Printed Thai Characters Recognition Using Rough Sets and Fractal Dimension

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Abstract

This paper investigated ring projections, fractal dimension, and rough set theory in an invariant Thai characters recognition system. The first step, we use a ring projection method to extract features from the printed Thai characters. The ring projection method is invariant to rotation, translation and scales, which based on the total number of foreground pixels as distributed along circular rings. Then the fractal dimensions of five subintervals of ring projection curves are computed using the box counting algorithm. The object's attributes are set up by these fractal dimension values. Finally, we have five fractal dimension attributes of each character. The rough sets receive the appropriate attributes of each character, and generate the decision-making rules for coarse and fine classification respectively. A new development method is used to recognize the character invariance to size, translation and rotation. The results of this research show that the recognition rate is high for the ideal printed Thai characters.

Keywords: Character recognition, Ring projection, Rough sets, Fractal dimension

1. Introduction

In research of the topic of invariant Thai printed character recognition in the past several years, a few researches have been tried to make computers recognize invariant Thai characters. The detail of these approaches is illustrated in [1-3]. The aim of invariant character recognition is to identify a character independently of its position (translated or rotate) and size (large or smaller).

In this research, we describe a method for character recognition that achieves excellent invariance under translation, rotation and scaling. The method has three steps: feature extraction using ring projection method, estimation fractal dimension of ring projection curves, and classification using rough sets. The first takes into account the ring projection of characters. The second step, we calculate the fractal dimension of the ring projection curves using the box counting algorithm. Finally, we get the fractal dimension values to set up the object's attributes. The rough sets receive the appropriate attributes of each object, and generate the decision-making rules for classification. The principle of the ring projection, fractal dimension and the knowledge based reduction and the creation of rough rule-based will be illustrated in the following section.

2. Feature extraction

In this paper, we use an invariant projection method to extract features from the Thai Characters. Ring projection [4] is defined as the total member of foreground pixels as distributed along circular rings. These rings have a radius dependent on a centroid of the shape, but independent of the shape's position, orientation, and scale as shown in Figure 1. We can derive the centroid of the character, as denoted by $C(x_o, y_o)$, and subsequently translate the origin of our reference frame to this centroid.

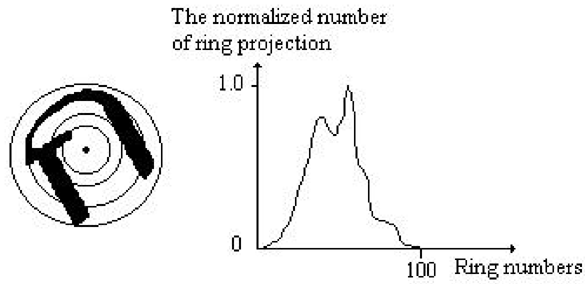

Figure 1 An illustration of the ring projection for the Thai character "ถ"rotated 30°

3. Fractal Dimension

There are numerous fractal features that can be generated from an image. The fractal dimension is a method, which measures the geometrical complexity of a projection curve. In this paper, we analyze the box-counting methodology from the standpoint of computing fractal features from projection curves. The estimation of the fractal dimension can be defined as follow [5]:

$$d = \lim_{r \to 0} [\ln N(r) / \ln(1/r)] \tag{1}$$

Where N(r) is the number of boxes covering the curve,
r is the size of the box, and
d is the dimension of the fractal set.

The dimension d can be estimated from the slope of a least squares straight line fit to a plot of ln N(r) VS ln r for several box sizes r. An approximation to the fractal dimension can be obtained from a logarithmic linear regression:

$$\ln(N(r)) = \ln(b) - d \ln(r) \quad (2)$$

It has been shown that the number of boxes of side r need to cover a fractal set obeys the power law $N(r) = \beta r^{-d}$. Figure 2 shows the box counting algorithm for a hypothetical curve C. The simplest way to calculate N(r) is to divide the E-dimensional image space into a grid of boxes with size length r and count the number of non-empty boxes.

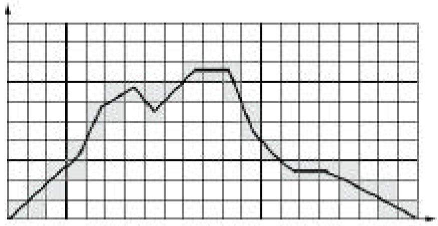

Figure 2 Box counting algorithm for a curve C

The box counting method permits to define the fractal dimension as in equation (1). If the profile being sampled is a fractal object, then N(r) should be proportional to r^{-d}, i.e. the following relation should be satisfied: $N(r) = \beta r^{-d}$, where β is positive constant.

Plotting the negative log of r against the log of N(r) produces one point on the plane $\{-\ln(r), \ln(N(r))\}$. For different box size r, a number of points are produced on log-log plane. The dimension d can be estimated from the slope of the linear regression straight line of these points. Figure 3 shows the logarithmic regression to find dimension.

