A Study on Image Classification Technique for Chinese Painting

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Abstract

With the development of the information technology and advancement of digital image processing techniques, an increasing number of digital images are being produced. In recent years, Content-Based Image Retrieval (CBIR) has been extensively researched and discussed. In this method, color histogram is used as an important feature in image retrieval. Nonetheless, the main problem of using color histogram in the retrieval is that color distribution is not considered, so the retrieved images may have similar colors but different color distributions. Precision of image retrieval will be affected as a result. In this study, annular histogram is used. Concentric circles are drawn around the center of image to record the color information. Besides, the method proposed by Jiang (Jiang, Huang, Ye, & Gao, 2006) is also modified and applied to Chinese painting images.

Texture is another feature for image retrieval (Huang, Dai, & Lin, 2006). So far, numerous texture-based retrieval methods are available. In this study, a new texture extraction method is proposed. This method converts images into ASCII codes and calculates the statistics of each code to generate a histogram as another feature for image retrieval. In the experiment of image classification precision, color distribution and texture are used as classification features. Textures on the Chinese paintings are converted into ASCII codes to obtain the distribution of textures. Later, color histogram is used to calculate the statistics of each color. Finally, images are classified using Decision Tree. The experimental results show that the precision of the proposed classification method is higher (Jia & Wang, 2004).

Keyword: Image Retrieval, Image Classification, Color Histogram, Texture Feature, Chinese Painting
1. Introduction

1.1 Background

Recent advancement in computer hardware has made storage of large collections of digital images both convenient and inexpensive. With people’s increasing access to the Internet, acquisition of digital information has also become more popular. Information technology is continuously changing our life styles. There has been a growing need for image retrieval technologies to process digital images.

In a traditional database, every image must be described before it can be incorporated to the database and form part of the index. To search for a certain image, we must use some techniques to retrieve the image from this database. Search engines that make databases of images available to their user generally have a selection process to determine which images should be added to the collection and a categorization process to assign general categories and other keywords to the selected images. Images on the World Wide Web (WWW) always have a caption or keywords.

The keyword approach has certain limitations. Human coding of keywords is very expensive and not every term required to reference an image can be completely inputed. In WWW databases, using HTML captions can help automate, but somehow provides only a limited indexing capability.

In addition, some of the returned images may be very different from what the user expects to derive with the keywords. Hence, using keywords alone is not enough. We might need to explore other methods that retrieve images using features in addition to keywords. Fig 1.1 shows two images returned from a web search with the keyword 'Chinese painting'.

(a) Chinese paintings                   (b) Non-Chinese paintings

**Fig 1.1:** Chinese paintings returned by keyword search
Content-Based Image Retrieval (CBIR) has become synonymous with retrieval based on low-level descriptors such as color (Cinque, Ciocca, Levialdi, Pellicano, & Schettini, 2001; Sun, Zhang, Cui, & Zhou, 2006), shape (Mehtre, Kankanhalli, & Wing Foon, 1998), spatial relationship (Kankanhalli, Mehtre, & Yiung Huang, 1999) and texture (Flickner et al., 1995; Huang et al., 2006). Researchers often use these features in image retrieval systems. The following is a brief explanation of the above-mentioned features:

1. **Spatial relationship**: The image retrieval system based on spatial relationship usually uses matrix and tree structure to record the spatial relationships of objects. Some researchers proposed to obtain spatial information by drawing circles or segmenting an image into blocks (Sun et al., 2006).

2. **Texture**: Typical textural features include uniformity, contrast, directionality, coarseness, frequency, density and roughness. However, computation of texture features is more complicated and time-consuming. (Flickner et al., 1995; Huang et al., 2006).

3. **Shape**: The image retrieval system based on shape features usually uses chain code, signature, and moment to describe object contours. It is suitable for the retrieval of images with simple objects, such as trademarks. Images with multiple colors and objects, such as nature images, may not be applicable. In the extraction of this feature, two major steps are involved. They are object segmentation and shape representation (Mehtre et al., 1998).

4. **Color**: Color feature is one of the most recognizable elements of image content and is widely used in image retrieval. The key issues in color feature extraction include the color distribution. (Jenni, Mandala, & Sunar, 2015; Shrivastava & Tyagi, 2014; Sun et al., 2006).

