Exploiting Gabor Feature Extraction Method for Chinese Character Writing Quality Evaluation

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Abstract. The automatic evaluation of Chinese character writing quality has a wide application prospect. Most of the existing evaluation methods of Chinese character writing quality are based on radical segmentation and feature judgment, which require the high accuracy of Chinese character segmentation. However, there are many problems in the real handwriting, such as continuous writing, uneven strength of writing, personalized writing style and so on, which lead to the difficulty of segmentation in the ordinary handwriting. To solve the above problems, we propose an effective method based on image texture where the uniformity of writing lines and writing style is taken as an effective criterion. In our method, Gabor transform is used to extract the image features of writing samples, and finally the statistical learning method of support vector machine is used to effectively evaluate the writing quality. Experiments on multiple real datasets including CHAED show that our method is effective and accurate. The advantage of this method is that it does not need to segment fonts, and the cost of global feature extraction is small.

1. Introduction

At present, calligraphy research based on image analysis plays an important role in the protection and popularization of Chinese traditional culture. There are quite a lot of research achievements in calligraphy, mainly focusing on the image denoising and enhancement of inscription[1-2], the retrieval of calligraphy font[3-7], the identification and evaluation of calligraphy style[8], the generation of specific style[9], and the evaluation of writing quality[10-11]. In essence, the core of many applications, such as calligraphy character retrieval, similar style retrieval, body recognition, style generation and so on, is the extraction of image features of fonts, including the unified features generated by hand-designed feature operators[12] and machine learning methods[13]. How to design the image characteristic operator which accords with the calligraphy characteristic intuitive feeling and the handwritten character characteristic expert evaluation, makes the evaluation result of machine and human consistent and interpretable, and has important theoretical research value for the high quality writing quality evaluation. In view of the defects of traditional writing quality evaluation methods, the feature descriptors are often only suitable for a certain font and style. The team led by Xiao Jianguo and others cut the Chinese characters according to the partial radicals, and then applied the aesthetic evaluation criteria, and achieved good results[14], but this method needs more radical segmentation and aesthetic evaluation rules. Recently, the team put forward a new model AGIS-Net to solve the problem of automatic generation of artistic pictograph image [15-16]. This model is a one-stage model,
which can transfer shape and texture style at the same time with only a few samples, and has achieved
good results. Although the results of the method based on image statistical characteristics are not well
explained, it is still an important research approach because of its wide adaptability and effective
evaluation. Wu, et al. applied this kind of method in the calligraphy character recognition [17] and the
body recognition [18], and obtained the good result. In this paper, Gabor feature is applied to the
evaluation of writing quality, and the texture features of Chinese characters are studied. SVM is
further applied to the evaluation, which is divided into two levels: excellent level and general level. It
is compared with the quality evaluation table scored by experts to form a new way for the quality
evaluation of handwritten Chinese characters.

2. Texture Feature Extraction of Chinese Characters Based on Gabor

Gabor filter is one of the main methods of image feature representation, which has good multi-scale
and multi-directionality. Biologists have proved that Gabor function can well simulate the response of
human visual cells when they are stimulated by the external environment. The key to the application
of Gabor filter lies in the selection of frequency, Gauss kernel size, direction and other parameters.
The Gabor function is defined as follows:

\[
W(t,t_0,\omega) = e^{-\omega^2(t-t_0)^2}e^{i\omega t}
\]  

(1)

Then, Gabor transformation can be expressed as:

\[
C(x(t))(t_0,\omega) = \int_{-\infty}^{\infty} x(t)W(t,t_0,\omega)dt
\]  

(2)

By substituting formula (1) into formula (2), we can get:

\[
C(x(t))(t_0,\omega) = \int_{-\infty}^{\infty} x(t)e^{-\omega^2(t-t_0)^2}e^{i\omega t}dt
\]  

(3)

After expansion of equation (3), we can get:

\[
C(x(t))(t_0,\omega) = \int_{-\infty}^{\infty} x(t)e^{\omega^2(t-t_0)^2}cos(\omega t)dt + i \int_{-\infty}^{\infty} x(t)e^{\omega^2(t-t_0)^2}sin(\omega t)dt
\]  

(4)

where \( C(x(t))(t_0,\omega) \) represents frequency domain information of the original signal \( x(t) \) at \( t_0 \) and \( \omega \),
which is a complex form and can be divided into real part and virtual part according to formula (5).

\[
C(x(t))(t_0,\omega) = \alpha_{\text{real}} + i\alpha_{\text{imag}}
\]  

(5)

Therefore, \( C(x(t))(t_0,\omega) \) can be expressed by amplitude \( \alpha \) and phase angle \( \varphi \) in polar coordinate
system:

\[
\alpha = \sqrt{\alpha_{\text{real}}^2 + \alpha_{\text{imag}}^2}
\]

\[
\varphi = \begin{cases}  
\arctan(\frac{\alpha_{\text{imag}}}{\alpha_{\text{real}}}) & \alpha_{\text{real}} > 0 \\
\pi + \arctan(\frac{\alpha_{\text{imag}}}{\alpha_{\text{real}}}) & \alpha_{\text{real}} < 0 \\
\frac{\pi}{2} & \alpha_{\text{real}} = 0 \text{and} \alpha_{\text{imag}} \geq 0 \\
-\frac{\pi}{2} & \alpha_{\text{real}} = 0 \text{and} \alpha_{\text{imag}} < 0 
\end{cases}
\]  

(6)

