An Interactive Grading and Learning System for Chinese Calligraphy

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Abstract

Chinese calligraphy is an oriental art. In this paper, an interactive calligraphic guiding system is rst proposed to grade the score of written characters by using the image processing and the fuzzy inference techniques. The written documents are automatically segmented. Three quantized features, the center, the size and the projections of each written character, are extracted to measure the score of calligraphy. Through this useful system, users could learn and practice Chinese calligraphy at home.

I. Introduction

Calligraphy is the art of writing Chinese characters. It originated at least four thousand years ago. The Chinese term 'Shufa' means 'the method of writing'. Now, teachers still teach calligraphy interactively in class. They teach students how to hold and wield the brush to write graceful characters. In order to write a graceful calligraphic character, eight skills should be learned through practice. Eight basic strokes – dot, dash, perpendicular downstroke, left-falling stroke, right-falling stroke, hook, upstroke to the right, and twist strokes – are included in the character 'YUN' of the 'Kai' font. They are the elementary skills in learning Chinese calligraphy[1].

In addition of the writing skills, there are four material components – brush, ink stick, paper, and ink slab – used in writing calligraphic characters. They are also referred to as 'four treasures of study'. More importantly, the standard specimens are of essential importance for novices. Thousand of rubbings of inscriptions copied from stone tablets are used as the writing specimens. Users imitate the characters from specimens to practice their handwriting. They can choose the specimens depending on their preference. Vast amounts of copybooks should be prepared for the imitation during practice calligraphy.

In this paper, an interactive calligraphic guiding system is rst proposed. The written characters are graded using image processing and fuzzy inference techniques. In addition, specimen documents are generated by computer with 5401 frequently used characters in various fonts such as the 'Kai' or 'Ming' fonts. These characters in various fonts are all written by calligraphers. In addition, the system also provides some improving instructions for users, who can practice calligraphy by using this system at home.

The architecture of the calligraphic grading system is designed as shown in Fig. 1. First, twelve characters are segmented from the paper with red mesh patterns using image processing techniques[2]. Three types of features, including the character center, the character size, and the projection of the character, are extracted to calculate the scores of calligraphy. These scores are inputted to a fuzzy system to obtain the grade of a character.

II. Image Preprocessing

Chinese calligraphic characters are frequently written on a coarse paper such as Xuan paper. Red grid patterns are printed on Xuan papers to imitate the standard calligraphic characters in specimens. Users write a Chinese calligraphic character within a region of 3 by 3 squares. These grids are referred as 'nine gong ge', 'nine red grids', or region of interest(ROI). In this section, calligraphic characters are segmented from the written document image using the following four steps.

Step 1: ROI Location

Users write twelve characters on a coarse paper. This paper is digitized to obtain an image by digital camera as shown in Fig. 2(a). Since the regular grids are usually printed in red color, they are easily obtained by detecting the speci ed patterns. Consider the color values of a pixel $\{R(x,y), G(x,y), B(x,y)\}$, if value $R(x,y)$ is larger than both values $G(x,y)$ and $B(x,y)$, pixel (x,y) is set to a grid pixel. The grid images are projected into X and Y axes to obtain the pro les as shown in Figs. 2(b) and 2(c). The red lines are found by identifying the location of a peak whose value is larger than $2\overline{m}$ in the projection pro le, where value $\overline{m}$ is the average number of grid pixels in the pro les. Ten peaks in X axis and thirteen peaks in Y axis are detected from the image.

Step 2: Thresholding

Twelve block images, e.g., ROIs, are segmented out in the previous step. An illustrated example is shown in Fig. 2(c). The second step is to nd out the calligraphic character from an ROI. The calligraphic characters written in black color embed in 3 by 3 red grids. Automatic thresholding to segment out the foreground objects has been proposed in literature[3], [4], [5], [6]. The most popular thresholding method, proposed by Otsu[3], is adopted in this study to choose the best threshold value. This method can minimize the within-group variance of the two groups of pixels that are separated by the threshold value. After analyzing the images with Otsu's method, the threshold value is selected to be 90. Thus, the pixel (x, y) whose color data $(R(x, y) + G(x, y) + B(x, y))/3 < 90$ is set to a character pixel, i.e., $(x, y) \in I$.

