Granular Computing-based Qualitative Criterion Cluster and the License Plate Characters’ Recognition

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Abstract

Qualitative criterion (QC) plays an important role in human recognition, judgment, memory and evaluation fields. During a study of character recognition, a series of concepts, such as qualitative criterion cluster (QCC), criterion skeleton code (CSC) and criterion skeleton (CS), based on the principle of granular computing are proposed in this paper. In addition, a novel method is also proposed to recognize character based criterion skeleton’s pattern matching. At last, experimental results on license plate characters’ recognition show that qualitative criterion cluster based granular computing is a valid method.

1. Introduction

In our daily life, our brains would make qualitative judgment, recognition, and memory in the first place. Next, evaluation, analysis and decision-making similar specialists can be done. In this paper, we discuss the first step, that is how to recognize a character? Usually, we can recognize a specific object if we know much about its attributes or features because we know that the combination of attributes or features which distinguishes thing from another. In addition, an attribute property whose contents are the specific allowed values for the attribute. There exists a transformation between quantitative to qualitative [1-2]. In judging of the property proposition p(o) of object o, qualitative criterion is a critical step. In [3], object o with quantity x of attribute a(o) whose truth value varies with the qualitative criterion [α, β] can be represented by the Qualitative Mapping

Vehicle’s license plate recognition (VLPR) system has been used for a very long time. Today, VLPR is the most widely used in Intelligent Transportation Systems (ITS). The key issues of VLPR is the location algorithm, segment algorithm and match algorithm [4-7]. In this paper, we mainly discuss the last step: license plate characters recognition. Although there exist a lot of matching algorithms in literature, most of them are not suitable for real time application because of the following difficulties: (1) Features vector of character are not representative features and the amount of feature points are too large which result in not fast enough for real time applications; (2) Due to the noise of character image, the preprocessing algorithm cannot remove all of the noise. Therefore, the match algorithm should robust to noise; (3) Figure 1 shows a sample of Chinese license plate which contains one Chinese character, two letters, four numbers and a dash. There is still no effective method to deal with this combination characters.

Figure 1. A sample of license plate of vehicle

2. Overview of the work

When we ready to recognize an object, the attributes of the object must be known. Then, through the combination of attributes, object can be distinguished and recognized. Our work focuses on how to recognize license plate characters accurately, especially such characters including about 30 Chinese characters, letters A-Z and digits 0-9. Although on other steps, such as location for license plate regions and segmentation of characters from the plate regions, we have developed relevant strategies. Facing the
judgment of object attributes, we need to know the related criteria. So, some important definitions and examples are as follows.

**Definition 1 (QCC)** Given a set of object attribute \( O = \{a_i (o) | i = 1, \ldots, n\} \). Each \( x_i \in X_i \) is the quantity value of \( a_i (o) \), \( p_{ij} (o) \) is the ith quality value, \( j = 1, \ldots, g_i \), and \( [\alpha_{ij}, \beta_{ij}] \in X_i \) is a qualitative criterion of \( p_{ij} (o) \). Then, \( \Gamma = \{[\alpha_{ij}, \beta_{ij}] \} \) is called the object’s qualitative criterion cluster (QCC), satisfying \( [\alpha_{ij}, \beta_{ij}] \cap [\alpha_{ij}, \beta_{ij}] = \emptyset \), \( i = 1, \ldots, n \), \( j = 1, \ldots, g_i \) and \( X_i = \bigcup_{j=1}^{g_i} [\alpha_{ij}, \beta_{ij}] \).

Let \( a_i (o) \) be the conjunction attribute with weights of attribute \( a_i (o) \), \( x = (x_1, \ldots, x_n) \in X \), \( X = X_1 \times \cdots \times X_n \subseteq \mathbb{R}^n \) be a quantity value of \( a_i (o) \), and \( [\alpha_{ij}, \beta_{ij}] \) be the ith attribute \( a_i (o) \)’s \( j \) th quality \( p_{ij} (o) \)’s qualitative criterion, \( i = 1, \ldots, n \), \( j = 1, \ldots, g_i \). Then, \( [\alpha_{ij}, \beta_{ij}] = (x_1, \ldots, x_n) \in [\alpha_{1j}, \beta_{1j}] \times \cdots \times [\alpha_{nj}, \beta_{nj}] \) is a qualitative criterion which has a different dimension.

The \( (l_1, \ldots, j_l) \) is a combination of \( i \) and \( j_l \). The \( v \) \( = v(l_1, \ldots, j_l) \) is the ordinal number of this combination. Because there are \( n \) different kinds of probable values for each \( i \), \( g_i \) different kinds of probable values for each \( j_l \), the number of combinations can be computed: \( G = g_1 \times g_2 \times \cdots \times g_n \) Therefore, \( v \in \{1, \ldots, G\} \).

Let \( \rho_v (o) = \sum_{i=1}^{n} \sum_{j=1}^{g_i} w_{ij} p_{ij} (o) \) be the object \( o \)’s conjunction property with weights, and whose criterion is \( [\alpha_{ij}, \beta_{ij}] \), \( \Gamma^n = \{[\alpha_{ij}, \beta_{ij}] \} \) be a cluster for all qualitative criterions \( [\alpha_{ij}, \beta_{ij}] \).