Moreover, with the development of Web 2.0 and growing prevalence of photo albums or blogs, more and more artists have set up their personal websites to display their works online. Through the Internet, other network users can quickly and conveniently browse these works, so a large amount of promotion and advertising costs can be significantly saved. Therefore, a good retrieval technology has its value and should be further investigated. Fig 1.2 shown Digitalized Chinese paintings.
1.2 Motive

Chinese painting is the gem of Chinese traditional arts. There are more and more digitalized Chinese Painting images available for access on the Internet. Using the traditional search engine based on query by keywords is hard to find the required image, mainly because of the characteristics of an image is hard to describe by text.

Due to the development of digital imaging, a huge amount of digital images are produced every day by digital imaging devices, such as digital cameras and digital camcorders. The convenience of the Internet has further facilitated the use and spread of digital images for us. In the past, storage of large amounts of digital images was almost impossible, because the computational speed and the hardware storage capacity were not insufficient. In the present, the advancement of hardware technologies has increased computer performance and capacity of storage devices, so storage and processing of digital images have become possible and also popular. Moreover, digital images also play an increasingly important role in today’s society. Hence, it is necessary to develop effective image retrieval systems.

Painting plays a very important part in our life. With the advent of the digital era, Chinese paintings, western paintings, oil paintings, and so on can all be appreciated on the Internet. Chinese paintings are especially representative of long histories. The promotion digitalization of Chinese paintings have increased the number of Chinese paintings available on the Internet. However, common search engines allow users to query the database only by keywords and cannot effectively help them find expected results if they intend to search for a certain Chinese painting. Moreover, much time will be wasted, because the search results are usually unexpected. Content-Based Image Retrieval (CBIR) is a method with relatively higher precision. In this retrieval method, feature selection is an important process.
1.3 Objective

Digital information has brought us a more convenient life. In the past, if people wanted to view Chinese paintings, they needed to go to art galleries or museums. With the advancement of information technology, through computers and the Internet, many Chinese paintings can be visible online.

Chinese painting is one of the oldest and still existant artistic traditions in the world. Essentially, traditional painting involves the same techniques used in Chinese calligraphy and is done with a brush dipped in black or colored ink. Oils are not used. As with calligraphy, the most popular materials are paper and silk. After a calligraphy work is finished, it will be mounted on scrolls, which can be either hung for display or rolled up for storage. Traditional paintings are also displayed in albums and on walls, lacquerwork, and other media. Fig 1.3 shows examples of Chinese paintings (a) human figures painting (b) landscape painting (c) flowers-and-bird painting.

![Examples of Chinese paintings](image_url)

**Fig 1.3:** Examples of Chinese paintings

From a considerable number of Chinese paintings, it can be discovered that the main feature of Chinese paintings lies in the use of drawing and color. In this study, a database is built with Chinese painting digital images. In Chinese painting images, the use of texture and color distribution are two important features. In the extraction of features on Chinese paintings, the texture feature is first converted into ASCII codes and statistically processed using the histogram method. As to the color feature, Sun's method was modified to increase the applicability of color distribution of Chinese painting images. Through these two steps, Chinese painting images can be accurately and quickly retrieved. Images used in this study are limited to only Chinese painting digital images. The image database used by Jia Li (Jia & Wang, 2004) is employed, along
with the Content Based Image Retrieval technology (CBIR) to test the image retrieval and classification precision and efficiency of the proposed method.

2. Literature Review

2.1 Introduction to Content-Based Image Retrieval

Traditional DBMS were designed to organize alphanumeric data into interrelated collections, so that information retrieval and storage could be done in a convenient and efficient manner. However, this technology is not well suited for the management of multimedia information. The diversity of data types and formats, the large size of media objects, and the difficulties in automatically extracting semantic meanings from image data are entirely foreign to traditional database management techniques. To effectively utilize this widely available multimedia information, efficient storage, browsing, indexing, and retrieval methods must be developed. Different multimedia data types may require different indexing and retrieval tools and methodologies. Since the 1970s, image retrieval has been a very popular research topic in two major research communities—database management and computer vision. These research communities study image retrieval from two different perspectives. The first is primarily text-based, and the second relies on visual properties of the data (Rui, Huang, & Chang, 1999).

In the early 1990s, due to the emergence of large-scale image collections, Content-Based Image Retrieval (CBIR) was proposed as a solution to these difficulties. In CBIR, images are automatically indexed by summarizing their visual contents through automatically extracted quantities or features such as color, texture, or shape. Since the introduction of CBIR, many techniques have been developed along this direction, and many retrieval systems have been built for both academic and commercial purposes (Rui et al., 1999).

A typical CBIR system is illustrated in Fig 2.1 (Rui et al., 1999). The image collection database contains raw images for the purpose of visual display. The visual feature repository stores visual features extracted from images to support CBIR. The text annotation repository collects key words and free-text descriptions of images. Multidimensional indexing can facilitate fast retrieval and make the system scalable to large image collections.
2.2 CBIR Feature Extraction

Feature extraction is the foundation of CBIR. Features can be categorized as general or domain-specific. General features typically include color, texture, shape and spatial relationships.

2.2.1 Color-Annular Color Histogram

Annular color histograms was first introduced by R.Aibing (Aibing, Srihari, & Zhongfei, 1999) to represent color spatial feature. Suppose $A_i$ be the set of pixels with color bin $i$ of an image and $|A_i|$ be the number of elements in $A_i$. Let $C_i$ be the centroid and $r_i$ be the radius of color bin $i$ which are defined in
R. Aibing (Aibing et al., 1999). With \( C_i \) as the center and with \( jr/N \) as the radius, for each \( 1 \leq j \leq N \), we can draw \( N \) concentric circles. Let \( |A_{ij}| \) be the count of the pixels of color bin \( i \) inside circle \( j \). Then the annular color histogram can be written as \((|A_{i1}|,|A_{i2}|,...,|A_{iN}|)\). The above process is illustrated in Fig 2.2.

![Fig 1.5: Annular color histogram (Aibing et al., 1999)](image)

**2.2.2 Texture**

Besides color, texture is another evident and indispensable feature for content-based image indexing and retrieval application through similarity matching. The texture features currently in use are mainly derived from multi-scale approach. Liu and Picard (Liu & Picard, 1996) used Wold features for image modeling and retrieval. Manjunath and Ma (Manjunath & Ma, 1996) employed features derived from the Gabor wavelet coefficients for indexing photographic and satellite images. In SaFe project, Smith and Chang (John & Shih-Fu, 1996) used discrete wavelet transform (DWT) based features for image retrieval. Recently, Do and Vetterli (Do & Vetterli, 2002) proposed wavelet based texture retrieval using generalized Gaussian density and Kullback-Leibler distance metric.

### 3. Proposed Method

#### 3.1 Introduction

The research on image analysis is mostly based on realistic imaging modalities, including photographs of real world objects, remote sensing data, MRI scans, and X-ray images. Furthermore, art paintings demand unconventional image analysis tasks. For instance, a significant genre of ancient Chinese paintings is the so called “mountains-and-waters” paintings. This genre depicts mountains, trees (an integral part of mountains), rivers/lakes, and sometimes small pagodas and thatch cottages, as shown in Fig 3.1. In terms of image
content, there is little to compare among these paintings. Characteristic strokes used by artists are an aspect that art historians often examine when studying and comparing paintings. Many impressionist masters formed their styles by special strokes. These include the swirling strokes of Van Gogh and the dots of Seurat. Zhang Daqian, an artist from the late Qing Dynasty to modern China, is renowned for creating a way of painting mountain landscapes using broad-range bold ink wash. Hence, it will be interesting to study how to mathematically characterize strokes, extract different stroke patterns or styles from paintings, and compare paintings and artists based on these features. There is ample room for image analysis researchers to explore these topics.

![Examples of mountains, trees Chinese paintings](image1.jpg)

**Fig 1.6** Examples of mountains, trees Chinese paintings

Throughout the long Chinese history, Chinese paintings have carried unique and perceptual styles. They may have various appearances due to the diverse uses of brush techniques, ink and colors. In different periods, the mainstream types of paintings (such as figure, landscape and flower & bird) are also different, depending on the preference of artists. In this paper, low-level features such as color, texture are used to characterize the particularity of Chinese paintings image and further differentiate artist's paintings. Figures 3.2 show Image Retrieval system structure.
There are many classifiers in machine learning and pattern recognition domain. Each classifier has its own strength and weakness. Support vector machine (SVM) has been extensively used as a classification tool in a variety of areas. Compared with other classifiers, decision tree is easier to train, requires a smaller training sample, and has better generalization ability. So it is more appropriate for our work and is chosen as the main classification tool. Besides, we use a combination of a decision tree classifier and image feature to detect Chinese paintings. Fig 3.3 shows the structure of the Image Classifications system.
3.2 CBIR Using Texture Features in Image to ASCII Code Histogram (IACH)

Jiang (Jiang et al., 2006) proposed a classification method for Chinese painting images. Among the features used to classify Chinese paintings, texture feature is considered very important. In Chinese painting, different painting techniques result in different texture features. Therefore, texture is an important feature in Chinese paintings. Besides, texture features extracted from paintings created by different painters may also vary with their painting styles. In the research of image retrieval, numerous texture feature extraction methods have been proposed. However, most of them are based on the frequency domain, so considerable computation cost and time are required. In this paper, a new method that extracts texture features by transforming images into ASCII codes is proposed. This method can reduce computation and enhance processing efficiency. Owing to this low-computation feature, this method can be further applied to real-time image processing systems in the future. Fig 3.4 shows the original images, and the images transformed through IACH.

![Fig 3.5 Chinese painting images transformed through IACH](image)

In the IACH method, 19 ASCII codes were used. These ASCII codes were most related to Chinese painting images derived from training with 600 images. The ASCII codes used in the IACH method are shown in Table 3.1. After images are transformed into these codes, a histogram can be statistically computed to extract texture features.
Table 3.1 ASCII codes used in IACH

<table>
<thead>
<tr>
<th>ASCII code</th>
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<tbody>
<tr>
<td>Space</td>
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<tr>
<td>“</td>
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<tr>
<td>&amp;</td>
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<tr>
<td>)</td>
</tr>
<tr>
<td>/</td>
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</tbody>
</table>

3.3 CBIR Using Color Features in Color Distribution Histogram (CDH)

Each Chinese painting image is proportionally resized and transformed from the RGB color space into HSV color space. In HSV, Hue is divided into 360 degrees, and Saturation and Value are equally divided into 100 shares and presented in percentage. The color space is transformed using Equation 3.1, where R denotes the Red value, B denotes the Blue value, and G denotes the Green value. Max() indicates that the maximums of the three values are taken, and Min() indicates that the minimums of the three values are used.

\[
H = \cos^{-1} \left( \frac{\frac{1}{2} [(R - G) + (R - B)]}{\sqrt{(R - G)^2 + (R - B)(G - B)}} \right)
\]

\[
S = \frac{\text{Max}(R,G,B) - \text{Min}(R,G,B)}{\text{Max}(R + G + B)}
\]

\[
V = \frac{\text{Max}(R,G,B)}{255}
\]

The color space is uniformly quantized into nine levels of hue, three levels of saturation and value given a total of 81 bins. Generally, the central portion of each image is more important. If circles are drawn around the center of the image, inner circles can be given a larger weight, and the statistic color information of each concentric circle can be computed as a feature for retrieval. The concentric circle drawing method is shown in Fig 3.6.
The entropy formula is used with an additional weight value. In J. Sun’s method, the weight for the outermost circle is the largest, and that for the innermost circle is the smallest. However, in Chinese painting images, the innermost circle is usually where the most important part lies. Therefore, in the calculation of eigenvalue, inner circles are given a larger weight, and outer circles are given a smaller weight. Assume that 3 concentric circles are drawn. In Equation 3.1, $f(1)$ is the innermost circle, and $f(3)$ is the outermost one.

\[
\begin{align*}
    f(1) &= 1 + 3/3 = 2 \\
    f(2) &= 1 + 2/3 = 5/3 \\
    f(3) &= 1 + 1/3 = 4/3
\end{align*}
\]

The $E_i$ value of each color bin can be calculated with Equation 3.2, and the similarity (distance) of the eigenvalue between two images can be further calculated to order the images for retrieval.

\[
E_i(P_i) = -g(P_i) \sum_{j=1}^{N} f(j) P_{ij} \log_2(P_{ij})
\]

### 3.4 Image Classification Using CDH and IACH

The image classification method is similar to decision tree. An image is selected from the database and classified using image retrieval methods. The image retrieval system that has been constructed will be used. The creator of the image is identified according to the first 10 images returned. Fig 3.7 shows the results returned from the image retrieval system. As shown in Fig 3.7, the first 10 images returned by the system are images painted by Zhang Daqian. Therefore, this input image can be classified as a work of Zhang Daqian. The image classification algorithms are shown in Fig 3.8 For else situations, the classification will be based on whether the first two images are of the same painter.
Fig 1.9 Image retrieval system returned results

Fig 3.8 Image classification algorithms
3.5 Similarity measurement

The $Q_{CDH}$ and $Q_{ACH}$ of the input image $Q_{image}$ are calculated and respectively deducted from $D_{CDH}$ and $D_{ACH}$ of the image $D_{image}$ in the database to obtain absolute values. Later, ranking is used as a similarity measurement method. As shown in Equation 3.3, $d(Q_{image}, D_{image})$ is the distance between two images.

$$d(Q_{image}, D_{image}) = |Q_{CDH} - D_{CDH}| + |Q_{IACH} - D_{IACH}|$$

4. Experimental Results

4.1 Image Database Initialization

4.1.1 Background on the Artists

A brief introduction of the artists is given below. According to the naming tradition of Chinese paintings, the following terminologies are used to denote the main categories of Chinese paintings: mountains-and-waters (landscape), flowers (a.k.a. flowers-and-birds), trees-and-grass, human figures, and animals (Jia & Wang, 2004).

(1) Shen Zhou (1427–1509) of the Ming Dynasty: 46 of his paintings are collected in the database.

(2) Dong Qichang (1555–1636) of the Ming Dynasty: 44 of his paintings are collected in the database.

(3) Gao Fenghan (1683–1748) of the Qing Dynasty: 47 paintings of his paintings are collected in the database.

(4) Wu Changshuo (1844–1927) of the late Qing Dynasty: 46 of his paintings are collected in the database.

(5) Zhang Daqian (1899–1983) of the late Qing Dynasty: 91 of his paintings in the database (Jia & Wang, 2004).

4.1.2 Building Image database

We resize all the images to either 256 x 384 (pixel) or 384 x 256 (pixel). Fig 4.2 shows two images from the database.
Fig 1.10: Two images from the database (256 x 384 and 384 x 256)

4.2 Image Retrieval Experiment Results

For image retrieval, the system should extract image features and compute the degree of similarity between a query and a database image. In our experiments, 274 images were chosen, consisting of 5 categories including Shen Zhou, Dong Qichang, Gao Fenghan, Wu Changshuo and Zhang Daqian. We evaluated the system’s efficiency and effectiveness. For effectiveness, we examined how many relevant images to the query were retrieved. The retrieval effectiveness can be defined in terms of precision.

A precision rate can be defined as the percent of retrieved images similar to the query among the total number of retrieved images. The precision rates are computed using following equations:

\[
\text{Precision} = \frac{N_{\text{correct}}}{N_{\text{correct}} + N_{\text{false}}} \tag{4.1}
\]

where \(N_{\text{correct}}\) denotes the number of retrieved images similar to the query. \(N_{\text{false}}\) is the number of retrieved images dissimilar to the query. The input image is randomly selected from the database. In the experiments, we used the top-10 retrieved images to compute precision (Sun et al., 2006). Tables 4.1 show average precision rates according to the image categories. Figures 4.4, 4.5 and 4.6 shows the top ten retrieval results of a query (the top left image is the query image and the retrieved image).
<table>
<thead>
<tr>
<th>Precision</th>
<th>Our method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shen Zhou</td>
<td>0.61</td>
</tr>
<tr>
<td>Dong Qichang</td>
<td>0.85</td>
</tr>
<tr>
<td>Gao Fenghan</td>
<td>0.69</td>
</tr>
<tr>
<td>Wu Changshuo</td>
<td>0.75</td>
</tr>
<tr>
<td>Zhang Daqian</td>
<td>0.9</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>0.76</strong></td>
</tr>
</tbody>
</table>