Step 3: Noise Removal

The prepared Chinese ink is sometimes dropped on the paper during the writing of calligraphic characters. Some noise exists in the segmented character image due to dropped ink. Here, two morphological operations, opening and closing, are performed on the thresholded images to eliminate and lter the noise. These two operations are composed of two basic morphological operations, i. e., dilation and erosion. The ltered result is displayed in Fig. 2(c).

Step 4: Calibration of ROI

In traditional optical character recognition(OCR), character normalization is an essential step. A character image is clipped to a bounding rectangle that includes the whole character pixels. It is next normalized to the size of a speci ed template in database. However, the character image cut from document images should be normalized to the size of ROI in a calligraphy assessment system. Users should write a calligraphic character within an ROI with proper size. Characters that are too small or too large are not graceful characters. In this step, all written characters and the corresponding template characters are calibrated to be the same size of ROI. In image processing module, each isolated character is segmented out from the documents.

III. Assessment Features

In class, teachers judge or grade calligraphic characters based on stroke distribution and structural balance. The grading rules are summarized in six points as listed below.

1) horizontality: The horizontal strokes should be written levelly and atly, e.g., characters '三', '王', and '主'.
2) verticality: The perpendicular strokes of characters are written uprightly, e.g., characters ' ', '卜', and ' '.
3) parallelism: The strokes of characters are parallel to each other, e.g., '勿' and ' '.
4) symmetry: The structure of Chinese characters is symmetric. E.g., characters '中', '華', and '士'.
5) uniformity: The strokes of characters are uniformly distributed within 3 by 3 grids, e.g., characters '資' and '訊'.
6) equality: The area of radical block is equal. For example, characters '品', '田', and ' ' satisfy this rule.

In this section, three types of assessment features, including the center of character, the size of character, and the projections of character, are devised. The quantized features are extracted for evaluating writing skills by computers.

Consider a written character image I and the corresponding template image T. Many types of membership functions(MFs) such as the triangular, the trapezoidal, the gaussian, the bell-shaped, or the sigmoidal membership functions are utilized to measure the membership of features, e.g., variables or fuzzy variables. In this study, the triangular MF $\Delta(x : a, b, c)$ can be speci ed by three parameters $\{a, b, c\}$ as follows:

$$\Delta(x : a, b, c) = \begin{cases} 0 & x < a \\ (x-a)/(b-a) & a \le x \le b \\ (c-x)/(c-b) & b \le x \le c \\ 0 & x > c \end{cases} \tag{1}$$

Similarly, another two kinds of linear MFs are also devised to measure writing skills. They are generally speci ed by two parameters as de ned below.

$$\Gamma(x : a, b) = \begin{cases} 1 & x < a \\ (b-x)/(b-a) & a \le x \le b \\ 0 & x > b \end{cases} \tag{2}$$

$$\Lambda(x : b, c) = \begin{cases} 0 & x < b \\ (x-b)/(c-b) & b \le x \le c \\ 1 & x > c \end{cases} \tag{3}$$

These three MFs are shown in Fig. 3(a).

A. The Center Feature

The center of a character is indicative of the balance of character structure in visualization. The center of a written character I and that of the template character T can be easily obtained from the following equation.

$$(\overline{x}_C, \overline{y}_C) = \frac{1}{|C|} \sum_{(x,y) \in C} (x, y). \tag{4}$$

Here, value $|C|$ is the numbers of character pixels of character C. The distance between two centers $(\overline{x}_I, \overline{y}_I)$ and $(\overline{x}_T, \overline{y}_T)$ is used to measure the visual balance of a character as designed below.

$$F_C = \frac{\sqrt{(\overline{x}_I - \overline{x}_T)^2 + (\overline{y}_I - \overline{y}_T)^2}}{\frac{1}{2}W} \tag{5}$$

Here the maximum distance between two centers is $\frac{1}{2}W$. Value W is de ned to be the width of a character image. This feature F_C is adopted for the uniformity assessment of a written character. It is inputted the fuzzy system with a set of two linguistic terms $\Omega_{F_C} = \{$'near', 'far'$\}$. The linear MFs for Ω_{F_C} are designed in the following equations.

