Recognizing the Hand Written Characters

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Abstract – In zoning-based classification, a membership function defines the way a feature influences the different zones of the zoning method. This paper presents a new class of membership functions, which are called fuzzy-membership functions (FMFs), for zoning-based classification. These FMFs can be easily adapted to the specific characteristics of a classification problem in order to maximize classification performance. In this research, a real-coded genetic algorithm is presented to find, in a single optimization procedure, the optimal FMF, together with the optimal zoning described by Voronoi tessellation. The experimental results, which are carried out in the field of handwritten digit and character recognition, indicate that optimal FMF performs better than other membership functions based on abstract-level, ranked-level, and measurement-level weighting models, which can be found in the literature.

Keywords – Fuzzy-Membership Function (FMF), Genetic Algorithm, Handwritten Character Recognition, Voronoi Tessellation, Zoning Method.

I. INTRODUCTION

In the field of handwritten character recognition, zoning offers an easy way to obtain spatial information on feature distribution. Therefore, zoning has been largely considered to be a useful technique to handle the enormous variability of handwritten characters, due to different handwriting styles and personal variations [1]. Given a pattern image \( B \), a zoning method \( Z_M = \{ z_1, z_2, \ldots, z_M \} \) is a partition of \( B \) into \( M \) subimages, which are called zones, that can each provide information related to a specific part of the pattern [2].

In the past, the static zoning methods used could be obtained by superimposing regular \( m \times n \) grids on a pattern image. In this case, the most-profitable zoning for a given classification problem was selected on the basis of a designer’s personal experience and on experimental tests. More recently, dynamic zoning methods have been introduced in which zoning design is considered as an optimization problem. In [3], a multiobjective evolutionary algorithm was used to define the zoning method based on two diverse optimality criteria: a minimal number of nonoverlapping zones and a minimal error rate. Gagne’ and Parizeau [4] used a hierarchical zoning and a genetic technique to optimize the feature-extraction step of a handwritten character recognizer. Genetic programming has also been used to simultaneously learn the best hierarchy and the best combination of fuzzy features. Impedovo et al. [5] identified the optimal zoning as the one which optimized the classification performance, estimated by the cost function (CF) that is associated with classification. In this case, a well-suited zoning representation was considered based on Voronoi tessellation [6]. Strictly speaking, the Voronoi tessellation is the partition of a plane into \( M \) zones \( z_1, z_2, \ldots, z_M \) that reflects proximity relationships among the given set of \( M \) distinct points \( p_1, p_2, \ldots, p_M \) in the plane. In other words, each point \( p_i \) determines a region \( z_i \) that is the locus of points that are closer to \( p_i \) than to any other point in the set. Since changing the position of the Voronoi points causes modification of the zoning methods, Voronoi tessellation allows the zoning to be easily adapted to the specific characteristics of the classification problem.

Although zoning methods have been extensively dealt with in the literature, so far little attention has been paid to the definition of feature-zone membership functions, i.e., functions that determine the way in which a feature influences the different zones of a zoning method [7]. Standard membership functions use static weighting models based on abstract-level, ranked-level, and measurement-level strategies [5], [7]. Unfortunately, they are unable to adapt themselves to the specific characteristics of feature distributions in order to achieve optimal performances.

This paper introduces a new class of fuzzy-membership functions (FMFs) and presents a real-coded genetic algorithm to detect, in a single optimization procedure, the optimal FMF, together with the optimal zoning, for the specific classification problem. The experimental tests were carried out in the field of handwritten numeral and character recognition, using datasets from the databases of the Center of Excellence for Document Analysis and Recognition (CEDAR), Buffalo, NY, and the Electrotechnical Laboratory (ETL), Tsukuba, Japan. The results demonstrate that FMFs can give better performance than other membership functions described in the literature. Additionally, they confirm the effectiveness of the genetic technique for the combined selection of the optimal zoning and optimal FMF.

The organization of this paper is as follows. Section II describes the problem of zoning-based classification, while Section III reports the standard membership functions and introduces the new class of FMFs. Section IV shows the genetic algorithm for the combined selection of the optimal zoning, together with the optimal FMF, and Section V reports the experimental results. The conclusion is reported in Section VI.