Table 4.3 Average precision rates according to the image categories

**Fig 1.11** Example of Image retrieval results (Zhang Daqian)
Fig 1.12 Example of Image retrieval results (Wu Changshuo)

Fig 1.13 Example of Image retrieval results (Dong Qichang)

4.3 Image Classification Experiment Results

Two cases of classification have been studied. The artists classified in case 1, 2 are (1) Shen, Dong, Gao, and Wu, (2) Shen, Dong, Gao, Wu, and Zhang, respectively. Shen and Dong are compared with each other because both of them were artists in the Ming Dynasty who focused on mountains-and-waters painting. Zhang possessed diverse painting styles and topics. His paintings are most likely to be confused with the others’ work, as will be shown shortly. We thus examine the classification results with and without him as one class.
Table 4.2 provides the detailed classification result for the five artists obtained by the IACH and CDH. Each row lists the percentages of an artist’s paintings classified to all the five artists. The experimental results indicate that our methods are better than the Li Jia (Jia & Wang, 2004) methods. Numbers on the diagonal are the classification accuracy rate for each artist. The classification accuracy for Wu is high (85%). In our methods, Shen, Dong, Gan and Wu classification rate is better than Li Jia (Jia & Wang, 2004). As shown in Table 4.1, the average classification accuracy of the two methods are 71% and 76% respectively.

<table>
<thead>
<tr>
<th>Accuracy (%)</th>
<th>Li Jia 2004 (Jia &amp; Wang, 2004)</th>
<th>Our method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shen Zhou</td>
<td>63</td>
<td>67</td>
</tr>
<tr>
<td>Dong Qichang</td>
<td>58</td>
<td>68</td>
</tr>
<tr>
<td>Gao Fenghan</td>
<td>65</td>
<td>83</td>
</tr>
<tr>
<td>Wu Changshuo</td>
<td>97</td>
<td>85</td>
</tr>
<tr>
<td>Average</td>
<td>71</td>
<td>76</td>
</tr>
</tbody>
</table>

Table 4.2 Comparing classification results obtained by different methods in four artists

5. Conclusions

Content-based image indexing and retrieval has been a very active research area. In the past decades, most research groups attempted to find the best feature to optimally characterize an image. However, the fact is that no single feature can efficiently characterize the content of an image. Besides, automatically extracted low-level features cannot efficiently capture the semantic concepts of the content, which constitutes the major obstacle to the development of efficient CBIR systems. Therefore, CBIR is expected to remain a challenging research topic for many years. In this paper, the effectiveness and efficiency of the proposed method was demonstrated. The experimental results showed a great potential for a success in CBIR and image classification. Future works are advised to establish algorithms to identify other important semantic information for digitalized Chinese Paintings images.
Besides, how to extract stroke styles of paintings using IACH and CDH was explored. We demonstrated that different types of strokes or washes of an artist can be extracted by the feature extraction approach. The proposed method can be applied in several applications: classification of paintings into artists, finding similar or dissimilar paintings of one artist to or from another artist’s work, and measuring similarity between images of one artist. We also performed experiments on a collection of paintings from five Chinese artists. There are several research directions for future works. First, more art-related images can be analyzed and identified using the developed method. Second, the modeling approach can be further enhanced. One interesting issue is to automatically determine the complexity of the model. At the current stage, the number of parameters in the mixture model is pre-chosen. Model selection techniques can be applied to adaptively choose the number of parameters according to the diversity of an artist’s painting styles. The diversity of an artist’s work is also an interesting aspect to investigate.

More effort should be made to facilitate the applications of such techniques to assist art historians or users of art image databases. Potential applications can be developed with image analysis techniques to help users find similar paintings or paintings of similar styles. Applications can also be developed to help art historians find possible connections among paintings. We will continue our effort for this aspect in the future.

Reference


