Multi-Scale Wavelet-Based Font Recognition of Chinese Character

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Abstract

Optical character recognition system research has been acquired great success. In this paper, a novel font recognition algorithm is proposed, which is based on multi-scale wavelet analysis. We adopt wavelet analysis and the grid method to deal with the character image, and extract wavelet energy density feature, and apply the BP Neural Network to classify the different fonts. The experiments show that the font recognition of Chinese character based on multi-scale wavelet analysis algorithm can effectively recognize the 4 kinds of the Chinese characters.

Keywords: font recognition; wavelet analysis; wavelet energy density; artificial neural network

1. Introduction

Chinese character recognition is an area of pattern recognition that received considerable attention due to the increasing computer data processing. Recently, Chinese character recognition system research has made great progress, and as an important aid of the digitization of the files has been widely used. But the system that is only able to recognize the characters cannot meet the demand. People want to design a system, which can reconstruct the structure of layout. To achieve this goal, we must recognize the font of characters.

These are the achievements in the field of font recognition at present: 1) A. Zramdini has researched the font of English characters[1]. The method is based on features extracted from global properties of the text image. Using the structure properties, such as the position of base line and the scale of blank between letters, distinguish the font of different kinds of English font. Chinese character structure is different from English letter, so A. Zramdini ‘s method is unqualified for the task that recognizes the font of Chinese character; 2) Y. Zhu proposes a new algorithm for font identification based on global texture of document image[2]. The key viewpoint is using texture analysis to extract global features through Gabor filters, and match them with template features in one single dictionary by calculating the weighted Euclidean distance. This method can only handle a block of characters, which consists of the same font. The system cannot deal with single character. In fact, we need a system, which can the recognize font of single character, because sometimes there is more than one font in a document or sometimes there are not enough characters to make a block that can be processed with Y. Zhu’s method. 3) L. Chen uses the method of wavelet analysis to differentiate Chinese character font[3]. He extracts wavelet coefficients from a single character image as wavelet feature, transforms the feature with Box-Cox, LDA technique is used to get the feature for font recognition and the feature is classified by a MQDF classifier. The recognition rate is 97.35%. The final feature is almost 256 dimensions, however, too large dimension can drop the recognition speed; the approximation coefficients contain so much information of the character, which disturbs the recognition of the font.

For Chinese character font recognition, the different fonts have different visual effects, and the visual differences are much less in fonts than in different characters. Wavelet analysis is fit for mark of local information in signal processing than Gabor; wavelet can process the signal with multi-resolution analysis (MRA); wavelet analysis is similar to human vision process, and also similar to the process of the computer, which treat with objects from wide to thin[4].

In this paper, a priori font recognition approach is adopted, which identifies font without any knowledge of the characters. It is much difficult than posteriori font recognition approach, which recognizes font using the knowledge of characters. The second section of the paper introduces the algorithm of the font recognition of single Chinese character based on multi-scale wavelet analysis. We use gridding method to order the wavelet energy density feature stabilization, and apply the BP Neural Network as the classifier to classify the different fonts. The third part describes the experiments, and we found that the recognition rate with wavelet energy density feature for font recognition is much higher than that with wavelet coefficient feature.

2. Multi-Scale Wavelet-Based Font Recognition of Chinese Character

Wavelet analysis is an effective method for signal processing. If $f(x)$ has finite energy, namely $\int_{\mathbb{R}} f(x)dx < 0$, then the aggregate of functions that meets this condition is the space, and the functions in the space are quadratic integral[5]. Let $\psi_{a,b}(x) = |a|^{-\frac{1}{2}} \psi_{a,b}(\frac{x-b}{a})$, if $\psi(x) \in L^1 \cap L^2$, and satisfies $C_\psi = \int_{\mathbb{R}} \frac{\left|\hat{\psi}(\omega)\right|^2}{|\omega|} d\omega < \infty$, then the wavelet transform of function $f(x)$ is defined as[6]:

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = |a|^{-\frac{1}{2}} \int_{\mathbb{R}} f(x) \psi_{a,b}(\frac{x-b}{a}) dx$$

Where a is scale index, which indicates the wavelet's width, and b is location index, which gives its position. Here $\psi_{a,b}(x)$ is wavelet bases or wavelet mother function, and a wavelet $\psi_{a,b}(x)$ is a function of zero average: $\int_{-\infty}^{+\infty} \psi(x)dt = 0$. The family of the function $\{\psi(a,b)\}$ is called analysis wavelet or the continuous wavelet. Any wavelet mother function that belongs to the space $L^2(\mathbb{R})$ ($L^2(\mathbb{R})$ is the Hilbert space) can be extended to the 2-Dimension space $L^2(\mathbb{R}^2)$. 2-D images are finite energy. Supposed $G(x,y)$ ($1 \le x \le N, 1 \le y \le N$) is a character imaging so that it is finite energy in space $L^2(\mathbb{R}^2)$, we can transform a 2-D image with wavelet.

2.1. Algorithm of multi-scale wavelet-based font recognition

2.1.1. Selecting of the mother wavelet

S. Mallat has proved that wavelet has been shown to be very useful for fast algorithm, data compression and signal compression. Most applications of wavelet bases exploit their ability to efficiently approximation particular classes of functions with few non-zero wavelet coefficients[5]. This ability relays on these mathematical properties: Vanishing moments, regularity, compact supported, symmetry and orthogonal[5]. Non-compact supported wavelet cannot analyze the local frequency of signals with wavelet analysis as well as compact supported wavelet, so we only choose the compact supported wavelet bases and the compact support must be as short as possible. Daubechies wavelets are optimal in the sense that they have a minimum size support for a given number.

Db wavelets are widely used in signal processing, image analysis and pattern recognition. In this paper, we choose the Db4 wavelet as the mother wavelet to analyze the character image at 2-level. Supposed $G(x,y)$ ($1 \le x \le N, 1 \le y \le N$) is a character image, and to perform $G(x,y)$ with the Db4 wavelet at K-level, then we gain 3K+1 sub images after the K-level transform. Original image is the estimation at the scale 2^0. There are 7 sub images after the 2-level wavelet analysis: $D^{(1)}_{2^{-1}} f$, $D^{(2)}_{2^{-1}} f$ and $D^{(3)}_{2^{-1}} f$ are the sub images of resolution in 2^{-1}. $A_{2^{-2}} f$, $D^{(1)}_{2^{-2}} f$, $D^{(2)}_{2^{-2}} f$ and $D^{(3)}_{2^{-2}} f$ are the sub images of resolution in 2^{-2}. $D^{(1)}_{2^{-2}} f$, $D^{(2)}_{2^{-2}} f$, $D^{(3)}_{2^{-2}} f$, $D^{(1)}_{2^{-1}} f$, $D^{(2)}_{2^{-1}} f$ and $D^{(3)}_{2^{-1}} f$ are the coefficients of detail.

2.1.2. Selecting of wavelet feature

The recognition accuracy often drops significantly if the feature that we choose is not appropriate, so we should select the feature, which is able to reflect the difference of the variety fonts. The feature selected should satisfy the requirements:

1) The influence by the character information will as little as possible.
2) The feature should be convenient for extracting and calculation.
3) The feature should use fewer dimensions to reflect the characteristic of the characters.

