity of the human brain system. In the process of recognizing handwritten character, image zoning is a mostly used technique for extracting special characteristics from pattern. Zoning is able to handle variation in handwritten pattern, which is due to different physical and psychological conditions of user. The system is concerned with the handwritten character recognition with optimal zoning described by Verona diagram. In fact, many researchers have proposed several image-zoning topologies according to static and dynamic strategies. But little attention has been paid to the role of feature-zone membership functions which defines how the features influence different zones of the zoning method. The membership functions defined up to now are non-adaptive, it follows global approaches that is unable to model local information on feature distributions. In this paper, different zone-based membership functions with adaptive capabilities are defined. The basic idea is to select best suited membership function for each zone of the zoning method. In addition, a genetic algorithm is proposed so that in a unique process the most favourable membership functions and the optimal zoning topology described by Voronoi tessellation is obtained.

Keywords

1. INTRODUCTION

In pattern recognition, Image zoning is widely used feature extraction technique. Image zoning is rightly considered effective for coping with the changeability of handwritten patterns which is due to different writing styles and personal variability of the writers.

Let \( B \) be a pattern image, an image zoning method \( Z_M \) can be generally considered as a partition of \( B \) into \( M \) sub images (\( M > 1 \)), or named zones (i.e., \( Z_M = \{ z_1, z_2, \ldots, z_M \} \)), each one providing local information on pattern images.

The problem with zoning design is related to the design of the topology to be used, which defines the way in which a pattern image must be segmented in order to extract as much discriminative information as possible. The two approaches are used as follows:
1. Static
2. Dynamic

Static topology: It is traditional approaches that are designed without using \( a \) priori information on feature distributions in pattern image.

Static topologies are designed using dividing image into \( u \times v \) regular grids i.e. uniform partitions of the pattern image into regions of equal shape as shown in fig.1.(a)

Dynamic topologies do not uses prior information on feature distribution. Dynamic topology is designed according to the result of optimization procedures.

Dynamic topology divides image into non-regular grids i.e. non-uniform splitting of the pattern image as shown in fig.2.(b)

Fig.1. Examples of zoning methods: static versus dynamic (Voronoi-based diagram).

In this case, zoning design is performed according to experimental evidences or on the basis of intuition and experience of the designer. Voronoi tessellation allows the design of dynamic zoning methods based on unconstrained topologies. Membership function plays a crucial role in exploiting the potential of a zoning method since it should be able to model spatial distributions of features in the different zones. The new class of membership functions allows the membership function to adapt to the specific feature distribution of each zone of the zoning method. The exponential weighted membership function generally leads to superior performance. Genetic approach is used to solve the optimization problem of zoning topology.

2. RELATED WORK:

In literature, the problem of zoning design is related to the design of the topology to be used. Topology defines the way in which a pattern image must be segmented in order to extract as much discriminative information as possible. As explain above two types of topologies were used static and dynamic. Suen also use a \( 3\times2 \) static
topology to define a model which evaluate the distinctive parts of handwritten characters and compare human and machine capabilities in character recognition by parts. Singh and Hewitt uses a modified Hough transform method to extract features for handwritten digit and character recognition. Phokharatkul present a system for handwritten character recognition based on antminer algorithm. They use a $4 \times 3$ regular grid for zoning design in order to extract closed-loop and endpoint features from the pattern image. Cha use $4x4$ topology to extract pixel density, gradient, structural, and concavity information from the pattern image. Kimura and Shridhar use a zoning topology based on a $4 \times 4$ regular grid and in each zone, the number of segments on the contour of the pattern with the same orientation is counted. Four basic orientations are considered: $0^\circ$, $90^\circ$, $+45^\circ$, and $-45^\circ$. Camastra and Vinciarelli \cite{7} use a $4 \times 4$ 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. \cite{8} apply zoning to the recognition of car plates. They extract pixel density features dividing the character input image from car plates using a $4 \times 4$ regular grid. Impedovo et al. \cite{9}, Aires et al. \cite{10} present a perception-oriented approach that uses Non-regular grids for zoning design, resulting in a non-uniform splitting of the pattern image. They manually define the zoning grid by using the confusion matrices looking for the relation between the zones, in order to make the zoning design process less empirical. Other approaches, based on automatic optimization schemes, generally concern constrained zoning methods based on predetermined templates. Valveny and Lopez \cite{11} use a zoning method for digit recognition located on surgical sachets which pass through a computer vision system performing quality control. In this case, the authors 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. Lazzerini and Marcelloni applied a method to handwritten characters for the fuzzy classification and recognition of 2-D shapes. 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 (REC).

S. V. Rajashekararadhya and P. V. Ranjan, \cite{13} uses zone based feature extraction algorithm for handwritten numeral recognition.