II. ZONING-BASED CLASSIFICATION

Given the set of class labels \( \Omega = \{ C_1, \ldots, C_k \} \) and the rejection class \( C \), the classification of a pattern \( x \) can be considered to be a mapping \( D \), which is defined as [5]

\[
D : S(x) \rightarrow \bigcup \{ C \}
\]

with \( S(x) \) being the description of \( x \) based on the features set \( F = \{ f_1, \ldots, f_r \} \). Moreover, when a zoning \( Z_M = \{ z_1, z_2 \) 

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528
This is defined as [7]

\[ S(x) = \{ (f_{i,q}, z_j, w_{i,q}) \} | q = 1, 2, \ldots, Q ; j = 1, 2, \ldots, M \]  \hspace{1cm} (2)

where \( f_{i,q} \) is an instance of feature \( f \) in pattern \( x \), and \( w_{i,q} \) is the influence of this instance on zone \( z_j \) if \( w_{i,q} \geq \theta \) (with \( \theta \) a threshold). If \( Q \) is the total number of features detected in \( x \).

In this case, let \( X^L = \{ x^L_i \} | r = 1, 2, \ldots, N^L \} \) be the learning set, and let \( S(x^L_i) \) the description set of \( x^L_i \) for \( r = 1, 2, \ldots, N^L \). The following statistical distributions for each class \( C_k \) are estimated in the learning phase.

1) The normalized total weight (NTW): This is defined as

\[ NTW^k(f_i, z_j) = \frac{1}{n^k} \sum W_{ij} \]

\[ (f_i, z_j, \mu_g) \in S(x^L_i) \]

\[ i = 1, 2, \ldots, T, j = 1, 2, \ldots, M \]  \hspace{1cm} (3)

with \( n^k \) being the number of learning patterns belonging to \( C_k \)

\[ (i.e., n^k = \text{card} \{ x^L_i \in X^L | f_i, z_j \in C_k \}) \].

2) The normalized relevance (NR): This is defined as

\[ NR^k(f_i, z_j) = \sum_{k=1,2,\ldots,K} NTW^k(f_i, z_j) \]

Where,

\[ NR^k(f_i, z_j) = 0 \text{ if } \sum NTW^k(f_i, z_j) = 0 \]

\[ k = 1, 2, \ldots, K \]

Unknown pattern \( x \) (with \( i \notin \{1,2,\ldots,T\} \)). The confidence value that \( x \) belongs to the class \( C_k \) is given by

\[ C_{nk}(x) = \sum_{q,i} w_{iq}^k z_j \]

\[ (f^*_{iq}, z_j, w_{iq}^k) \in S(x) \]

The pattern \( x \) is classified as belonging to the class \( C_k \) if and only if

\[ \frac{C_{nk}(x)}{C_{nk探寻}(x)} > \]

With

\[ K^* = \arg \max_{k \in \{1,2,\ldots,K\}} C_{nk}(x) \]

and \( \{1,2,\ldots,K\} \)

III. NEW CLASS OF FUZZY-MEMBERSHIP FUNCTIONS

For whatever zoning method considered, membership functions play a fundamental role in zoning-based classification since they determine the way in which a feature influences the different zones of the zoning method. In general, the degree of influence an instance of a feature \( f \) has on a zone \( z \) is defined by a weight that only depends on relative positions between the instance of the feature and the zone, and therefore, a membership function is defined by a set of weights \( W = \{ 1, 2, \ldots, M \} \) defined according to proximity criteria [7]. In particular, let \( Z_m = \{ z_1, z_2, \ldots, z_M \} \) be the zoning method defined by the set of Voronoi points \( P = \{ p_1, p_2, \ldots, p_M \} \) and let \( q \) be the position of feature \( f \) (it is worth noting that the position \( q \) of a feature \( f \) is assumed to be located at the center of gravity of \( f \) when structural features are considered, such as lines, loops, cavities, arcs, etc.). In order to introduce the membership functions proposed so far in the literature, let us define the ranked index sequence (RIS) as

\[ \text{RIS} = i_1, i_2, \ldots, i_m, i_m+1, \ldots, i_M \]  \hspace{1cm} (7)