Then
\[
\Gamma = \begin{pmatrix}
[\alpha_{1j_1}, \beta_{1j_1}] & \cdots & [\alpha_{1g_1}, \beta_{1g_1}]
\vdots & \ddots & \vdots \\
[\alpha_{nj_l}, \beta_{nj_l}] & \cdots & [\alpha_{ng_n}, \beta_{ng_n}]
\end{pmatrix}
\]
is a granule constructed by \( G \) different \( n \)-dimension super-cuboids \( [\alpha_{ij}, \beta_{ij}] \). Every two criteria have no communities-joint. Thus, the mapping \( r : x \times \Gamma^n \rightarrow \{0, 1\} \) is called a qualitative mapping whose qualitative criterion is \( (\{\alpha_{ij}, \beta_{ij}\}) \) or \( \{\alpha_{ij}, \beta_{ij}\} \). If for any \( x \in X \), there exists \( [\alpha_{ij}, \beta_{ij}] \in \Gamma^n \) property \( \rho_v \in \rho_o \) as \( [\alpha_{ij}, \beta_{ij}] \) the criterion. So:
\[
\Sigma_{j_l=1}^{g_l} \bigwedge_{i=1}^{n} \mu_{\Gamma ^n} \bigwedge_{i=1}^{n} \mu_{\Gamma ^n} \bigwedge_{i=1}^{n} \mu_{\Gamma ^n} \bigwedge_{i=1}^{n} \mu_{\Gamma ^n}
\]
is the ordinal number of this combination. Because there are \( n \) different kinds of probable values for each \( i \), \( g_i \) different kinds of probable values for each \( j_l \), the number of combinations can be computed: \( G = g_1 \times g_2 \times \cdots \times g_n \) Therefore, \( v \in \{1, \ldots, G\} \).

Let \( \tau_v (x) = \begin{pmatrix}
\rho_v (o) \iff x \in [\alpha_{ij}, \beta_{ij}]
\vdots \\
\rho_v (o) \iff x \in [\alpha_{ij}, \beta_{ij}]
\end{pmatrix}
\)

The \( \tau_v (x) \) is a vector of \( \{1, \ldots, G\} \) operators testing whether \( x \in [\alpha_{ij}, \beta_{ij}] \) or whether the \( x \) satisfying the property(proposition) \( \rho (o) \)’s qualitative criterion.

A special case is \( n=2 \), discussing two-aspect attribute \( a_1 (o) \), \( a_2 (o) \) of the object \( o \). It looks a net structure in a 2-dimension coordinate system (Figure 3).

![Figure 2. The QCC in spatial coordinate system](image-url)
Example A character image 'A's filled pattern space (see definition 3) can be regarded a 2-dimension granule. Through horizontal and vertical segregation, we can get \( g_1 \times g_2 \) granules (small grids). Here, there must exist a qualitative criterion for each connected-filled granule (or valid-filled granule) in every direction. Qualitative criterion \([a_{1j}, \beta_{1j}]\) can be regarded up-down criterion in vertical direction, and \([a_{2j}, \beta_{2j}]\) be left-right criterion in horizontal direction.

Definition 2 (CSC, CS) Given an object o’s qualitative criterion cluster \( \Gamma = \{[a_{ij}, \beta_{ij}]\}, i = 1, \ldots, n \), \( j = 1, \ldots, g \), \( \hat{a}_{ij}, \hat{\beta}_{ij} \) be called criterion skeleton code (CSC); All CSCs of the object can be form a pattern which is called criterion skeleton (CS). This pattern is the criterion feature pattern under \( G = g_1 \times g_2 \times \cdots \times g_n \) subdivided. Where \( \hat{a}_{ij} = (a_{ij} + \beta_{ij})/2 \), \( \hat{\beta}_{ij} \) is radius. Considered different criterion skeleton code s’ contribution in character image, we introduce a conception: granule density \( \hat{\omega}_{ij} \), then

\[
\hat{\omega}_{ij} = \frac{\sum_{j=1}^{g} \hat{a}_{ij} \cdot \hat{\omega}_{ij}}{\sum_{j=1}^{g} \hat{\omega}_{ij}} \tag{3}
\]

Obviously, since we have CSC, can be regarded as feather, the number of them are far smaller than other methods, matching algorithm will be more faster.

Example For the character image 'A', qualitative criterion cluster at the 1st dimension coordinate system is \( \{[a_{1j}, \beta_{1j}]\} \), the set of criterion skeleton code \( \{\hat{a}_{1j}, \hat{\beta}_{1j}\} \) can be regarded left-right CSC; qualitative criterion cluster at the 2nd dimension coordinate system is \( \{[a_{2j}, \beta_{2j}]\}, \{\hat{a}_{2j}, \hat{\beta}_{2j}\} \) is regarded up-down CSC.
4. Experiments and result analysis

The proposed method has been prototyped using MATLAB and tested using some samples of license plate. Figure 7 shows the process of plate location, and character segmentation process. Figure 8 shows the qualitative criterion skeleton of each character. Then using these skeleton feature, pattern matching became easily and quickly. Through computing comparability of criterion skeletons between the target character and other characters in character library built at first, there must exists the most higher comparability, then the final decisions are making based on comparability of criterion skeleton. Figure 9 shows the recognized results and comparability for each character.

5. Conclusions

In this paper, a novel recognition method is presented, highlighting granular computing-based qualitative criterion cluster and other conceptions. Experiment on vehicle’s license plate character recognition demonstrate the effectiveness of the proposed approach, and this prototyped system will be integrated for some application in the future and this novel characters’ recognition algorithm can be extend to other image-based object recognition fields for the next research work.

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7. References