3. IMPLEMENTATION DETAILS:

3.1 System Architecture:

The fig. 2 shows fundamental phases involved in handwritten character recognition system.

![Fig. 2 The Process of character Recognition.](image)

After data acquisition, input data is processed such as noise filtering, signature location and rotation. The Preprocessed data is given for feature extraction using image zoning, in which image is divided according to optimal zoning. The extracted features are then classified according to stored database. For this purpose zoning based classifier is used. The input is then recognized and according to result of classifier signature is verified.

3.2 Feature Extraction by Zoning Method.

For feature extraction Image Centroid and Zone (ICZ) based Distance metric feature extraction system is used. Algorithm for that is as follows:\cite{13}.

**Input:** signature image.

**Output:** Feature for Classification and Recognition.

**Method Begins**

Step 1: Compute the input image centroid.

Step 2: Divide the input image into n zones.

Step 3: Compute the distance between the image centroid to each pixel present in the zone.

Step 4: Repeat the step 3 for the entire pixel present in the zone.

Step 5: compute average distance between these points.
Step 6: Repeat this procedure sequentially for the entire zone.
Step 7: Finally n such features will be obtained for classification and recognition.

Let $ZM = \{Z_1, Z_2, \ldots, Z_M\}$ be a zoning method. An important aspect for zoning-based classification is the way in which each feature detected in a pattern $x$ has influence on each zone of $ZM$. Let us consider the classification of a pattern $x$ into one class of $\{C_1, \ldots, C_k\}$ using the feature set $F = \{f_1, \ldots, f_T\}$. In this case, $x$ can be described by the feature matrix $Ax$ of $T$ rows (features) and $M$ columns (zones) so that it will generates $T \ast M$ features for classification and recognition[01].

$$Ax = \begin{pmatrix}
A_{1}(1,1) & A_{1}(1,2) & \ldots & A_{1}(1,j) & \ldots & A_{1}(1,M) \\
A_{2}(1,1) & A_{2}(1,2) & \ldots & A_{2}(1,j) & \ldots & A_{2}(1,M) \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
A_{T}(1,1) & A_{T}(1,2) & \ldots & A_{T}(1,j) & \ldots & A_{T}(1,M)
\end{pmatrix}$$

With $Ax(i,j) = \sum_{k=1}^{M} w_{ij}$

where $w_{ij}$ is the weight that defines the degree of influence of feature $f_j$ (detected in $x$) on zone $z_j$.

Now, the influence weight $w_{ij}$ of an instance of $fi$ on zone $z_j$ is determined on the basis of the distance between the position of the instance of $f_i$ & $z_j$.

it is advantageous that the position of a feature $f_i$ is assumed to be located at the center of gravity of $fi$ when structural features are considered, such as lines, loops, cavities, arcs, etc.

Let $Z_M = \{z_1, z_2, \ldots, z_M\}$ be a zoning method corresponding to the Voronoi points $P = \{p_1, p_2, \ldots, p_M\}$, where $z_j$ is the Voronoi region corresponding to the Voronoi point $p_j$ where $j = 1, 2, \ldots, M$.

Let $q_i$ be the point in which the instance of feature $fi$ is found; let $d_{ij} = \text{dist}(q_i, p_j)$ be the Euclidean distance between $q_i$ and $p_j$.

Euclidean distances $d_{ij} = \text{dist}(q_i, p_j) = [(pxi−qxi)^2 + (pyi−qyi)^2]^{1/2}$, for $j = 1, 2, \ldots, 9$

From that Euclidian distance the ranked index sequence (RISi) associated with the instance of feature $fi$ is calculated. RIS denotes sequence of the zones ranked according to Euclidean distance.

$$\text{RIS}_i = \langle i_1, i_2, \ldots, i_k, k_1, i_{k_1}, \ldots, k_j \rangle$$

With:

1. $i_k \in \{1, 2, \ldots, M\}$ for $k = 1, 2, \ldots, k_1$
2. $i_{k_1} \neq i_{k_2}$ for $k_1, k_2 = 1, 2, \ldots, K, k_1 \neq k_2$

i.e. $d_{i_1} < d_{i_2}, k_1 < k_2, \forall k_1, k_2 = 1, 2, \ldots, K$

we also assume that in the case of same distance i.e. $d_{ik_1} = d_{ik_2}$, $ik_1$ precedes $ik_2$, if $k_1 < k_2$.

Furthermore, let $\text{count}_i(j)$ be the function providing the position of the index $j$ in the sequence RISi. The following feature-zone membership functions can be considered.

