Zoning and Metaclasses Improving the Character Recognition

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Abstract

The contribution of this paper is twofold. First we investigate the use of the confusion matrices in order to get some insight to better define perceptual zoning for character recognition. We will see that this idea can be used as a tool to support the design of zoning. The features considered in this work are based on concavities/convexities deficiencies, which are obtained by labeling the background pixels of the input image. Four different perceptual zoning (symmetrical and non-symmetrical) are discussed. Experiments show that this mechanism of zoning could be considered as a reasonable alternative to exhaustive search algorithms. The second contribution is a methodology to define metaclasses for the problem of handwritten character recognition. The proposed approach is based on the disagreement among the characters and it uses Euclidean distance computed between the confusion matrices. Through comprehensive experiments we demonstrate that the use of meta-classes can improve the performance of the character recognition system.

Keywords: Character Recognition, Zoning Mechanism, Metaclasses, Confusion Matrix.

1. Introduction

The handwriting character recognition is a special subject and has become important as ICR systems (Intelligent Character Recognition) become more powerful and commercially available. On the other hand, there is a gap between human reading capabilities and the recognition systems.

The letter tendency to be confused conveys important information to define the perceptual similarity of letters. The basic idea is that two letters that look a lot alike will often be confused with one another. Figure 1 presents this idea considering letters: "B" and "E". A good strategy is to predict which pairs of letters are confused and which are not. The metaclass approach is a typical solution for this kind of confusion [9]. The idea is to cluster the confusion and use this approach to build up robust recognition systems.

We are experts in recognition of characters from early childhood onwards. But, when we observe only a part of the letter, its identification is not that obvious. In the first observation, we process global information, while in the second, we process local information. We go through the characters stored in one's brain, choose a possible candidate which contains the same part, and then try to add others parts to it to form this possible character [16]. Another possibility is to decompose a possible character in the same way as the given partition does. If the first one does not fit, try another one, and so on until the suitable part is found [16]. Based on this concept, methods for local information analysis on partitions of the character, also known as zoning, have been proposed to evaluate the recognition rates of the distinct parts of characters. Most of the works define zoning empirically [8,16] while others use complex and expensive search mechanisms to find the best zoning [15].

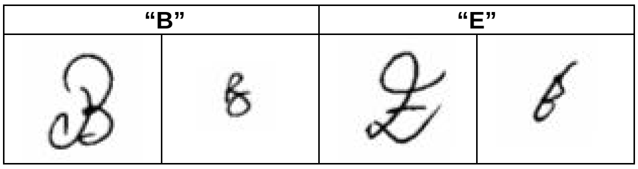


Figure 1 Similarity between letters "B" and "E".

In summary, this work applies first a Global feature extraction based concavities/convexities deficiencies, and a Local perceptual zoning mechanism. The zoning mechanism allows scrutinizing the elements (features) individually.

The contribution of this paper is twofold. First we investigate a mechanism to define perceptual zoning for character recognition. Differently of most works in the literature which define zoning empirically, use take into account the confusion matrices in order to get some insight to better define the zoning. Four different perceptual zoning (symmetrical and non-symmetrical) are discussed. Based on experimental results, we can affirm that this is a reasonable alternative to exhaustive search algorithms [15]. The second contribution of this paper is a methodology to define metaclasses for the problem of handwritten character recognition. The proposed approach is based on the disagreement among the characters and it uses Euclidean distance computed between the confusion matrices. Through comprehensive experiments we demonstrate that the use of meta-classes can improve the performance.

The paper is divided into six sections. Section 2 summarizes the handwriting character recognition problem. Section 3 explains our approach based on perceptual zoning considering a non-symmetrical strategy. Section 4 presents the Distance-based Disagreement (DbD) measure applied to define the metaclasses of characters. In Section 5, the database used in the experiments is presented and the experimental results are discussed, and, in the final section, our conclusion and a plan for future works are presented.