So that

\[ i_m \in \{1,2,\ldots,M\} \]

\[ \forall m = 1, 2, \ldots, M \]

Abstract-level membership functions: In this the degree of influence of each zone is defined by Boolean weights as follows

\[ \text{a) Winner-takes-all (WTA), i.e.,} \]

\[ m = 1, \text{ if } m = i_1 \]

\[ m = 0, \text{ otherwise.} \]  \hspace{1cm} (8)

\[ \text{b) k-Nearest zone (k-NZ), i.e.,} \]

\[ m = 1, \text{ if } m \in \{i_1, i_2, \ldots, i_k\} \]

\[ m = 0, \text{ otherwise.} \]  \hspace{1cm} (9)

Note that for \( k = 1 \), the 1-NZ function is equal to the WTA membership function.

\[ \text{c) Ranked-based (R), i.e.,} \]

\[ m = M-m \]  \hspace{1cm} (10)

\[ \text{Measurement-level membership functions:} \]

In this, the degree of influence of each zone is defined by real weights as follows.

\[ \text{a) Linear (L), i.e.,} \]

\[ \mu_m = \frac{1}{d_{im}} \]  \hspace{1cm} (11)

\[ \text{b) Quadratic (Q), i.e.,} \]

\[ \mu_m = \frac{1}{d_{im}^2} \]  \hspace{1cm} (12)

\[ \text{c) Exponential (E), i.e.,} \]

\[ \mu_m = \frac{1}{d_{im}^{p \text{dim}}} \]  \hspace{1cm} (13)

In addition, a new class of membership functions, which is named FMF, is introduced in this paper for zoning-based classification. An FMF is weighting function for which

\[ \mu_m = \frac{1}{d_{im}^{p \text{dim}}} \]  \hspace{1cm} (13)

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IV. ZONING DESIGN USING FUZZY-MEMBERSHIP FUNCTIONS

In the literature, the problem of optimal zoning design for handwritten character recognition was recently defined as follows [3,7].

(I) Find the set of optimal voronoi points \( P^* = \{p_1^*, p_2^* \ldots p_j^* \} \) so that
\[
\text{CF}(Z^*) = \min \text{CF}(Z)
\]
With
(a) \( z=\{z_1,z_2,\ldots,z_j\} \), \( j \) is the voroni region related to \( p_j \) \( \forall j=1,2,\ldots,M \);
(b) \( Z^*=\{z_1^*,z_2^*,\ldots,z_j^*\} \), \( j \) is the optimal voronoi region related to \( p_j^* \) \( \forall j=1,2,\ldots,M \), and the CF was defined as [8]
\[
\text{CF} = n \text{ error rate} + \text{rejection rate}
\]
(15)
With [9]
(a) Error Rate = \( \frac{\text{card}(x_r \in X^L \setminus D(S(x_r)))}{\text{card}(X^L)} \), i.e., the percentage of patterns misclassified by the zoning-based classifiers;
(b) Rejection Rate = \( \frac{\text{card}(S(x_l) \cap D(S(x_l)))}{\text{card}(X^L)} \), i.e., the percentage of patterns rejected by the zoning-based classifier.
(c) \( \eta \) being the cost value associated with the treatment of an error with respect to a rejection.

It is worth noting that the error rate and the rejection rate of the zoning-based classifier are estimated using the patterns of the learning set, according to the decision rule of [6].

In this paper, the design of the optimal zoning is considered along with the design of the optimal FMF. In this case, the optimization problem concerning the combined selection of the optimal FMF, together with the optimal zoning method, as represented by voronoi tessellation, is defined as follows.

(2) Find the set of optimal weights \( \omega^* \)
\[
\{\mu_1^*, \mu_2^* \ldots \mu_m^*\} \] together with the set of optimal voronoi points \( p^* = \{p_1^*, p_2^* \ldots p_M^*\} \) so that
\[
\text{CF}(Z^*,\text{FMF}^*) = \min \text{CF}(Z,\text{FMF})
\]
{Z,FMF}
With
a) \( \text{FMF} = \{\mu_1,\mu_2,\ldots,\mu_m,\mu_M\} \), where \( \mu_m \) is the weight for the zone in the \( m \)th position of \( RIS \) \( \forall m=1,2,\ldots,M \);
(b) \( \text{FMF}^* = \{\mu_1^*,\mu_2^* \ldots,\mu_m^*\} \), where \( \mu_m^* \) is the optimal weight for the zone in the \( m \)th position of \( RIS \) \( \forall m=1,2,\ldots,M \);
(c) \( Z=\{z_1,z_2,\ldots,z_j\} \), \( j \) is the voroni region related to \( p_j \) \( \forall j=1,2,\ldots,M \);
\( Z^*=\{z_1^*,z_2^*,\ldots,z_j^*\} \), \( j \) is the optimal voronoi region related to \( p_j^* \) \( \forall j=1,2,\ldots,M \); and where the CF was defined according to (16).

What follows is a description of the real-coded genetic technique used for the optimization problem, which concerns the combined selection of the optimal FMF, together with the optimal zoning method (17).

Step 1: the initial population \( \Phi_0 = \{\Phi_1, \Phi_2, \ldots \Phi_{\text{npop}}\} \) was created by generating \( \text{npop} \) random individuals \( \Phi_{\text{npop even}} \), with
\[
\Phi_i = (P,W)
\]
Where
1) \( P = (p_1, p_2, \ldots, p_M) \) is the set of \( M \) voronoi points, with \( p_j = (x_j, y_j) \) being the voronoi point of the zone \( z_j \) of \( z_{\text{M}} = \{ z_1, z_2 \ldots, z_M \} \);
2) \( W = (\mu_1, \mu_2, \ldots, \mu_m, \mu_M) \) is the set of weights of the FMF and \( \mu_m \) is the weight value associated with the zone in the \( m \)th position of the RIS.

Step 2: the fitness value of an individual \( \Phi_i = (P,W) \) was taken as the classification cost \( \text{CF}(Z,\text{FMF}) \), which was obtained by (16), where \( z \) is the voronoi tessellation corresponding to the set \( p \) and FMF is the FMF of weights \( w \).

Step 3: From the initial population, the new population of individuals is generated by genetic operators (A) selection, (B) crossover, (C) mutation and (D) elitism [10] as following:
\[
\{(p_1^* , p_2^* \ldots p_j^* , p_m^*)\}, \{ (\mu_1^*, \mu_2^* , \ldots \mu_m^* , \mu_M^*)\}
\]
be two individuals selected for crossover, then the two offspring individuals
\[
\{(p_1, p_2, \ldots, p_j, p_m)\}, \{ (\mu_1, \mu_2, \ldots, \mu_m, \mu_M)\}
\]
and
\[
\{(p_1^* , p_2^* , \ldots p_j^* , p_m^*)\}, \{ (\mu_1^*, \mu_2^* , \ldots \mu_m^* , \mu_M^*)\}
\]
Of the next generation were obtained as a linear combination of the parent individuals, according to the random values \( a, \beta \) [0,1]:
\[
p_j^* = a p_j^* + (1-a) p_j, \beta = \alpha p_j^* + (1-\alpha) p_j
\]
and
\[
\mu_m^* = \beta^* \mu_m + (1-\beta^*) \mu_m^* \]

(C): Given an individual \( \Phi_i = (P,W) = \{(p_1, p_2, \ldots, p_m)\}, \{ (\mu_1, \mu_2, \ldots, \mu_m)\}\), the mutation operator used two distinct procedures for \( P = (p_1, p_2, \ldots, p_m) \) and \( W = (\mu_1, \mu_2, \ldots, \mu_m) \).

Let \( p_j = (x,y) \) be an element of \( P \) selected for mutation, according to mutation probability \( p_{\text{Mut Prob}} \). The nonuniform mutation operator changed \( p_j = (x,y) \) into the
new element \( p_i = (x_i, y_i) \) that could then be defined as follows [see Fig.2(a)]:

\[
\begin{align*}
    x_i &= x_i + \delta \cdot \cos(\mu) \\
    y_i &= y_i + \delta \cdot \sin(\mu)
\end{align*}
\]

\[\ldots (18)\]

Where \( \mu \) is a random value generated according to a uniform distribution and \( \mu \in [0,2\pi] \) and \( \delta \) is a displacement determined according to the following equation:

\[
\delta = \delta_{\text{displ}} \cdot (1 - \sqrt{1 - \text{iter}/N_{\text{iter}}})b
\]

\[\ldots (19)\]

Being \( V \) a random value generated in the range \( [0,1] \) according to uniform distribution, \( \delta_{\text{displ}} \) is the maximum displacement allowed, \( b \) is a parameter determining the degree of non-uniformity, iter is the counter of generations performed, and \( N_{\text{iter}} \) is the maximum number of generation. It is worth noting that, in (19), when the inter was small, it initially caused the operator to search the space almost uniformly and then locally during the later stages\([5],[10]\).

Similarly, by letting be an element of \( W \) selected of mutation, according to a mutation probability \( \mu_{\text{Mut.Prob}} \). The nonuniform mutation operator changed \( \mu_m \) with

\[
\begin{align*}
    p_{\mu_m} &= \mu_{m+1} + \delta \cdot \cos(\mu) \\
    y_{\mu_m} &= y_{m+1} + \delta \cdot \sin(\mu)
\end{align*}
\]

\[\ldots (20a)\]

\[
\begin{align*}
    p_{\mu_m} &= \mu_{m+1} + \delta \cdot \cos(\mu) \\
    y_{\mu_m} &= y_{m+1} + \delta \cdot \sin(\mu)
\end{align*}
\]

\[\ldots (20b)\]

\[
\begin{align*}
    p_{\mu_m} &= \mu_{m+1} + \delta \cdot \cos(\mu) \\
    y_{\mu_m} &= y_{m+1} + \delta \cdot \sin(\mu)
\end{align*}
\]

\[\ldots (20c)\]

Where \( e \) is a random Boolean value generated according to a equally distributed probability function, and \( n \) is a random value generated in the range \([0,1]\) according to uniform distribution. In addition, the following rules were used to guarantee that the membership values \( \mu_n \) are positive, monotonically decreasing, and normalized [according to (14)].

1) Positivity:
   - If \( \mu_{m,M} \geq 0 \), then \( \mu_{m,M} = 0 \)
2) Monotonicity:
   - If \( \mu_{m,n} \leq \mu_{m,n+1} \), then \( \mu_{m,n+1} = \mu_{m,n} \).
   - For \( m=M-1, M-2, \ldots \) \[21b\]
3) Total energy (with \( T_e = \sum_{m=1}^{M} \mu_{m,n} \)):
   - \( \mu_{m,n} = 0 \), from \( m=1,2,\ldots,M \) \[21c\]

Fig.2(b) shows an example of FMF values after mutation. Since \( RIS = (4,2,3,1,5,6) \) we have \( i_1 = 4, i_2 = 2, i_3 = 3, i_4 = 1, i_5 = 5, \) and \( i_6 = 6 \).

(1): The elitism strategy substituted one random individual of the current population with the best individual of the previous population\([10]\).

In the genetic process, Steps 2 and 3 were repeated until at least one of the following stop conditions occurred.
1) \( N_{\text{iter}} \) successive populations were generated.
2) No improvement was registered in \( L \) successive populations.

When a stop condition occurred, the process stopped, and the optimal FMF along with the optimal zoning was obtained form the best individual of the last-generated population.

V. PROPOSED SYSTEM

1. More recently, dynamic zoning methods have been introduced in which zoning design is considered as an optimization problem.
2. This paper introduces a new class of fuzzy-membership functions (FMFs) and presents a real-coding genetic algorithm to detect, in a single optimization procedure, the optimal FMF, together with the optimal zoning, for the specific classification problem.
3. The experimental tests were carried out in the field of handwritten numeral and character recognition, using datasets.
4. The proposed system confirms the effectiveness of the genetic technique for the combined selection of the optimal zoning and optimal FMF.

VI. MODULES

1) Training Phase
2) Testing Phase
3) Symbol image detection
4) Symbol image matrix mapping

VII. MODULES DESCRIPTION

Training Phase has various functionalities such as:
1. Analyze image for characters
2. Convert symbols to pixel matrices
3. Retrieve corresponding desired output character and convert to Unicode
4. Linearize matrix and feed to network
5. Compute output
6. Compare output with desired output Unicode value and compute error
7. Adjust weights accordingly and repeat process until preset number of iterations.

Testing Phase

Testing Phase has various functionalities such as:
1. Analyze image for characters
2. Convert symbols to pixel matrices
3. Compute output
4. Display character representation of the Unicode output.

VIII. SYMBOL IMAGE DETECTION

The process of image analysis to detect character symbols by examining pixels is the core part of input set preparation in both the training and testing phase.
Symbolic extents are recognized out of an input image file based on the color value of individual pixels, which for the limits of this project is assumed to be either black RGB (255,0,0,0) or white RGB (255, 255, 255, 255). The input images are assumed to be in bitmap form of any resolution which can be mapped to an internal bitmap object in the Microsoft Visual Studio environment. The procedure also assumes the input image is composed of only characters and any other type of bounding object like a boarder line is not taken into consideration.

IX. ALGORITHM

The training routine implemented the following basic algorithm
1. Form network according to the specified topology parameters
2) Initialize weights with random values within the specified
3) load trainer set files (both input image and desired output text)
4) analyze input image and map all detected symbols into linear arrays
5) Form network according to the specified topology parameters
6) Initialize weights with random values within the specified
7) load trainer set files (both input image and desired output text)
8) analyze input image and map all detected symbols into linear arrays
9) separately
10) for each character : (a) calculate the output of the feed forward network
(b) compare with the desired output corresponding to the symbol and compute error
(c) back propagate error across each link to ad just the weights
11) move to the next character and repeat step 6 until all characters are visited
12) compute the average error of all characters
13) repeat steps 6 and 8 until the specified number of epochs
(a) Is error threshold reached? If so abort iteration.
(b) If not continue iteration

X. EXPERIMENTAL RESULTS

Two groups of experiments were carried out using the set \(1 = \{0, 1, 2, \ldots, 9\}\) of handwritten numerals and the set \(2 = \{A, B, C, \ldots, Z\}\) of handwritten characters. Experiments on handwritten numerals have been performed using 18 468 patterns of the CEDAR database. Experiments on handwritten characters have been performed using 29 770 patterns of the ETL database. The patterns were thinned and normalized to 72×54 pixels [11]. Successively, the feature set \(F = \{f_1, \ldots, f_6\}\) was considered for pattern description [5] as follows:
- \(f_1\) — holes (\(\cdot\));
- \(f_2\) — vertical-up cavities \((\cup)\);
- \(f_3\) — vertical-down cavities \((\cap)\);
- \(f_4\) — horizontal-right cavities \((\preceq)\);
- \(f_5\) — vertical-up endpoints \((\uparrow)\);
- \(f_6\) — vertical-down endpoints \((\downarrow)\);
- \(f_7\) — horizontal-right endpoints \((\rightarrow)\);
- \(f_8\) — horizontal-left endpoints \((\leftarrow)\).

Fig. 3(a) shows two handwritten patterns. Fig. 3(b) shows the geo-metrical features extracted from the thinned images.

In the latter, the structural features (that were localized at their center of gravity) are \(f_1, f_2, f_3, f_4\) and \(f_5\).

Tables II and III show the experimental results [for \(e = 0.05\) of (6) and \(\eta = 2\) of (16)] achieved, respectively, on handwritten numerals and characters. Each row of Tables II and III reports the performances of the optimal zoneings \(Z^*\) (with \(M = 4, 6, 9, 16,\) and 25 being the number of zones of the zoning method) defined by considering different membership functions. Accuracy estimation was performed by \(K\)-fold cross-validation technique, with \(K = 10\) [12]. Several combinations of working parameters have been tested, and the following

Table I: Handwritten Numerals: Performance Versus Membership Function

<table>
<thead>
<tr>
<th>Zoning</th>
<th>Recognition Rate</th>
<th>Membership Function</th>
<th>Abstract</th>
<th>Ran.</th>
<th>Measurement</th>
<th>Fuzzy</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTA ([5, 7])</td>
<td>2-ZN ([7])</td>
<td>3-ZN ([7])</td>
<td>R ([7])</td>
<td>LWM ([7])</td>
<td>QWM ([7])</td>
<td>EWM ([7])</td>
</tr>
<tr>
<td>(Z^*)</td>
<td>0.81</td>
<td>0.78</td>
<td>0.62</td>
<td>0.68</td>
<td>0.51</td>
<td>0.58</td>
</tr>
<tr>
<td>(Z^*)</td>
<td>0.87</td>
<td>0.83</td>
<td>0.75</td>
<td>0.62</td>
<td>0.53</td>
<td>0.61</td>
</tr>
<tr>
<td>(Z^*)</td>
<td>0.92</td>
<td>0.86</td>
<td>0.83</td>
<td>0.55</td>
<td>0.56</td>
<td>0.66</td>
</tr>
<tr>
<td>(Z^*)</td>
<td>0.85</td>
<td>0.85</td>
<td>0.81</td>
<td>0.53</td>
<td>0.55</td>
<td>0.63</td>
</tr>
<tr>
<td>(Z^*)</td>
<td>0.87</td>
<td>0.84</td>
<td>0.79</td>
<td>0.52</td>
<td>0.53</td>
<td>0.62</td>
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<table>
<thead>
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<th>Reliability Rate</th>
<th>Membership Function</th>
<th>Abstract</th>
<th>Ran.</th>
<th>Measurement</th>
<th>Fuzzy</th>
</tr>
</thead>
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<td>QWM ([7])</td>
</tr>
<tr>
<td>(Z^*)</td>
<td>0.82</td>
<td>0.80</td>
<td>0.63</td>
<td>0.70</td>
<td>0.54</td>
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<tr>
<td>(Z^*)</td>
<td>0.89</td>
<td>0.85</td>
<td>0.76</td>
<td>0.62</td>
<td>0.56</td>
</tr>
<tr>
<td>(Z^*)</td>
<td>0.93</td>
<td>0.88</td>
<td>0.84</td>
<td>0.57</td>
<td>0.58</td>
</tr>
<tr>
<td>(Z^*)</td>
<td>0.89</td>
<td>0.86</td>
<td>0.83</td>
<td>0.54</td>
<td>0.57</td>
</tr>
</tbody>
</table>

Table II shows that, whatever the number of zones considered, FMF performed better than other membership functions that are previously considered in the literature. In particular, the best result occurs for the optimal zoning \(Z^*\) and the optimal FMF (see Fig. 4). In this case, the recognition rate and reliability rate are, respectively, 95% and 97%, which makes results better than those obtained by the technique given in [5] (i.e., 92% and 93%) and in [7] (i.e., 93% and 96%, at the best).

In addition, Table III shows that FMF outperformed abstract-level, ranked-level, and measurement-level membership functions [5], [7]
XI. CONCLUSION

This paper has introduced a single optimization process to address the problem of zoning-based classification. Unlike previous approaches in the literature, here, the problem of optimal zoning design was con-sidered, together with the design of the optimal membership function. This paper has introduced a new class of fuzzy membership functions and presented an integrated approach that uses a real-coded genetic algorithm while exploiting the potential of Voronoi tessellation for zoning representation. This approach was employed to find, in a single optimization process, both the optimal fuzzy membership function and the optimal zoning method, for which the cost function associated with the classification problem was at its lowest.

The experimental results, which are obtained in the field of handwritten digit and character recognition, confirm the soundness of consider-ing the problem of optimal zoning design, together with that of optimal membership-function design. Furthermore, they show that fuzzy membership functions can provide a significant improvement in the clas-sification performance with respect to standard membership functions based on abstract-level, ranked-level, and measurement-level weight-ing models, as previously considered in the literature.

REFERENCES


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