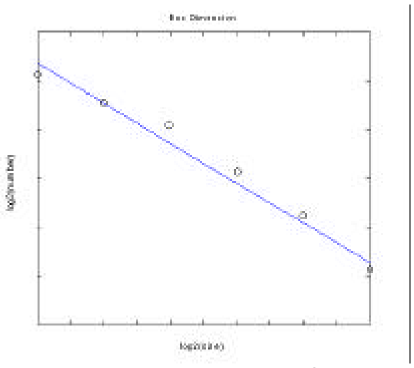

Figure 3 Logarithmic regression to find dimension

4. Rough Sets

Information systems (sometimes called data table, attributes value system, condition-action table, knowledge representation systems) are used for representing knowledge. Rough sets [6, 7] have been introduced as a tool to deal with inexact, uncertain or vague knowledge in artificial intelligence applications. The idea of rough sets works with lower and upper approximations they are interior, and closure operations in a certain topology as shown in Fig. 4. They are generated by available data about the elements of the set. In other words, the rough set approach is based on the ability to classify data obtained from observation and from measurements.

4.1. Information Systems

An information system can be expressed as a pair S = (U, A). Where U is a nonempty, finite set of objects known as the universe, and A is a finite of attributes. For every element there exist a set of its values known as a domain of *a*, denoted as V_a. For every attribute $a \in A$ (*a* belongs to A), there exists a function u: $U \to V_a$, which assigns a unique attribute value from V_a to every object $x \in U$. Now consider subsets of attributes $B \subseteq A$, where B uniquely defines equivalence relations.

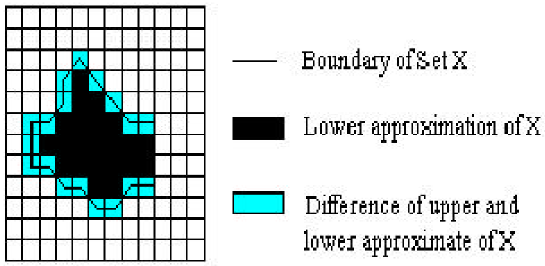

Figure 4 Rough approximation.

$$IND(B) = \{(x,y) \in U^2 : a(x) = a(y) \text{ for every } a \in B)\} \quad (3)$$

The family of all equivalence classes of the equivalence relation IND (B) is denoted U/IND(B). With every $X \subseteq U$, and $B \subseteq A$ we associate two sets defined as follows:

$$\underline{B}X = \cup \{ Y \in U/IND(B): Y \subseteq X\} \quad (4)$$

is the lower approximation or positive region of X, and

$$\overline{B}X = \cup \{Y \in U/IND(B): Y \cap X \neq \phi\} \quad (5)$$

is the upper approximation or possible region of X.

A set $BN_B(x) = \overline{B}X - \underline{B}X$ will be called B-boundary of X.

4.2. Core and Reduction of Attributes

The set of attributes in the information system describes objects in the system. We use the set of attributes to classify the objects into classes that are determined by anywhere from one to several attributes. Sometimes it happens that the set of attributes provides more information about objects that is needed to distinguish them. In such a situation some of the attributes may be reduced without losing the ability to group the objects.

4.3. Decision Rules

We can obtain the decision rules from an information system or a reduction of condition attributes. Some condition values may be unnecessary in the decision rules, so we can remove them from the rules or change them into "don't care" values. The process of conditional values removed is called values reduction.

Let S = (U, A, C, D) be an information system with n objects, where U is a finite set of objects, A is a set of attributes further classified into disjointed condition attributes C and decision attributes D, A = C U D, $V = \cup V_a$, V_a is the domain of the attribute $a \in A$. Hence, decision rules are often presented as implications and are often called "If ... Then …" rules. If a, b, c, d are the condition attributes of set A, D is decision attribute.

5. Classification

We propose a two-stage pattern classification method based on the ring projection. After obtaining the ring projection values, we compute the fractal dimension of the five subintervals of the ring projection curves. The fractal dimension can be obtained by counting the number of boxes covering the boundary of the curve for different r sizes in each interval r_i. So, we have five fractal dimension attributes of each character.

5.1 Coarse classification

After segmentation of Thai characters from the sentence, we compute the ring projection values of each character, and divide these values into five subintervals. Then, the fractal dimension of each interval is computed. The procedure of applying decision table techniques can be described the following step:

Step: 1

The first step of the algorithm is to redefine the value of each fractal dimension attribute as shown in Table 1. In Table 1 contains the attributes represented by the set $\{d_1, d_2, \ldots, d_5\}$ and the decision D, where $d_1, d_2, \ldots, d_5$ are the typical range in each subinterval of ring projection vectors. By the consideration of the typical ranges of the fractal dimension attributes, we may classify them into nine possible output $D_1, D_2, \ldots, D_9$ for the first step of coarse classification.

Table 1 Example of database with range values

Ch.	d_1	d_2	d_3	d_4	d_5	Dec.
ก	VS	M	S	M	M	D_7
ก	VS	M	S	M	M	D_7
ก	VS	M	L	M	S	D_9
…	…	…	…	…	…	…
ฆ	M	L	M	M	M	D_9
ฆ	M	M	L	M	S	D_3
ฆ	L	M	M	M	S	D_6
…	…	…	…	…	…	…
ฮ	S	S	S	M	S	D_1
ฮ	S	S	M	L	M	D_2
ฮ	S	S	M	M	S	D_1

Step2:

The next step of the algorithm is to verify if any attribute can be eliminated by repetition. In table 1, it can be verified that it does not occur.