2. Handwriting Character Recognition

Character recognition techniques have potential application in any domain where a large mass of document image-bearing texts must be interpreted or analyzed. Conventionally, such images are processed by human operators who act according to what has been written or simply key in what they read onto a computer system that carries out further processing, say of postal address. However, automation of the entire process requires a high recognition rates, as well as maximum reliability.

Generally speaking, an off-line handwriting character recognition system includes four stages: image preprocessing, segmentation, feature extraction, and classification. Preprocessing is primarily used to reduce noise or variations of handwritten characters. Segmentation consists in locating and extracting the handwritten information from the image. Feature extraction is essential for data representation and extracting meaningful features for later processing. Classification assigns the characters to one of the several classes.

The baseline system used in this work takes into consideration a Global Approach for feature extraction combined with a Local Approach based on zoning mechanism, and uses Class-Modular architecture feedforward MLP (Multiple Layer Perceptron) in the classification stage. Oh & Suen have demonstrated that class-modular NN can produce better results than just one single NN [10]. Based on this, and other works we have done [5,11], we have chosen this architecture for this experiment.

The system gets as input a 256 grey-level image. Then, a preprocessing step, which is composed of binarization [12] and a bounding box definition. The feature set is based on Concavities/Convexities deficiencies. These deficiencies are obtained by labeling the background pixels of the input images [13]. The entire and definitive symbols were adapted to handwritten characters, and then we have 24 different symbols [1].

The next section presents the perceptual zoning and discusses about the symmetrical and non-symmetrical topologies.

3. Zoning Mechanism

Suen et al. and Li et al. applied a zoning mechanism in their experiments using hand printed characters [8,16]. They analyzed 4 different configurations. Therefore, circumscribed the letter by a rectangle which is partitioned into Z parts, say Z = 2, 4, and 6 as presented in Figure 3. They observed that letter “D” always lies on the top (100%), letters “A”, “K” and “G” give higher recognition rates (100%) than “P”, “I” and “T” (54%) and, the recognition rates considering Z = 2LR, 2UD, 4 and 6 were: 86.12%, 85.88%, 61.73%, and 42.91%, respectively. The authors comment about the case 2LR for “Y” and explain that this zoning is perfect for recognition; but it brings a difficulty to “B” because the left half is confusing with “E”. Therefore, it should be noticed that different partitions may produce big differences in recognition rates. In addition, more partitions bring more confusing parts. For instance, in Z = 6 a character is confused with 6 characters, e.g., letter “B” is confused with: “C”, “G”, “J”, “O’, “S”, “U”.

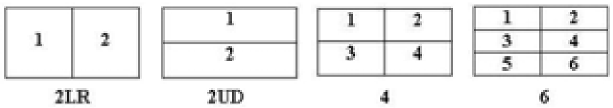


Figure 3 Zoning mechanism: Z =2 (Left-Right and Up-Down), 4, and 6 parts.

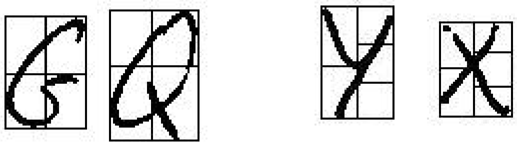
In this paper we analyze the significant parts of the characters using the confusion matrix obtained in the recognition process. The idea consists in looking for the relationship between the regions and the confusion, thus allowing us to understand which parts of the character are making up the confusions. The main confusions observed in this process are presented in Table 1. Some examples are also depicted in Figure 4. In order to get some basis for comparison, the first zoning we have used was Z=4 (Figure 4a). Then, after analyzing the confusions we realized the 5-part zoning (both vertical and horizontal) could provide more information to solve confusions among non-symmetrical shapes, such as “G” and “Q“; “D” and “O”; “Y” and “X” (Figure 4b). The idea is to give more emphasis to similar parts by increasing the number of zones.

Table 1: Confusion: Z = 4.

