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Chinese Painting Classification Method Based on PCA

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Abstract. In this paper, a kind of Chinese painting classification method based on PCA is proposed. The image was pretreated using this method, then reduced by Gabor transform and classified based of PCA. Experiments in the self-built image library show that this method has high classification accuracy.

Introduction

Many traditional paintings are rare and precious, and most of the paintings are distributed in museums around the world. With the development and popularization of computer network, the Chinese ancient books and paintings are viewed through the web. People can not only appreciate excellent, master works, but also can obtain more information and improve the accuracy of authenticity appraisal. In addition, there are many kinds of Chinese paintings, and since ancient times, there have been a large number of famous names. With the development of digitization, the capacity of Chinese painting digital image will grow at an alarming rate. With the improvement of people's economic life and cultural living standards, there will be more and more demand for Chinese paintings. Therefore, it is not enough to satisfy people's needs relying solely on annotations for keyword retrieval. More attention is paid to finding a certain type of painting, for example, look for "paintings of people in qing dynasty" or "paintings of horses in Chinese paintings". Therefore, it is an effective way to solve this problem by using image classification technique to classify the Chinese painting based on content automatic classification.

In recent years, content-based image classification[1] and retrieval[2] have developed. Although these methods are aimed at ordinary images, some more mature methods are also feasible in the automatic classification of Chinese paintings[3-4]. Therefore, these studies have important reference value. Traditional Chinese painting can be divided into landscape painting, figure painting and flower-and-bird painting. Landscape painting mainly describes mountains, rivers and other natural scenery. The flower-and-bird painting mainly describes the combination of plants, animals, or both. Figure painting mainly describes the activity of a person's portrait or character in a certain state. The classification of Chinese painting is easier for people to separate, but it is a difficult thing for the computer. The main reason is that there are a lot of changes in the form, including shape, color, painting style and so on. Therefore, the automatic classification and retrieval of Chinese paintings is a necessary and meaningful research topic after the Chinese painting is digitized.

Chinese Painting Classification Method Based on Principal Component Analysis

In this paper, a kind of national drawing classification method is proposed based on PCA. First, the image is pretreated, and then Image dimension reduction is conducted using Gabor[5]. Finally, the PCA method[6-7] was adopted to classify the Chinese paintings, as shown in Figure 1.

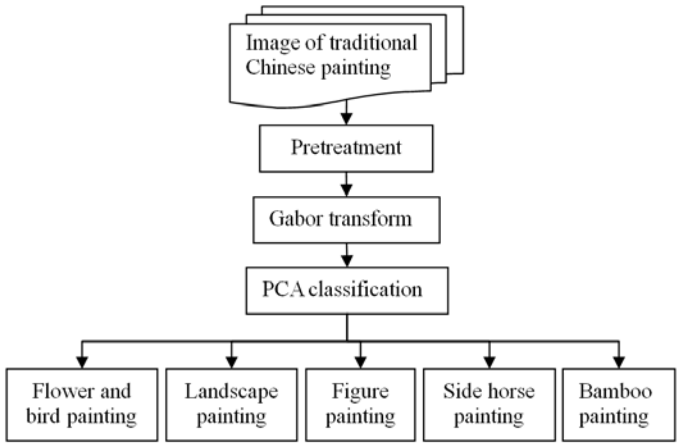

Figure 1. A flowchart of national painting classification method based on PCA.

Pretreatment of Image

Traditional Chinese paintings are not well preserved. Many traditional Chinese paintings are age-old and save improperly, so the color is bleak and there are many unpredictable noises. In addition, the feature extraction is mainly based on the region in the classification and retrieval process. Therefore, Chinese painting images need to be pretreated before classification and retrieval, and the following work is mainly included:

(1) Smooth filtering and region extracting

Firstly, the median filter[8] is used to remove the noise in the image, and then, the global threshold method based on the grayscale histogram[9] is used for binary processing.

The feature extraction method is based on statistical method. Objects in the image do not need to be extracted strictly. Therefore, it is feasible to adopt two-value method based on threshold. The target and background are relatively isolated in the sample. Histograms have obvious twin peaks. the valley point between the two peaks can be chosen as the threshold value. We adopt global optimal threshold based on grayscale histogram.

(2) Connecting breakpoint, removing isolated point

The filtering process removes some of the noise from the image, but because Chinese painting is usually painted on the rendered paper, some background printing points are extracted as prospects when binary processing is performed, existing as an isolated point. It is needed to do some processing to get rid of the isolated points.