### 3.3 Zone based membership function:

Membership function plays a crucial role in exploiting the potential of a zoning method since it should be able to model spatial distributions of features in the different zones. The membership functions allows the membership function to adapt to the local distribution of feature of each zone of the zoning method.

1. **Abstract-Level Membership Functions:** Abstract level membership function assigns Boolean values (0 or 1) on the basis RISi. The type of abstract level membership function are as follows.

   a) **The winner-takes-all (WTA) membership function:**

   The traditional zoning based classifier uses this membership function. In this case, the results are as follows

   $$w_{ij} = 1, \text{ if } \text{count}_i(j) = 1$$

   $$w_{ij} = 0, \text{ otherwise.}$$

   b) **The k-nearest zone (k-NZ) membership function:**

   This is a generalization of the WTA function. In this case, the results are as follows

   $$w_{ij} = 1, \text{ if } \text{count}_i(j) \in \{1, 2, \ldots, k\}$$

   $$w_{ij} = 0, \text{ otherwise.}$$

2. **Ranked-level membership functions:** This membership functions assign rank (integer weights) on all zones according to their position in the RISi.

   a) **The ranked-based (R) membership function:**

   In this case, the result is as follows

   $$w_{ij} = M - k, \text{ where } M = \text{no of zones.}$$

   And $k = \text{count}_i(j)$.

3. **Measurement-Level Membership Functions:** This membership functions at measurement level assign real values according to the distance between the zones and the instance of the feature $fi$. Three measurement-level membership functions are considered.

   a) **Linear weighting model (LWM)**

   $$w_{ij} = 1/d_{ij}$$

   b) **Quadratic weighting model (QWM)**

   $$w_{ij} = 1/d_{ij}^2$$

   c) **Exponential weighting model (EWM)**

   $$w_{ij} = 1/e^{d_{ij}}$$

### 3.4 CLASSIFICATION IN ZONING WITH ADAPTIVE MEMBERSHIP FUNCTIONS:

Voronoi tessellation allows the design of dynamic zoning methods based on unconstrained topologies.
The cost function \( CF \) of a zoning-based classifier, which depends on both zoning method (\( ZM \)) and membership function (\( FM \)), is defined as follows:

\[
CF(\text{ZM}, \text{FM}) = \eta \cdot \text{Err}(\text{ZM}, \text{FM}) + \text{Rej}(\text{ZM}, \text{FM})
\]

Where:

1) \( \text{Err}(\text{ZM}, \text{FM}) \) and \( \text{Rej}(\text{ZM}, \text{FM}) \) are the misrecognition rate and the rejection rate of the zoning-based classifier, respectively; 2) Coefficient \( \eta \) is the cost value associated with the treatment of an error with respect to a rejection. For optimal zoning design following formula is given:

\[
\text{Find the sets } \{p^1, p^2, \ldots, p^M\} \text{ (Voronoi points) and } \{\lambda_1, \lambda_2, \ldots, \lambda_M\} \text{ (falling values) so that }
\]

\[
\text{CF}(\text{ZM}, \text{FM}) = \min_{(\text{ZM}, \text{FM})} \text{CF}(\text{ZM}, \text{FM})
\]

With:

1) \( Z_M = \{Z_1, Z_2, \ldots, Z_M\} \), \( \lambda_j \) being the Voronoi region corresponding to \( P_j \); \( \forall j = 1, 2, \ldots, M \);
2) \( Z_M = \{Z_1, Z_2, \ldots, Z_M\} \), \( \lambda_j \) being the Voronoi region corresponding to \( P_j \); \( \forall j = 1, 2, \ldots, M \);
3) \( F_M = \{\lambda_1, \lambda_2, \ldots, \lambda_M\} \), \( \lambda_j \) being the falling value of the adaptive membership functions associated to zone \( \forall j = 1, 2, \ldots, M \);
4) \( F_M = \{\lambda_1, \lambda_2, \ldots, \lambda_M\} \), \( \lambda_j \) being the falling value of the adaptive membership functions associated to zone \( \forall j = 1, 2, \ldots, M \);

**Fitness functions for genetic algorithm.**

Fitness function is used to check goodness of solution. Fitness function for genetic algorithm is as follows:

\[
\text{CF}(\text{ZM}, \text{FM}) = \eta \text{Err}(\text{ZM}, \text{FM}) + \text{Rej}(\text{ZM}, \text{FM})
\]

In order to solve optimization as in above formula, a real coded genetic algorithm is proposed.

### 3.5 GENETIC ALGORITHM APPROACH

A real-coded genetic approach is used so that in unique process optimal zoning and best suited adaptive membership function is obtained.