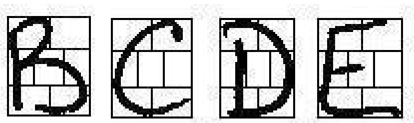
Character	**Confusion**	**Character**	**Confusion**
B	D, O	K	M
C	E	N	W
D	O	R	A
H	M	S	D
I	F, J	W	U, V
G	Q	X	K
J	D	Y	X

Following the same concept, we have investigated 7-part zoning. In this case, the idea was to solve confusions among non-symmetrical shapes but representing differentially the character middle zone, such as “D” and “C“; “N” and “W”; “Y” and “X” (Figure 4c). Figure 5 shows the three non-symmetrical zoning we have build based on the confusion matrices.

Differently from Suen et al. and Li et al. [8,16], we have observed that more cells in the zoning do not bring more confusing parts, when those cells are non-symmetrical. Our experimental results (Section 6) demonstrate that this strategy is reliable and very useful to help defining zoning.



(a) “G” and “Q” (b) “Y” and “X”



(c) “B”, “C”, “D”, and “E”

Figure 4 Zoning mechanism based on confusion parts of the letters.

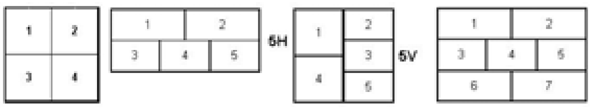


Figure 5 Zoning mechanism: Z =4, 5H, 5V, and 7 parts.

4. Metaclasses of Characters

A metaclass can be defined as a class of classes. Therefore, a metaclass of characters is formed by the union of two or more of the original classes to break down the complexity of their recognition process [9]. The concept of metaclasses has been applied to different problems of pattern recognition. For example, in [9] the authors have used metaclasses to recognize dates in Brazilian bank cheques. In this case, they grouped in the same metaclass words having the same suffix, for example, “Setembro”, “Novembro”, and “Dezembro” (September, November, and December). Similar strategy has been employed by [3,11]. The authors have applied this concept to classify words extracted from legal amount of Brazilian bank cheques. The rule used to build the metaclasses also was based on the suffix.

As stated before, in this work we have used the concept of metaclass to classify handwritten characters. The strategy to build such metaclasses is based on a measure of disagreement, which is computed from the confusion matrices. The next paragraphs detail this measure.

The measure of disagreement we have used in this work is based on the disagreement between classifiers proposed by [2]. They applied the disagreement concept to measure the difference between two classifiers C_1 and C_2 trained on a classification problem. Their main interest was to group classification problems in a consistent way, which may be helpful in selecting appropriate tools for solving the problems. The disagreement $d_j(C_1, C_2)$ between two classifiers C_1 and C_2 trained on a classification problem $P_j (j = 1,\ldots,K)$, where K is the size of the problems set is given by Eq. 1:

$$dj(C1,C2) = Prob(C1(x) \sim= C2(x) \mid x \in Pj) \qquad (1)$$

where, $Ci(x)$ returns the label for the pattern x according to classifier Ci. C candidate classifiers constitute an M x M disagreement matrix D_j^C for problem Pj, with elements $D_j^C (m,n)=dj(Cm,Cn)$.

Considering that C candidate classifiers are available, the simplest solution to determine the better ensemble is to evaluate all possible combinations. However, this may have an extremely high computational cost. In light of this, we opted by designing a method that does not use first-order information (classifier's score output) to evaluate such a disagreement. The idea is to use information from the confusion matrix for each individual classifier and compute distances between those matrices that represent classifier disagreements. Since the confusion matrix give us a consistent analysis of the classifier’s behavior, such distances provide a mechanism for a priori evaluation of the possible classifier combinations and the metaclasses of characters.

The Confusion Matrix can be denoted as a matrix $A = [RRi,j]$ where RRi,j corresponds to the total number of entities in class C_i which have been classified in class C_j; and the principal diagonal indicates the total number of samples in class C_i correctly recognized by the system [19]. From matrix A, it is possible to compute classifier global performance measure, as defined by Eq. 2:

$$RR_i = \frac{1}{N} \sum_{i,j=1}^{N} RR_{i,j} \qquad (2)$$

The distances can be obtained considering that all confusion matrices are of the same size, as defined by Eq. 3:

$$D^{p,q} = \sum_{i=1}^{N} \sum_{j=1}^{N} \left| RR_{i,j}^{p} - RR_{i,j}^{q} \right| \qquad (3)$$