$$\begin{aligned} \mu_{near}(x) &= \Gamma(x : 0.1, 0.9); \\ \mu_{far}(x) &= \Lambda(x : 0.1, 0.9). \end{aligned} \tag{6}$$

B. The Size Features

As stated in section 2, characters with proper size are graceful. The ROI of a written character I and that of the template character T are calibrated in the image processing module. Thus, the size of the bounding rectangle of a character is also an effective assessment feature. Consider the bounding rectangle of character I and that of character T being of sizes (w, h) and (w', h'), respectively. The size feature includes two parts: the area of bounding rectangle and the ratio of the width over the height, as de ned in the following formula.

$$F_A = \frac{wh - w'h'}{w'h'}, \text{ and } F_R = w/h - w'/h'. \quad (7)$$

The MFs of fuzzy variable F_A with term set $\Omega_{F_A} = \{$'small', 'proper', 'large'$\}$ are de ned as follows.

$$\begin{aligned} \mu_{small}(x) &= \Gamma(x : -1, 0); \\ \mu_{proper}(x) &= \Delta(x : -0.4, 0, 0.4); \\ \mu_{large}(x) &= \Lambda(x : 0, 1); \end{aligned} \quad (8)$$

Similarly, the MFs of fuzzy variable F_R with term set $\Omega_{F_R} = \{$ 'tall', 'proper', 'short'$\}$ for the ratio feature are extracted in the following equations.

$$\begin{aligned} \mu_{tall}(x) &= \Gamma(x : -0.5, 0); \\ \mu_{proper}(x) &= \Delta(x : -\frac{1}{6}, 0, \frac{1}{6}); \\ \mu_{short}(x) &= \Lambda(x : 0, 0.5). \end{aligned} \quad (9)$$

From the above de nitions, the area feature F_A is used for the measurement of equality in writing skills, and the ratio feature F_R is adopted for the uniformity assessment.

C. The Projection Features

The assessment of character strokes is an essential step in grading the written calligraphic characters. However, it is very dif cult to automatically and precisely segment out each stroke from a character through computer algorithms. In this section, three statistical features are devised to measure the properties of strokes. The rst two projection features are used for the measurement of the horizontality, verticality, and parallelism properties of character strokes. In addition, a symmetry feature is used to measure symmetry.

Assume that a character includes horizontal strokes. The character generates the projection peaks in a small range in Y axis. Similarly, vertical strokes generate the obvious projection peaks in X axis. However, if the vertical or horizontal strokes are slanted in writing, the peaks are not apparent. Based on the observation, if the written strokes are consistent with those of the template characters, the differences between two projections both in X and Y axes must be small.

The projections of a written character I in X and Y axes are represented as $P_I(x)$ and $P_I(y)$, respectively. Similarly, the projections of the corresponding template character T are denoted by $P_T(x)$ and $P_T(y)$. The differences between two projections in X and Y axes are formulated as

$$\begin{aligned} D_x &= \frac{\sum_{x=1}^{w} |P_I(x) - P_T(x)|}{\sum_{x=1}^{w} [P_I(x) + P_T(x)]}, \\ D_y &= \frac{\sum_{y=1}^{h} |P_I(y) - P_T(y)|}{\sum_{y=1}^{h} [P_I(y) + P_T(y)]}. \end{aligned} \quad (10)$$

For example, a character 'men'(door) as shown in Fig. 4 is a symmetrical character. The projections of the template character are drawn in black color, and those of the written character are drawn in red color. The differences between the projections are pointed out by arrows.