The initial population \( \text{Pop} = \Phi_1, \Phi_2, \Phi_3, \ldots, \Phi_N \) for the genetic algorithm is created by generating \( N \text{pop} \) random individuals (\( N \text{pop even})\). Each individual is a vector

\[
\Phi_j = \left[ \begin{array}{c}
P_1 \\
P_2 \\
\vdots \\
P_J \\
\vdots \\
P_M
\end{array} \right]
\]

where each element \( \frac{P_j}{\lambda_j} \) consists of:

1) \( p_j \): a point defined as \( p_j = (x_j, y_j, \ldots, z_M) \), that corresponds to the Voronoi point of the zone \( Z_j \) of \( Z_M = \{z_1, z_2, \ldots, z_M\} \);
2) \( \lambda_j \): a falling value for the membership function of the zone \( Z_j \) which defines adaptive model.

From the initial population, the following genetic operators are used to generate new populations of individuals

1) **Individual Selection:** \( N \text{pop}/2 \) random pairs of individuals are selected for crossover, according to a roulette wheel strategy (RWS)

2) **Crossover:** is the operation in genetic algorithm where we mix two solution and forms new solution. Let following two solutions are considered for crossover

\[
\frac{P_1^E}{\lambda_1^E}, \frac{P_2^E}{\lambda_2^E}, \ldots, \frac{P_J^E}{\lambda_J^E}, \ldots, \frac{P_M^E}{\lambda_M^E}
\]

Then after crossover result obtained is the linear combination of parent individuals and is as follows :

\[
\frac{P_1^C}{\lambda_1^C}, \frac{P_2^C}{\lambda_2^C}, \ldots, \frac{P_J^C}{\lambda_J^C}, \ldots, \frac{P_M^C}{\lambda_M^C}
\]

Where \( \alpha \) and \( \beta \) are random variables.

3) **Mutation:** If there is random change of one or more individual then a non-uniform mutation operator is used.

So if \( \frac{P_j}{\lambda_j} \) changes to \( \frac{P_j}{\lambda_j^*} \)

We have \( p_j = (x_j, y_j^*) \)

4) **Elitist Strategy:** By the above operations \( N \text{pop} \) individuals are generated. The individual having minimum cost i.e. minimum value of fitness function is added in the previous to form current population. Steps from 1) to 4) are repeated until \( \text{Niter} \) successive populations of individuals are generated. The stopping criteria are when the optimal zoning is in which individual with higher probability is selected.
obtained by the best individual of the last-generated population.

3.6 Implementation Details
In handwritten character recognition system, four modules are created such as Creating the Character Recognition System, Training, Abstract-level membership functions and Testing Phase. In character recognition system, the matrixes of each letter of the alphabet must be created along with the network structure. The first thing to think about when creating a matrix is the size that will be used. A large matrix size of 20 x 20 was created. In training phase, different functions are performed such as Analyze image for characters, Convert symbols to pixel matrices, Retrieve corresponding desired output character and convert to Unicode and matrix is feed to network, Compute output, Compare output with desired output Unicode value and compute error Adjust weights accordingly and repeat process until preset number of iterations. Membership functions at abstract-level assign Boolean influence weights on the basis of the first k zones in RISi (Ranked Index Sequence).

A character matrix is an array of black and white pixels; the vector of 1 represented by black, and 0 by white. In testing Module the different activities will be performed such as Analyze image for characters, Convert symbols to pixel matrices, Compute output, Display character representation of the Unicode output. The process of image analysis is done by examining pixels in both the training and testing phase. The color value of individual pixels, which for the limits of this project is assumed to be either black RGB(255,0,0) or white RGB(255,255,255). The new image is considered as bitmap image and is added to an internal bitmap object by using the Microsoft Visual Studio environment. For this implementation frontend is designed in Java and is used for Windows XP and above system.

4. CONCLUSION AND FUTURE SCOPE
The technique of handwritten character recognition addressed the problem selection of membership function for zoning-based Classification. Voronoi tessellation is used for obtaining the optimal zoning. After that, new class of adaptive zone-based membership functions was introduced. The main idea was to obtain a best suited membership function for each zone for exploiting the specific characteristics of feature distribution in that zone. Successively, a real-coded genetic approach was proposed for determining—in a unique optimization process—the best suited adaptive membership functions and the optimal Voronoi-based topology most profitable for a given classification problem. We proposed system that efficiently and intelligently recognizes both static (offline) and dynamic (online) handwritten character.

Our future work is to improve classifier that is technique for zoning design can be applied to any zoning based classifier. In bank check processing, the error rate must be kept a low as possible. In this system the number of zones must be a defined a priori, so advancement in technique can be achieved for optimization.

ACKNOWLEDGMENTS
We are very much thankful to all authors; those are mentioned in the references and all the respected peoples who helped us for designing and development of our work.

REFERENCES:


