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Penmanship Learning Support System: Feature Extraction for Online Handwritten Characters

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Abstract. This paper proposes a feature extraction method for online handwritten characters for a penmanship learning support system. This system has a database of model characters. It evaluates the characters a learner writes by comparing them with the model characters. However, if we prepare feature information for every character, information must be input every time a model character is added. Therefore, we propose a method of automatically extracting features from handwritten characters. In this paper, we examine whether it correctly identifies the turns in strokes as features. The resulting extraction rate is 80% and in the remaining 20% of cases, it extracted an area near a turn.

Keywords: Penmanship, Evaluation of characters, Features, Turns

1 Introduction

Classes and correspondence courses on penmanship are very popular. In the penmanship classes, the learner attends there regularly. Therefore, the time to attend there is needed, and it is not suitable for a busy person. In a correspondence course, the learner learns the shape and balance of a character according to a model character in the text and the accompanying explanation at favorite time. Afterward, the learner sends the teacher his fair copy of the character, and the teacher corrects it and sends the result back to the learner. This is the general flow of a correspondence course, which lacks real-time feedback due to the time required for sending materials. Therefore, we developed a penmanship learning support system that automatically evaluates characters. The purpose of this system is to reproduce the environment of the penmanship classroom at home. In other words, the learner can learn penmanship freely without being limited in place and time. In this research, we extract features from the model character and that produced by the learner. We then evaluate the characters by comparing the length of features and the angles between them. In this paper, we describe the feature extraction method. We want to extract the beginnings, endings, turns, and curves of the strokes. We do not describe the hardware and software here because we describe them in [1].

2 Feature Extraction

The character data has coordinates at 10 ms intervals. We call each of the points located at these intervals a Point. We extract the points that become feature candidates from the Points and then define the selected Points as features.

First, we describe the method of extracting the points that are feature candidates. It can be divided into three stages. In the first stage, we let the beginning and ending points P_B and P_E , respectively, of the stroke be feature candidates. In the second stage, we search for the feature parts. We describe the procedure below.

1-1. Replace P_B with a base point P_b .

1-2. Replace the second Point from P_b with a moving point P_m .

1-3. For all Points that exist between P_b and P_m , evaluate the distance D_P between it and the straight line $P_b P_m$. Evaluate the Point P_{\max} and the distance D_{\max} for which D_P is the maximum.

1-4. If D_{\max} is more than δ_1 (which is 2 in this paper), let P_{\max} be a feature candidate point. Replace P_{\max} with P_b . If the second Point from P_b is P_E , end. Otherwise, move to step 1-2.

1-5. Otherwise, P_m is moved to the following Point. If P_m is P_E , end. Otherwise, move to step 1-3.

In the third stage, we let the turns in a stroke be feature candidate points. We show the extraction method below.

2-1. Evaluate $\angle FC_i P_{ij} FC_{i+1}$ of the adjoining feature candidate points FC_i , FC_{i+1} and Point P_{ij} that exists between them. ($1 \leq i \leq N_{FC} - 1$, $1 \leq j \leq N_P$; N_{FC} is the number of feature candidate points, and N_P is the number of Points that exist between FC_i and FC_{i+1} .)

2-2. For all j , find P_{ij} satisfying $\angle FC_i P_{ij} FC_{i+1} < \delta_2$. (δ_2 is a threshold; a value of 100 is used in this paper.) If it is not found, move to step 2-5.

2-3. Let distance $D_{P_{ij}}$ denote the minimum of the two distances between FC_i and P_{ij} and between FC_{i+1} and P_{ij} .

2-4. Let P_{ij} for which $D_{P_{ij}}$ is the maximum be feature candidate points.

2-5. For all i , repeat steps 2-1 to 2-4.

Next, we describe the method of deleting an unnecessary feature candidate point. We examine three consecutive feature candidate points FC_{i-1} , FC_i , and FC_{i+1} and delete FC_i that matches the following deletion condition:

3-1. $\angle FC_{i-1} FC_i FC_{i+1}$ is more than 100° .

3-2. The distance between FC_i and the straight line $FC_{i-1}FC_{i+1}$ is less than seven pixels.

3 Experimental Results

We extracted features from the 46 hiragana characters. Fig. 1 shows an example of the resulting feature extraction from three characters. Table 1 shows the resulting extraction of turns in strokes.

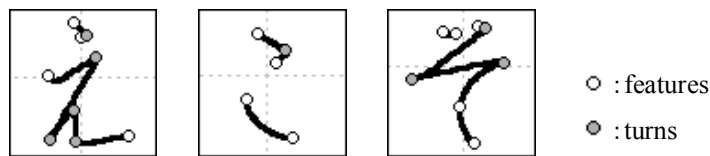


Fig. 1. Example of feature extraction result (“え,” “こ,” and “そ” from the left).

Table 1. Feature extraction of turns in strokes.

Number of turns in strokes	Number of extractions	Extraction rate (%)	Average distance of the error extraction (pixel)
80	64	80	1.88

The average distance of the error extraction is the average of the difference in the distance between the turns of 16 features extracted by mistake and the actual features. It can be said that the turns will almost be extracted because they are gaps of less than two pixels.

4 Summary

In this paper, we proposed a feature extraction method for online handwritten characters and examined the turns in strokes that it extracted. The resulting extraction rate is 80%. In the remaining 20% of the cases, it has extracted the area near a turn in a stroke (the average error distance is 1.88 pixels).

References

1. Sawamoto, T., Hayano, Y., Muranaka, N., Tokumaru, M.: The Penmanship (script learning) Support System, Human Interface Symposium 2008, pp. 383—388 (2008) (in Japanese)