Two features D_x and D_y are both fuzzy variables with term sets $\Omega_{D_x} = \{$'less', 'much'$\}$ and $\Omega_{D_y} = \{$'less', 'much'$\}$, respectively. Their MFs of the same forms are both de ned in Eq. (11).

$$\begin{aligned} \mu_{less}(x) &= \Gamma(x : 0.1, 0.9); \\ \mu_{much}(x) &= \Lambda(x : 0.1, 0.9). \end{aligned} \quad (11)$$

In addition, the symmetry feature F_S is de ned for the symmetrical characters.

$$F_S = \left| \sum_{x=1}^{w/2} [P_I(x) - P_I(w - x)] \right| - \left| \sum_{x=1}^{w/2} [P_T(x) - P_T(w - x)] \right|. \quad (12)$$

The linguistic terms for fuzzy variable F_S are de ned to be a set $\Omega_{F_S} = \{$'left', 'proper', 'right'$\}$. The MFs for Ω_{F_S} are designed in Eq. (13). This feature is devised for the assessment of symmetrical properties depending on the structure of Chinese characters.

$$\begin{aligned} \mu_{left}(x) &= \Gamma(x : -1, 0); \\ \mu_{proper}(x) &= \Delta(x : -0.4, 0, 0.4); \\ \mu_{right}(x) &= \Lambda(x : 0, 1). \end{aligned} \quad (13)$$

IV. Fuzzy Assessment System

The core techniques for fuzzy theory are based on three basic concepts: (1) fuzzy set; (2) linguistic variables; (3) fuzzy if-then rules. In this section, these techniques will be described for building up a calligraphy assessment system.

The assessment system is composed of two stages. In the rst stage, the writing skills of strokes are assessed based on the assessment features explained in the previous section. Three scores are computed out and integrated together to obtain the character structural score in stage II. They are both based on the fuzzy rule inference techniques as described in the following contexts.

Stage I: Stroke Assessment Stage

The assessment features are extracted by using image processing techniques. The fuzzy sets and MFs of linguistic variables are well de ned in section 3. Here, the MFs of two terms 'low' and 'high' for the output variables are devised. Next, we will de ne the fuzzy rules and the defuzzi cation step to obtain the score of each feature.

Three consequent types of fuzzy rules – crisp consequence, fuzzy consequence, and functional consequence – are frequently used in the inference process. In this study, the fuzzy consequences of rules are designed to measure the score of assessment features as listed in Table (I). The clipping method and the center of area(COA) defuzzi cation rules are utilized in the inference and the defuzzi cation processes, respectively. The discrete output result of applying COA defuzzi cation can be expressed as $x = \sum_i \mu(x_i) \cdot x_i / \sum_i \mu(x_i)$.

After the defuzzi cation step, six scores for assessment features are obtained and expressed as S_C, S_A, S_R, S_{D_x}, S_{D_y}, and S_S. Consider the rst feature, the center of a character, F_C, the assessment score S_C is easily calculated to be $S_1 = S_C$ based on the fuzzy rules RC1, RC2, and the COA defuzzi cation method. Using rules RA1 to RA3, RR1 to RR3, two sub-features, the area F_A and the ratio F_R features of a character, are extracted to obtain the scores S_A and S_R, respectively. These two features are combined together with the same weights to generate a score $S_2 = (S_A + S_R)/2$. Similarly, three features, D_x, D_y, and F_S, are also integrated by averaging three scores in the same weights, i.e., $S_3 = (S_{D_x} + S_{D_y} + S_S)/3$.

The score, or grade, is assessed in the rst stage of fuzzy grading system. More importantly, the instructions should be given to help users improve their writing skills. In this study, the instructions for each written character are generated based on the assessment features. Since the score of each assessment feature is normalized to a range of $[0, 1]$, i.e., $S_C, S_A, ..., \in [0, 1]$ the quanti ed data in the improvement instruction is thus de ned as $(1 - S) * 100\%$. For example, if the score of the center feature F_C is calculated to be $S_C = 0.8$, the improvement instruction for this assessment feature is generated to suggest users as 'The center of your written character should be nearer to the center of the standard character by 20%.'

Stage II: Character Assessment Stage

As mentioned in the previous section, three assessment scores S_1, S_2, and S_3 are computed out in stage I. These three scores are adopted to be the linguistic variables of the fuzzy grading system in stage II. In this study, all the fuzzy sets(e.g., set {'very low', 'low', 'average', 'high', 'very high'}) of three linguistic variables and their corresponding MFs are the same forms as shown in formula (14).

$$\begin{aligned} \mu_{very\ low}(x) &= \Gamma(x : 0.3, 0.4); \\ \mu_{low}(x) &= \Delta(x : 0.3, 0.4, 0.5); \\ \mu_{average}(x) &= \Delta(x : 0.4, 0.5, 0.6); \\ \mu_{high}(x) &= \Delta(x : 0.5, 0.6, 0.7); \\ \mu_{very\ high}(x) &= \Lambda(x : 0.6, 0.7). \end{aligned} \tag{14}$$

Next, the linguistic terms used in the grading module are de ned as a term set of ve elements Ω_O = {'poor', 'marginal', 'average', 'good', 'excellent'}. The MFs for these terms are de ned in Eq. (15).

$$\begin{aligned} \mu_{poor}(x) &= \Gamma(x : 30, 40); \\ \mu_{marginal}(x) &= \Delta(x : 30, 40, 50); \\ \mu_{average}(x) &= \Delta(x : 40, 50, 60); \\ \mu_{good}(x) &= \Delta(x : 50, 60, 70); \\ \mu_{excellent}(x) &= \Lambda(x : 60, 70). \end{aligned} \tag{15}$$

As mentioned in [7], the fuzzy rule-based inference consists of four steps: (1) fuzzy matching; (2) inference; (3) combination; (4) defuzzi cation. 125 fuzzy rules are devised in the second stage. The fuzzy matching is performed to obtain the matching degree for the conjunctive conditions. The fuzzy conclusions are combined by applying the '$\max$' fuzzy disjunction operator to the membership grades of an output variable. As same as the rules in stage I, the clipping method and the COA rules are used in the inference and the defuzzi cation processes again. Thus, the structural score of a character is calculated by this fuzzy grading system.

V. Experimental Results

The specimen documents are generated by computer with various character fonts such as the 'Kai' or 'Ming' fonts. These characters of various fonts are all written by calligraphers. They are registered with 'nine gong ge' and displayed on the monitor for imitating. A digitized image of size 1024×768 is grabbed by a CCD camera. This image is automatically processed by the proposed system. A grade and several instructions for each character are given by computer. Twelve characters are graded and averaged to obtain the score of a written document. Besides, they are also graded by three teachers. The assessment scores are classi ed into three ranks 'A', 'B', and 'C'. If the ranks of a document graded by computers and teachers are consistent, con dence in the proposed approach is high. The improvement instructions for every character are also given by computers.

To test the validity and effectiveness of our proposed method, 180 fth grade students from two elementary schools were requested to write the calligraphic characters. 45 students per school were randomly selected to use the proposed system once per week. These 90 students were made up experiment set I, to evaluate the proposed grading system. The other students were the comparison set, set II. Their written documents were only graded by teachers, without any instructions.

The grading results are analyzed to show the validity of proposed approach. The con dence levels for set I in two schools are 63.33% and 62.22% based on the ranks of documents. One month later, the con dence levels between the computerized system and human for schools I and II have improved to 67.78% and 71.11%, respectively. Moreover, a comparison between sets I and II is also made to show the score improvement of writing skills as shown in Table II. The

TABLE I

THE FUZZY RULES FOR VARIOUS LINGUISTIC VARIABLES.

Variables	Rules
F_C	RC1: IF feature x is near, THEN score S_C is high.
F_C	RC2: IF feature x is far, THEN score S_C is low.
F_A	RA1: IF feature x is small, THEN score S_A is low.
F_A	RA2: IF feature x is proper, THEN score S_A is high.
F_A	RA3: IF feature x is large, THEN score S_A is low.
F_R	RR1: IF feature x is tall, THEN score S_R is low.
F_R	RR2: IF feature x is proper, THEN score S_R is high.
F_R	RR3: IF feature x is short, THEN score S_R is low.
D_x	RPX1: IF feature x is less, THEN score S_{D_x} is high.
D_x	RPX2: IF feature x is much, THEN score S_{D_x} is low.
D_y	RPY1: IF feature x is less, THEN score S_{D_y} is high.
D_y	RPY2: IF feature x is much, THEN score S_{D_y} is low.
F_S	RPS1: IF feature x is left, THEN score S_S is low.
F_S	RPS2: IF feature x is proper, THEN score S_S is high.
F_S	RPS3: IF feature x is right, THEN score S_S is low.

scores of written documents for the users in set I guided by the system instructions are all prior to those of users in set II taught through the traditional method after one month.

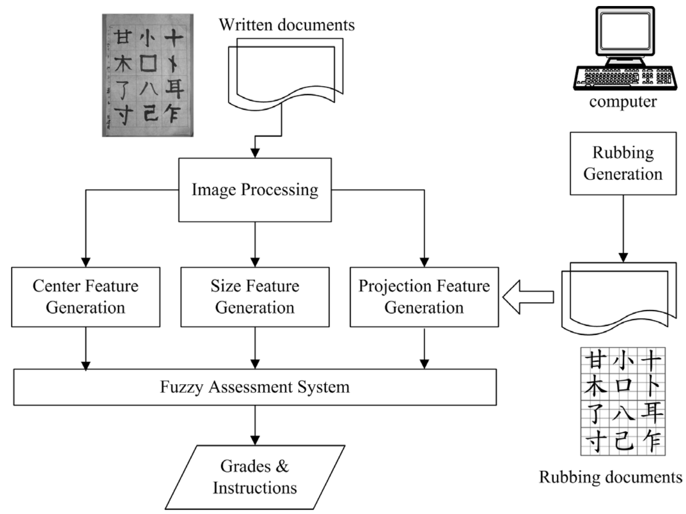


Fig. 1. The system architecture.

VI. Conclusions

In this paper, we have proposed an useful tool for learning Chinese calligraphy. The image processing and fuzzy inference techniques are applied to automatically determine the score of a written document. In addition, instructions are also provided to improve writing skills. This system increases students' interest and improves their writing skills.

Acknowledgements

This work is partially supported by Chung-Hua University under grant no. CHU-TR-004.

References

[1] B. Guo, *Gate to Chinese Calligraphy*. Beijing: Foreign Languages Press, 1995.

[2] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*. Addison-Wesley, 1992.

[3] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Trans. System, Man, and Cyber.*, vol. 9, pp. 62–66, 1979.

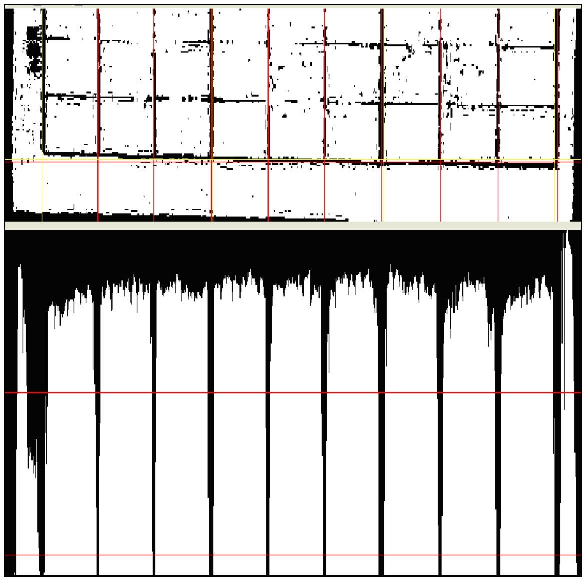
[4] J. Kittler and J. Illingworth, "Minimum error thresholding," *Pattern Recognition*, vol. 19, pp. 41–47, 1986.

[5] S. Cho, R. M. Haralick, and S. Yi, "Improvement of kittler and illingworth's minimum error thresholding," *Pattern Recognition*, vol. 22, pp. 609–617, 1989.

[6] P. K. Sahoo *et al.*, "A survey of thresholding techniques," *Computer Vision Graphics and Image Processing*, vol. 41, pp. 233–260, 1988.

[7] J. Yen and R. Langari, *Fuzzy Logic: Intelligence, Control, and Information*. Prentice Hall, 1999.