As it can be observed from Equation 3, such a measure, which we call Distance-based Disagreement (DbD), computes the disagreement between classifiers p and q using the information contained in the confusion matrices of each individual classifier. Table 2 show an example of this measure computed for classes “A” and “B”. In such a case we have considered four classifiers, which are based on the four zoning strategies presented in Figure 6. For example, the biggest disagreement found for character “A” is yielded when classifiers C_{5H} (5-part-horizontal zoning (Figure 6b)) and C_7 (7-part zoning (Figure 6d)) are considered. For the character “B”, on the other hand, the biggest disagreement is produced by classifiers C_{5H} and C_{5V}. The classifiers are the class-modular neural networks presented in Section 2.

Based on this measure, the next step consists in defining the metaclasses. The idea is to find clusters of classes that can be represented for a given classifiers. The question that arises is what criterion should be used for that. Would the maximum disagreement be a good one?

Table 2: DbD computed for characters "A" and "B".

"A"		"B"	
Classifier	**DD**	**Classifier**	**DD**
4-7	0,089552	5v-7	0,149254
5V-7	0,119403	4-7	0,238806
4-5H	0,149254	4-5H	0,298507
4-5V	**0,149254**	**4-5V**	**0,328358**
5H-5V	0,179104	5H-7	0,358209
5H-7	0,179104	5H-5V	0,41791

The main difficulty with diversity measures is the so-called accuracy-diversity dilemma. As explained by [4], it is not clear how to choose the degree of diversity which produces the best performance, leading to an expected tradeoff between diversity and accuracy. These authors have mentioned that no convincing theory or experimental study has emerged to suggest that there is any measure that can reliably predict the generalization error of an ensemble. It is clear, based on the literature that we need to find a balance point between diversity and accuracy [7,18]. In light of this, we have adopted the idea proposed by [4]. They argue that the ensembles selected through median diversity will fare better than randomly selected ensembles or ensembles selected through maximum diversity. They intuitively explain this phenomenon with the notion that in pattern clustering more diversity is associated with many clusters not getting the clustering structure right, leading to lower individual accuracy.

Therefore, our criterion to clustering is the median DbD value. For instance, in the previous example both characters "A" and "B" would belong to the same metaclass because in both cases the pair of classifiers (4-5V) produces the DbD value closest to the median value. Table 3 reports the 5 metaclasses of characters we have found.

Table 3: Metaclasses of characters.

Metaclass	Characters	Pair of Classifiers
1	A,B,C,D,Q,R,S,Z	4-5V
2	E,I,J,M,Y	4-7
3	G,X	4-5H
4	F H,K,L,N,O,P,T	5H-7
5	U,V,W	5V-7

We can observe from Table 3 that the most frequent confusions are grouped in the same metaclass, e.g., "U" and "V", "F" and "P", etc. On the other hand, we can notice for example that the class "O", which is often confused with "D" and "Q", belongs to other metaclass. This can be explained by the fact that during clustering, the DbD values for "D" and "O" were too small. Considering that we are using median values, they have fallen into different classes.

5. Experimental Results and Discussions

The experiments were carried out using the handwritten character database from IRESTE/University of Nantes (France), called IRONOFF (IReste ON/OFF Dual Database), which is composed of 26 classes of uppercase characters from Form B: B27 … B52 fields [17]. The IRONOFF database was selected because it is fully cursive. It was collected from about 700 writers, mainly of French nationality. The off-line data were scanned at 300 dpi with 8 bits per pixel.

The experiments were carried out using 3 subsets, which we called the training, validation, and testing sets. Their composition is as follows: 60%, 20%, and 20% for training, validation, and testing, respectively. The database sums up 10,510 images of handwritten characters.

In order to better understand this, Table 4 reports the performance of the four classifiers depicted in Figure 5. Remembering that each classifier is a class-modular neural network with 26 outputs. The recognition rates for the classifiers C_4, C_{5H}, C_{5V}, and C_7 are 83%, 81.7%, 80.9% and 84.7%, respectively. The confusion matrix for C_{5H} presents better results to following letters: "G" and "Y". This zoning mechanism contributes for the recognition of the letters which are not vertically symmetric, as presented previously in Figure 5b. On the other hand, 7-part zoning is better for the following classes: "B", "C", "D", "E", "K", "N", "P", "R", "U", "W, and "X" (see Table 4).

It can be noticed from Table 4 that a non-symmetrical zoning mechanism yields the best recognition rate (84.7%), what demonstrates that this approach could be considered as an alternative to empirical zoning. In the first observation, we are processing global information while in the second we are processing local information. This kind of analysis is exactly provided by this system. When the system applies the feature extraction (labeling the background pixels) and then uses the zoning mechanism to compute the labels to each Z part, we design a system capable to do Global and Local analysis, as presented in Section 2. Being the zoning non-symmetrical we are given to the system the ability for representing better the parts where the confusion is evident. So far we have discussed the some concepts of perception as a tool to support the design of zoning as well as the concept of metaclasses of characters and how they have been defined. In the next paragraphs we give an overview about the strategy we have applied to recognize handwritten characters. In our first experiment we have build a system using an ensemble of four classifiers, where the decision rule was given by the Max Rule [6]. Figure 6 illustrates this system, which achieves a recognition rate of 84.7%.

Table 4: Recognition Rate (%).

Character	C_4	C_{5H}	C_{5V}	C_7
A	**92,5**	86,6	89,6	91,0
B	65,7	64,2	74,6	**79,1**
C	82,1	79,1	68,7	**88,1**
D	73,1	65,7	68,7	**82,1**
E	83,6	85,1	89,6	**95,5**
F	**92,5**	91,0	89,6	**92,5**
G	82,1	**86,6**	80,6	80,6
H	**88,1**	85,1	70,1	76,1
I	**76,1**	71,6	**76,1**	71,6
J	**83,6**	79,1	79,1	82,1
K	77,6	76,1	77,6	**80,6**
L	**92,5**	89,6	86,6	91,0
M	**92,5**	82,1	85,1	88,1
N	68,7	77,6	70,1	**86,6**
O	86,6	89,6	**88,1**	83,6
P	86,6	92,5	91,0	**94,0**
Q	**82,1**	64,2	76,1	80,6
R	86,6	89,6	88,1	**91,0**
S	**79,1**	**79,1**	**79,1**	76,1
T	95,5	**97,0**	**97,0**	**97,0**
U	80,6	85,1	82,1	**86,6**
V	**95,5**	82,1	88,1	82,1
W	70,1	74,6	65,7	**79,1**
X	76,1	74,6	70,1	**79,1**
Y	77,6	**89,6**	85,1	82,1
Z	**89,6**	88,1	88,1	86,6
Average	**83,0**	**81,7**	**80,9**	**84,7**

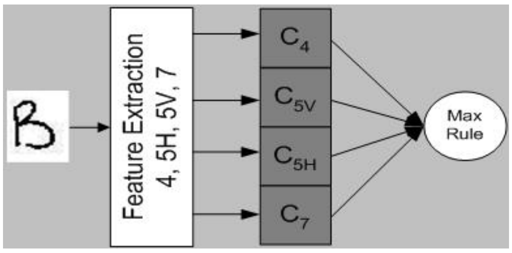


Figure 6 First level of the system composed of four class-modular neural networks.

Thereafter, we have elaborated a system that takes into consideration the concept of metaclasses, which is depicted in Figure 7. When a pattern is presented to the system, the four feature vectors are extracted and then, the classifiers associated to the metaclasses are activated. For example, for metaclass 1 the classifiers associated are C_4 and C_{5H}, while for metaclass 2 are C_4 and C_7. The next step consists in applying the Sum Rule [6] to combine the outputs of the associated classifiers.

It is worth of remark that at this stage only the outputs related to the metaclass are used to produce the result. Consider for example the metaclass 3, which is composed of classes "G" and "X". In such a case, only these two outputs are used in the Sum Rule for this metaclass. In the end, the five scores are submitted to a Max Rule [6] that points out the best metaclass for the given input pattern.

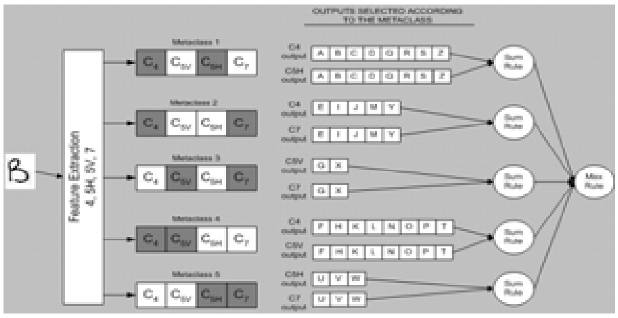


Figure 7 Metaclass identification.

Suppose for example that the system have chosen metaclass 1. Remember that this metaclass is composed of classes "A", "B", "C", "D", "Q", "R", "S", and "Z". Based on Table 4, we can assert that the best feature sets we have to classify these classes are C_4 and C_7. Therefore, the final decision is taken considering the outputs produced by these two classifiers. As we can observe in Figure 8, the Max Rule [6] takes into consideration only the outputs related to the metaclass in question, in this example, metaclass 1.

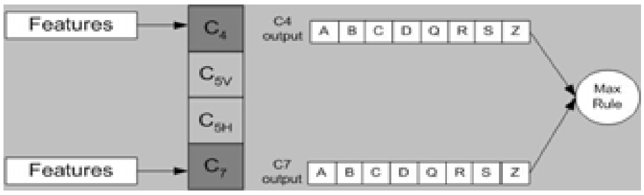


Figure 8 The classification using metaclass concept.

Using the concept of metaclass we improve the performance of the system in about 5%. The final performance was 90.4%. Table 5 reports the recognition, rejection and error rates for each class independently. The result reached by our system compare favorably to other published methods. For example in [14] the authors using an MLP reached a recognition rate of 87.1% for the same database.

6. Conclusions

In this paper, we explored the perceptual zoning based on the confusion matrix and it information about the confusion parts of the letters. The perceptual regions had been verified and used to define character metaclasses, observing it that the similarities are evidenced among the classes. The study based on zoning mechanisms presented in this paper can contribute to the resolution of the confusions found for the system. The second contribution of this paper is a methodology to define metaclasses for the problem of handwritten character recognition. The proposed approach is based on the disagreement among the characters and it uses Euclidean distance computed between the confusion matrices. Through comprehensive experiments we demonstrate that the use of metaclasses can improve the performance and that our results compare favorably to other published methods. Finally, the experiments have shown the viability of our approach, which focuses on human visual perception. Future work will provide the validation of our approach to more than 2 classifiers combination. We also plan to compare the idea of perceptual zoning with search algorithms such as genetic algorithms.

Table 5: Recognition, Rejection and Error Rates (%) considering metaclasses and best classifier for each class (Test Set).

Characters	Recognition	Rejection	Error
A	97,0	3,0	0,0
B	85,1	14,9	0,0
C	89,6	10,4	0,0
D	83,6	14,9	1,5
Q	86,6	13,4	0,0
R	95,5	4,5	0,0
S	88,1	4,5	7,5
Z	91,0	7,5	1,5
E	97,0	3,0	0,0
J	88,1	11,9	0,0
M	94,0	6,0	0,0
F	95,5	4,5	0,0
P	95,5	4,5	0,0
T	97,0	3,0	0,0
G	89,6	10,4	0,0
X	85,1	14,9	0,0
H	94,0	4,5	1,5
K	85,1	11,9	3,0
L	95,5	4,5	0,0
N	88,1	10,4	1,5
O	89,6	9,0	1,5
I	79,1	20,9	0,0
Y	91,0	9,0	0,0
U	89,6	9,0	1,5
V	97,0	0,0	3,0
W	82,1	4,5	13,4
Average	**90.4**	**8.3**	**1.4**

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