The form of some objects in Chinese painting is depicted by means of pen and ink. When the foreground object is extracted, there are breakpoints or gaps within the object area. Therefore, some preprocessing operations are needed to fill the gap. Our system uses the principle that if the number of black dots around a pixel is larger than the number of white points, the point is considered black point, otherwise it is white.

Gabor Transform

Wavelet transform is essentially a multi-scale bandpass filter to filter the signal. It decomposes the signal into different bands and then analyzes it. It has the advantages of good time-frequency domain local performance and multi-resolution analysis. The main reasons for using wavelet to decompose images include the following aspects. Firstly, after decomposition of image with wavelet transform, the resolution of subband image decreases, and the corresponding computational complexity is greatly reduced. Second, wavelet decomposition provides good spatial and frequency local information. Traditional Chinese painting image information in the low frequency part describes overall image (shape), high frequency section describes the detail of the image information, cover, rotating light, a little distortion affects only the high frequency part of the image, etc. The low-frequency information obtained by wavelet transform can be used to describe the characteristics of the classification.

Under the inspiration of image decomposition and reconstruction of the image decomposition and reconstruction proposed by Burt and Adelson, Mallat established a fast algorithm of discrete orthogonal wavelets - Mallat algorithm. The corresponding two-dimensional Mallat wavelet decomposition algorithm is shown in Figure 2. $\widetilde{H}$ and $\widetilde{G}$ are respectively high - and low-pass discrete linear filters. P_j corresponds to the low frequency part of P_{j-1}, which is the approximate image of P_{j-1}. D_j^1, D_j^2 and D_j^3 correspond to detail images in horizontal, vertical and diagonal directions.

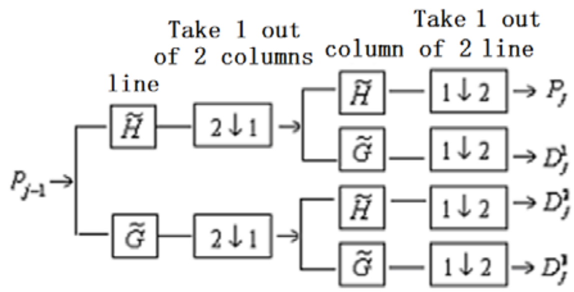

Figure 2. Wavelet transform schematic 1.

One image is divided into four subplots by the first order decomposition of wavelet transform, as shown in Figure 3. LL is an approximation of the original image. LH and HL are subgraphs of horizontal and vertical directions. HH is a high frequency subgraph of the image.

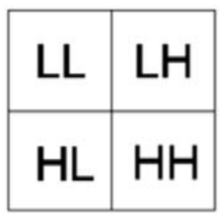

Figure 3. Wavelet transform schematic 2.

The Gabor transform has good properties in image analysis and understanding.

(1) Gabor filters have biological significance. Studies have shown that Gabor kernel function is similar to that of the receptive field shape of the cortical cells in the human brain visual region.

(2) The Gabor filter can fully describe the texture information of the image. The wavelet characteristics of Gabor filtering showed that the result of Gabor filtering is a powerful tool to describe the local gray distribution of the image. Therefore, the texture information of the image can be extracted by Gabor filtering. It is one of The most extensive application of Gabor filters.

(3) The study of two-dimensional Gabor wavelet indicated that the original image can be reconstructed by selecting several Gabor kernel functions properly. Therefore, the Gabor kernel function can be used in modeling and representation of objects.

(4) The DC component is removed from the Gabor kernel function. Therefore, it is insensitive to the influence of the local light.

(5) The results of Gabor filtering can describe the gray distribution information in different directions.

(6) Generally, large scale filtering can describe more global information and cover the effects of noise in the image. The small scale filter can describe the more detailed local structure, which is affected by the noise.

(7) Gabor filtering can tolerate the image having a certain translation, rotation, depth rotation, scale change and so on.

PCA Classification

Principal component analysis is an effective method of feature extraction. It makes full use of the two order statistical information in the data for feature extraction and dimensionality reduction, Widely used in the field of image recognition.

The specific steps of the PCA can be described as follows:

Consider the K sub image input as a one dimensional vector, X_k, so covariance matrix is obtained

$$W = \frac{1}{N}\sum_{i=1}^{N}\left(X_i - \overline{X}\right)\left(X_i - \overline{X}\right)^T \quad (1)$$

N is Total number of training samples, $\overline{X}$ is Average image of training sample set.

$$\overline{X} = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (2)$$

W is $N^2 \times N^2$*dimensional,* It is difficult to calculate the eigenvalues of the W and the eigenvectors of the orthogonal normalization, and the singular value decomposition theorem (SVD) is used to transform it into a low dimensional matrix. By this method, the eigenvectors of the m maximum eigenvalue $\{\lambda_1, \lambda_2, \cdots, \lambda_m\}$ $\left(\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m\right)$ corresponding to *W* are obtained, as shown in formula 3.

$$WU = U\Lambda \qquad (\Lambda = diag(\lambda_1, \lambda_2, \cdots, \lambda_m)) \quad (3)$$

The projection of the training sample on U is,

$$Y_i = U^T\left(X_i - \overline{X}\right) \quad (4)$$

The projection matrix U of principal component components has the following characteristics.

(1) Minimize the reconstruction error of all samples. $E = \min \sum_{i=1}^{N}\left|X_i - \overline{X} - UU^T\left(X_i - \overline{X}\right)\right|$;

(2) The maximum sample concentration is concentrated in the variance of low dimensional projection.

(3) The correlation of the original features was eliminated.

Experimental Results and Analysis

A total of 500 Chinese paintings were used in the experiment. Among them, landscape painting, flower and bird painting, figure painting, pommel horse painting and bamboo painting are all 100. Since the format and size of the collection of pictures are different, this will inevitably affect the effect of the experiment. So we first adjusted the image to BMP format, and adjusted the picture size to 384×256 or 256×384.

Table 1 shows the classification results of Chinese painting images. As can be seen from this, for landscape painting, flower-and-bird painting, figure painting, pommel horse painting, bamboo painting, the Gabor+PCA, which is proposed in this paper, is more than 80% accurate in classification. The classification accuracy of the figure painting was the highest, up to 86%. Compared with Gabor+PCA method, the accuracy of PCA method is reduced, indicating that Gabor method can improve the classification accuracy of Chinese painting.

Table 1. Classification accuracy of Chinese painting images.

	landscape painting	**flower and bird painting**	**figure painting**	**pommel horse painting**	**bamboo painting**
PCA	80%	82%	81%	76%	78%
Gabor+PCA	83%	85%	86%	82%	82%

Conclusion

This paper presents a new automatic classification method of Chinese painting. Firstly, the image of the country is pretreated, which mainly includes smoothing filter and region extraction and connecting breakpoint. Then the image is reduced by wavelet transform. Finally, PCA was used for classification. We analyze and discuss the experimental results, and the results show that our method has high classification accuracy.

References

[1] Z. Akata, S. Reed, D. Walter, H. Lee, B Schiele. Computer Vision & Pattern Recognition, 2015. pp. 2927-2936.

[2] T. Xiao, T. Xia, Y. Yang, C. Huang, X. Wang. Learning from massive noisy labeled data for image classification, Computer Vision & Pattern Recognition, 2015. pp. 2691-2699.

[3] W. Hu, H. Zhang, B. Zhang. Identification of Organic Binders in Ancient Chinese Paintings by Immunological Techniques. Microscopy & Microanalysis the Official Journal of Microscopy Society of America Microbeam Analysis Society Microscopical Society of Canada, 2015, 21(5). pp.127.8

[4] M. Sun, D. Zhang, Z. Wang, J. Ren, J.S. Jin. Monte Carlo Convex Hull Model for classification of traditional Chinese paintings. Neurocomputing , 2016, 171, pp.788-797.

[5] Z. Lu, C. Yang, D. Qin, Y. Luo. Estimating the parameters of ultrasonic echo signal in the Gabor transform domain and its resolution analysis. Signal Processing, 2016, 120, pp. 607-619.

[6] E. Rahmani, N. Zaitlen, Y. Baran. Sparse PCA corrects for cell type heterogeneity in epigenome-wide association studies. Nature Method, 2016, 13 (5), pp. 443.

[7] P.Y. Louis. Ergodicity of PCA : equivalence between spatial and temporal mixing conditions. Electronic Communications in Probability, 2016 , 9 (2), pp. 119-131

[8] A. Kleefeld, M. Breuß, M. Welk, B. Burgeth. Adaptive Filters for Color Images: Median Filtering and Its Extensions. International Workshop on Computational Color Imaging, 2015, pp. 149-158.

[9] B. Shahangian, H. Pourghassem. Automatic brain hemorrhage segmentation and classification algorithm based on weighted grayscale histogram feature in a hierarchical classification structure. Biocybernetics & Biomedical Engineering, 2016 , 36 (1), pp. 217-232.