(a)



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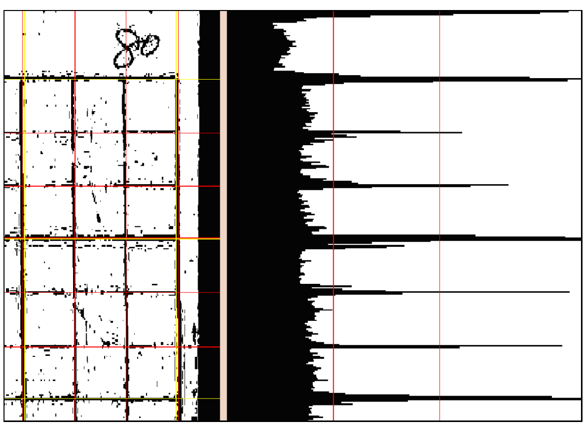

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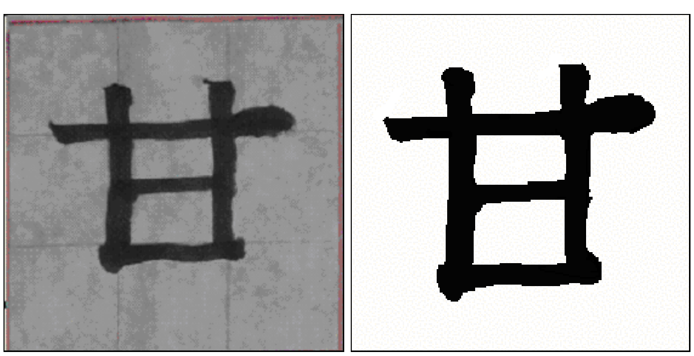

(d)

Fig. 2. The image processing module. (a) The original image, (b) the horizontal projection for grid pixels, (c) the vertical projection for grid pixels, and (d) the gray character image and the ltered result.

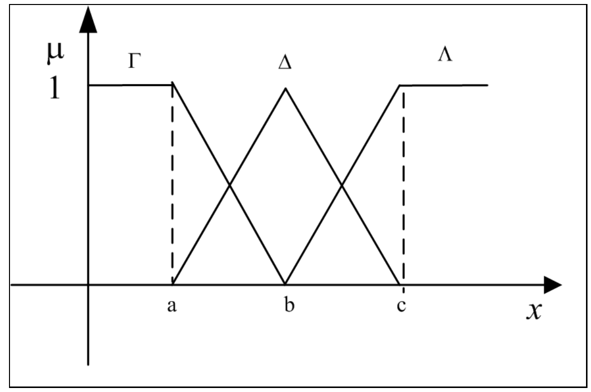

Fig. 3. The membership functions for the designed linguistic variables.

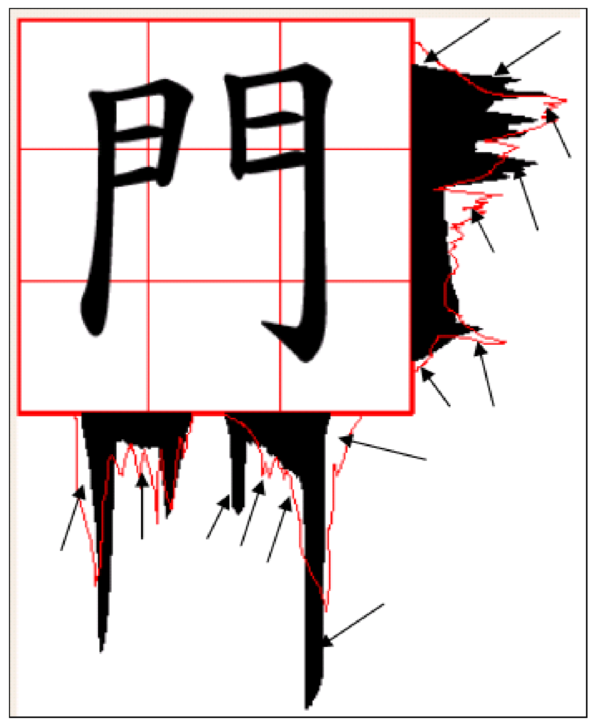

Fig. 4. An example for the projection assessment features.

TABLE II

THE IMPROVEMENT OF WRITING SKILL AFTER USING THE PROPOSED SYSTEM.

Schools	Sets	By teachers		By systems	
		Before	After	Before	After
I	I	81.11	90.09	67.79	73.0
I	II	80.49	82.6	66.58	66.33
II	I	82.39	89.71	69.27	75.29
II	II	81.86	83.3	68.33	68.92