Step 3:

In this step, many examples are identical. The examples are merged.

Step 4:

The next step verifies if the decision table contains only indispensable attributes. This task can be accomplished eliminating step-by-step each attribute and verifying if the table gives the correct classification.

Step 5:

The core set of examples is computed. We can eliminate each attribute step-by-step and verify if the decision table continues to give the correct answer.

Step 6:

This step computes the reducted set of relations that conserve the same inductive classification of the original set of examples. Table 2 illustrates the calculation of reduct rules.

Step 7:

According to the table 2, we can express the knowledge existent in the table 2 by the following set of rules.

d_1 (VS) d_2 (M) d_5(M) $\Rightarrow$ D_7 (rule 1)
d_1(S) d_2 (M) d_5(S) $\Rightarrow$ D_9 (rule 8)
……………….. **…………...**
d_1 (L) d_2 (M) d_5(M) $\Rightarrow$ D_4 (rule 34)

Table 2 Reduct of the set of examples

No.	Attributes			Dec.
	d_1	d_2	d_5	
1	VS	M	M	D_7
2	VS	M	VS	D_9
3	VS	M	S	D_9
4	S	S	S	D_1
5	S	S	M	D_2
6	S	VS	S	D_5
7	S	L	0	D_9
7'	0	L	M	D_9
8	S	M	S	D_9
9	S	VS	M	D_5
10	S	VS	VS	D_4
11	M	S	M	D_5
12	S	S	VS	D_3
13	L	S	M	D_5
14	L	M	S	D_6
15	M	M	S	D_3
16	M	L	0	D_9
16'	0	L	M	D_9
17	L	S	S	D_4
18	M	S	S	D_4
19	M	VS	0	D_5
20	M	M	M	D_1
21	M	S	VS	D_6
22	VS	S	S	D_7
23	S	M	M	D_7
24	VS	S	M	D_8
25	L	0	VS	D_6
26	S	M	VS	D_9
27	VS	L	0	D_9
28	L	L	0	D_3
29	S	L	0	D_9
30	M	M	VS	D_3
31	VS	VS	VS	D_1
32	VS	VS	S	D_2
33	VS	VS	M	D_2
34	L	M	M	D_4

5.2 Fine classification

In this stage, we must classify characters in each class using the max-min boundaries of ring projection of each character. To set up the object's attributes from the ring projection vectors that r = 1, 2, 3, …, 100 (total 100 values) for attributed a_1, a_2, a_3, …, a_{100} respectively. So, we have 100 attributes for each character at this stage. From all sets of attributes using the same character, we find the maximum value of attributes a_1, a_2, a_3, …, a_{100} and also to find the minimum value of the attributes. We use these sets of maximum and minimum values of attributes as the boundaries for the fine groups of these characters. In the decision rules, the answer is considered from the matching of the number attributes which are on the boundaries of an attributes set. The groups have only one member, this classification is the final recognition. Some cases are not good enough for the aim of clustering because this cannot separate some characters in each group. It is necessary to separate these characters by applying ring projection to explicit ring areas of similar characters in the same group.

6. Experimental Study Results

In our experiments the learning sets consist of 1,392 training characters (four fonts, four sizes in each font). The largest characters have 28x28 pixels. The smallest characters have 14x14 pixels. The decision rules in coarse classification can be obtained directly from the reduction of the set of examples in Table 2. In the fine classification, we compute making-decision from a set of attributes that have one hundred condition max-min attributes based on the total pixels in a ring projection of each group character. The unknowns used in this experiment are 5,568 Thai characters tested with 4 fonts that have 4 different sizes, and 4 rotations for each size. The results of these experiments have consistently shown 95 % accuracy recognition rate from images with size between 28×28 and 22×22 pixels. The performance of the model decreases slightly for smaller characters.

7. Conclusion

This paper investigated ring projections, fractal dimension, and rough set theory in an invariant printed Thai characters recognition system. In particular we emphasize character invariant with respect to translation, rotation and scale differences in input character images. The problem of invariance is difficult because of the large number of training samples for which the classifier needs to be trained. The ring projection method is invariant to rotation, translation and scales, which are based on the total number of foreground pixels as distributed along circular rings. The fractal dimension method is used to calculate the geometrical complexity of ring projection curves, which depend on the size of box. In the experiment, we use the set of fractal dimension attributes to generate decision rules about the character on the basis of training examples. A rough rule-based system is used to classify the characters into coarse classes. The next step, we use the decision-making of max-min boundaries to classify the characters in each coarse class from the other. A new development method can be recognized the character invariance to size, translation and rotation respectively. This method takes advantage of properties of ring projection, fractal dimension and rough set theory. We evaluated the system accuracy with the ideal Thai characters that have different fonts, different sizes, and different orientations. The results when applied the system to the unknown characters show an average recognition rate of 95% accuracy. This correspondence shows that the rough sets can be applied to invariant Thai character recognition with good results.

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