In essence, the texture feature extraction of Chinese characters is to make Gabor function convolute
the Chinese character samples. If the gray distribution of Chinese character image is \( I(z) \), the process
of convolution is expressed as follows:

\[
G_{\mu,\nu} (z) = I(z)^* \varphi_{\mu,\nu} (z)
\]  

(7)

\( G_{\mu,\nu} (z) \) is a complex number whose amplitude and phase are expressed by the following two formulas:

\[
M_{\mu,\nu} (z) = \sqrt{\text{Re}(G_{\mu,\nu} (z))^2 + \text{Im}(G_{\mu,\nu} (z))^2}
\]  

(8)

\[
P_{\mu,\nu} (z) = \tan^{-1}(\frac{\text{Im}(G_{\mu,\nu} (z))/\text{Re}(G_{\mu,\nu} (z))}{\text{Re}(G_{\mu,\nu} (z))}}
\]  

(9)
In view of the common Chinese character radicals are mainly in the four directions of horizontal, vertical, left and right, which exactly correspond to the Gabor filtering space $0, \pi/2, \pi/4, 3\pi/4$, it is only necessary to select these four directions for Gabor texture feature extraction of Chinese character image. The filtered image of the sample "Le" in the Chinese character library is shown in Figure 1. Then extract 5 scales and 4 directions of Chinese characters, select the frequency of Gabor filter as $f_{\text{max}} = 0.22$, and take half size of image size as the size of filter window, as shown in Figure 2 and Figure 3, which are the amplitude image and real feature obtained from experiment respectively.

The characteristics of a single Chinese character can represent the writing characteristics of the whole text and also reflect the writing level of the whole text. In this paper, the whole Chinese character is cut, all Chinese character samples are put together into a uniform size, and the features of 5 scales and 4 directions are extracted. After 20 filtered images are obtained, the mean $E = \frac{\sum_{i=1}^{n} x_i}{n}$ and variance $\Delta = \frac{\sum_{i=1}^{n} (x_i - M)^2}{n}$ are calculated by formula respectively, which are used as feature vectors.

![Figure 1. Four Characteristics of Word "乐(Le)" in Four Directions after Filtering](image1.png)

![Figure 2. amplitude characteristics of word "阿(a)" after filtering](image2.png)

![Figure 3. real part features of word "阿(a)" after filtering](image3.png)

3. Experiment and Analysis

3.1. Data Preparation

The experimental data of this paper comes from the CHAED font database compiled by SUN Rongju and others in the font Computing Technology Laboratory of the Institute of computer science and technology of Peking University. It contains 100 Chinese characters written by 30 people, and 10 writing methods are collected for each character to form a 1000 character font database, with 33 manual scoring data. As shown in Figure 4, examples of Chinese characters with different writing quality and different structures are shown.

![Figure 4. Examples of Chinese characters](image4.png)
3.2. Characteristic Measurement of Stroke Clarity and Symmetry

In this part, Gabor features are used to measure the symmetry of writing lines and the clearness of strokes. For good writing, the strokes are clear and the structure is symmetrical; for poor works, the strokes are not clear and the structure is not symmetrical due to the distortion of the strokes and the imbalance of the proportion. Clarity and symmetry are two similar characteristics, so we choose the same group of samples for the experiment. In the experiment, 100 Chinese characters were selected to write well-balanced and in line with the standard. In addition, 100 Chinese characters without these features were selected to extract Gabor features for decision classification. The experimental data set is shown in Figure 5. The final recognition rate is 91%, which shows that Gabor feature can represent the symmetry of writing.

![Figure 5. Experimental data set of stroke clarity and symmetry](image)

(a) Clear and symmetrical training set  (b) Training set of unclear symmetry  
(c) Clear and symmetrical test set  (d) Ambiguous symmetrical test set

3.3. Consistency Judgment of Writing Style

The style of Chinese characters written by the same person is unified, and the style of different people is different. In this part of experiment, Gabor feature is used to judge the consistency of writing style. The preparation of experimental data is as follows: for the same regular script work, different people...
use transparent paper to cover it for copying and identify different writing styles. As shown in Figure 6, the experimental data set selects 100 Chinese characters for each of the two people’s copy samples. The training set and the test set respectively include 100 Chinese characters for each of the two people. The test result of style consistency is 65%.

This part of the experimental style identification rate is not high because of the two samples, both from the same calligraphy copy, the original style is the same. This algorithm plays an important role in the verification of the same writing in the public security department.

3.4. Chinese Character Writing Quality Evaluation Experiment

In this part of the comprehensive experiment of Chinese character writing quality evaluation, we need machine to give excellent and general judgment. The experimental data set is shown in Figure 7. By comparing with manual scoring, the recognition rate of this algorithm is 95%.

In conclusion, this paper tests the performance of Gabor filter in calligraphy feature identification from three aspects, and the experiment shows that the effect is ideal.

4. Conclusion

In this paper, a binary evaluation method based on Gabor filter feature representation is proposed to evaluate the writing quality of Chinese characters. According to the Gabor features of five scales and four directions, the mean and variance are used as statistical features, and SVM is input for classification and discrimination. The performance of Gabor features in stroke clarity, structure uniformity and style consistency is tested respectively, and a comprehensive quality evaluation is carried out and good results have been achieved in the price experiment. The research of calligraphy quality evaluation is a research field with extensive application value, which involves feature extraction, image morphology and image semantic understanding. The method proposed in this paper does not depend on the accuracy of font segmentation, which provides a new research idea and method for the research of calligraphy quality evaluation based on statistical learning.

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