In the experiments, we choose wavelet energy density as the wavelet feature for font recognition. Experimental result proves that the wavelet energy density feature is efficient. A character image decomposes into seven sub images after transformation with db4 compact supported wavelet at 2-level: $D^{(1)}_{2^{-1}} f$, $D^{(2)}_{2^{-1}} f$, $D^{(3)}_{2^{-1}} f$, $A_{2^{-2}} f$, $D^{(1)}_{2^{-2}} f$, $D^{(2)}_{2^{-2}} f$ and $D^{(3)}_{2^{-2}} f$. Because $A_{2^{-2}} f$ is the approximation of the original image, which contains much character information and disturbs the recognition of the font, we do not consider the approximation image $A_{2^{-2}}f$. We extract the wavelet energy density feature from $D_{2^{-1}}^{(1)}f$, $D_{2^{-1}}^{(2)}f$, $D_{2^{-1}}^{(3)}f$, $D_{2^{-2}}^{(1)}f$, $D_{2^{-2}}^{(2)}f$ and $D_{2^{-2}}^{(3)}f$ that contain font information.

Wavelet energy[7] and wavelet energy density are defined respectively:

$$EnergyG\left(x, y\right) = \sum_{x}^{N}\sum_{y}^{N}\left|\mathrm{Coef}_{(x,y)}\right| \qquad (1)$$

$$EnergyDP = \frac{EnergyD_{2^{-i}}^{(j)}}{EnergyG(x, y)} \qquad (2)$$

Where $EnergyG\left(x, y\right)$ is the wavelet energy of image $G\left(x, y\right)$ ($1 \le x \le N$, $1 \le y \le N$), $\mathrm{Coef}_{(x,y)}$ is the wavelet coefficient. In this paper, the absolute value of wavelet coefficient is used. Where $EnergyDP$ is the wavelet energy density of $D_{2^{-i}}^{(j)}$, and $EnergyD_{2^{-i}}^{(j)}$ is the wavelet energy of $D_{2^{-i}}^{(j)}$.

2.1.3. Wavelet analysis

Firstly, we normalize the given character images from the actual size into 64*64 pixels. Secondly, we transform the images with Db4 compact supported wavelet at 2-level. $D_{2^{-1}}^{(1)}f$, $D_{2^{-1}}^{(2)}f$ and $D_{2^{-1}}^{(3)}f$ are 32*32, while 16*16 is the size of $D_{2^{-2}}^{(1)}f$, $D_{2^{-2}}^{(2)}f$ and $D_{2^{-2}}^{(3)}f$.

2.1.4. Gridding

Gridding is an effective method that can improve the ability of classification, which synthesizes the statistical feature and structure feature. The decomposition sub images should be meshed, and extract the wavelet energy density feature form each gridding, in order to ensure the stabilization of the feature. We partition the gridding uniformly in our experiment. A 4*4 grid is used to partition the detail images $D_{2^{-1}}^{(1)}f$, $D_{2^{-1}}^{(2)}f$ and $D_{2^{-1}}^{(3)}f$ into 16 equal-sized regions; 2*2 grid is used to partition the detail images $D_{2^{-2}}^{(1)}f$, $D_{2^{-2}}^{(2)}f$ and $D_{2^{-2}}^{(3)}f$ into 4 equal-sized regions. Then we extract wavelet feature from those grids. As fig.1 shows, a 4*4 grid is used to partition sub image $D_{2^{-2}}^{(2)}f$.

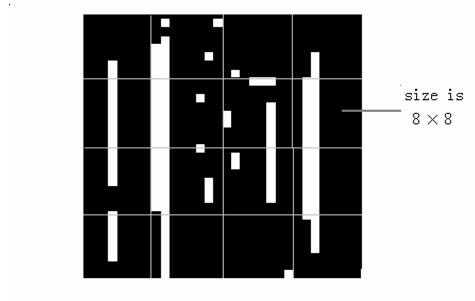

Fig. 1: 4*4 grid is used to partition 32*32 into 16 equal-sized regions

2.1.5 Wavelet feature extraction

$\mathrm{Energy}D_{2^{-2}}^{(1)}f$, $\mathrm{Energy}D_{2^{-2}}^{(2)}f$, $\mathrm{Energy}D_{2^{-2}}^{(3)}f$, $\mathrm{Energy}D_{2^{-1}}^{(1)}f$, $\mathrm{Energy}D_{2^{-1}}^{(2)}f$ and $\mathrm{Energy}D_{2^{-1}}^{(3)}f$ are wavelet energy. According to Eq (1) and (2), the general formula of wavelet energy can be defined as:

$$EnergyD_{2^{-i}}^{(j)} = \sum_{x \in D_{2^{-i}}^{(j)}}^{N/2^i}\ \sum_{y \in D_{2^{-i}}^{(j)}}^{N/2^i}\left|\mathrm{Coef}_{(x,y)}\right| \qquad (3)$$

We define the wavelet energy density as the ratio of wavelet energy in each grid to the wavelet energy of the sub images, containing the grid. Suppose a grid is $\mathrm{Gridding}(x, y)$ ($x \in D_{2^{-i}}^{(j)}$, $y \in D_{2^{-i}}^{(j)}$), and then we define the wavelet energy density of the grid as:

$$EnergyGridding(x, y)\_DP = \frac{EnergyGridding(x, y)}{EnergyD_{2^{-i}}^{(j)}} \qquad (4)$$

We calculate the wavelet energy density of each grid with the formula (3) and (4). Finally, we extract [(16*3=48)+(4*3=12)]=60 dimensions wavelet feature.

2.2 Classifier design

An artificial neural network is used in our experiments. Artificial neural networks, which could be more user-friendly and robust than the traditional approaches[8], have proven to be very powerful tools for pattern recognition and image analysis due to its self-organizing, adaptive nature and stronger learning capability. BP neural networks especially interested since they are the most common. The classifier used in the implementation is a 2-layer back-propagation network with 60-dimension wavelet energy density as the input, and with 4 outputs, which are the 4 different fonts of Chinese character in table 1.

3. Experimental result

The sample set used in the implementation is the

'Founder group' Chinese simplified form library that each font contains 3755 Chinese characters. We choose 4 different fonts: Bold, Fang song Ti, Kai Ti and Song Ti. Each character we choose 10 samples, which are acquired in the different resolution. So there are 3755*10*4=150200 samples. In the experiment, we use 17550 samples of each font chosen stochastically for training, and the residual un-training samples are used for testing. In order to find the feature, which is better, we compare wavelet energy density feature with wavelet coefficient feature. We have tried both these method to recognize Chinese character font with the same sample set. The experimental results are in the tables below and show that the recognition rate with wavelet energy density feature is more accurate than wavelet coefficient feature.

	Bold	**Song**	**Fang**	**Kai Ti**
Bold	**99.85%**	**0.00%**	**0.00%**	**0.15%**
Song	**0.05%**	**98.85%**	**0.65%**	**0.45%**
Fang	**0.00%**	**0.60%**	**99.10%**	**0.30%**
Kai	**0.20%**	**0.35%**	**0.50%**	**98.95%**
Average: 99.1875%				

Fig.2: Average classification rates of 4 different fonts with wavelet energy density

	Bold	**Song**	**Fang**	**Kai Ti**
Bold	**99.10%**	**0.20%**	**0.15%**	**0.55%**
Song	**0.30%**	**97.55%**	**1.55%**	**0.60%**
Fang	**0.25%**	**1.85%**	**97.65%**	**0.35%**
Kai	**0.75%**	**0.65%**	**0.85%**	**97.75%**
Average: 98.0125%				

Fig. 3: Average classification rates of 4 different fonts with wavelet coefficient.

4. Summary

This paper has proposed a novel font recognition method based on multi-scale wavelet analysis. Firstly, we normalize the given patterns from the actual size into 64*64 pixels; secondly, transform the normalized images with Db4 wavelet; thirdly, using the gridding method improves the ability of classification as we extract the wavelet energy density feature in each grid; finally, BP neural network is used to classify the different fonts. The experimental results demonstrate the validity of the algorithm and show a satisfying recognition rate.

5. References

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