

## Wuhan University Journal of Natural Sciences

Article ID 1007-1202(2012)01-0055-06 DOI 10.1007/s11859-012-0804-9

## New Method of Image Retrieval Based on Interest Image Region Blocks and Comprehensive Features

#### D PENG Xiaohua<sup>1</sup>, ZHU Yu<sup>1,2†</sup>, LIN Zhongzheng<sup>1</sup>

1. School of Information Science and Engineering, East China University of Science and Technology, Shanghai 200237, China;

2. College of Information Science and Technology, Shihezi University, Shihezi 832003, Xinjiang, China

© Wuhan University and Springer-Verlag Berlin Heidelberg 2012

**Abstract:** We propose an image retrieval method based on interest image region by asymmetrical blocking. An image is segmented into the interest region and background region on a certain rule. For the interest image regions, the color histogram of the uneven blocks is extracted as the color characteristic. We also collect the mean and variance value of the Gabor filtering results of background blocks as texture features of the background image. Then, the images can be retrieved by synthesizing the image color and texture features. We test our approaches by analyzing the results of recall and precision indicators for the Corel image database. The experiment results show that the proposed method performs effectively and accurately, which is more effective to retrieve the distant-view images, and the achieved precision increases by about 10% without loss of the retrieval call compared with some other traditional search methods.

**Key words:** image retrieval; color histogram; Gabor filter; image block; interest region

CLC number: TP 391.4

Received date: 2011-08-26

† To whom correspondence should be addressed. E-mail: zhuyu@ ecust.edu.cn

#### 0 Introduction

The technique of content-based image retrieval (CBIR) is a kind of "looking for picture from picture" search mode. It is a big breakthrough of "seeking picture from keyword". CBIR has become the state-of-the-art image search technique and has been used in medical science, e-commerce, agriculture, and many other application fields. How to improve the image retrieval efficiency is the essential point for the design of a CBIR system.

A general content-based image retrieval (CBIR) system usually makes use of different visual features<sup>[1]</sup>, such as color, texture, and shape. Among these features, color is an important element to express the image content, which is also the main visual feature during the process of image identifying. Comparing with other visual features, color has less dependence on the image's size, direction, perspective, and the changing invariance for translation, rotation, and scale transformation. Because of these advantages, it shows strong robustness in image processing. So far, retrieval based on the color feature is still an important part of the image retrieval based on content. Texture<sup>[2]</sup> is another important characteristic feature of image. Its essence is for portraying the gray spatial regular distribution of the pixel neighbor domain, which does not depend on color or brightness. Therefore, it can reflect the basic characteristics of surface properties of image. Texture analysis is widely applied on the scene analysis, medical images, and remote sensing images analysis, etc. The key of retrieval based on the image texture is extracting the feature's quantita-

Foundation item: Supported by the National Natural Science Foundation of China (50803016)

**Biography:** PENG Xiaohua, female, Master candidate, research direction: image processing and image retrieval. E-mail: claudiahua@sina.com

tive description by imaging processing technology. The common methods of extracting texture feature are based on statistics and spectrum analysis<sup>[3]</sup>.

Combing the two features mentioned above, extracting the color information of the whole image appended the entire texture feature to search image<sup>[4-6]</sup> is the conventional method of comprehensive retrieval. It can optimize the result of searching to some degree by various methods. However, these conventional methods cannot take full advantage of colligation features. On the other hand, the image interest region<sup>[7]</sup> can be comprehended as the interest parts in the image for people. For image retrieval, generally, it only requires to find out the pictures with the similar interest area, which is also the reason why the interest region is the main research subject in the retrieval. Therefore, contrasting with the previous methods<sup>[4-6]</sup>, we propose a new method that based on the separation of the interest region and background region and the extraction of their color and texture properties, respectively. First, an image is segmented into the interest region and background region on a certain rule. The multiple color blocks are unevenly divided from the image corresponding to the interest image region and one texture block is just formed from the background region; Second, the color histogram feature and the texture information can be extracted from the above two regions respectively; Third, these color and texture features can be synthesized to conduct the image retrieval. Because the color feature from the uneven image blocks includes space information, the new method can improve the search results effectively, especially for the distant-view image.

# 1 Separation of the Interest and Background Region

It is important to apply image blocking for images retrieval, which can increase the space character. Generally, the size and number of the blocks are determined by the original image size<sup>[8]</sup>. The interest area usually has the most significant local characteristics with relatively concentrated distribution. Based on these considerations, uneven image blocking is employed to acquire more than one color blocks and only one texture block. The multiple color blocks are corresponding to the interest image region and the texture information is for background piece.

• Division of background region (texture block)

Taking the Corel image database as an example, all

the color images in the library are of the same size as  $384 \times 256$  or  $256 \times 384$ . The greatest common multiple of length and width of these images is  $2^7$ , recorded as N = 7. In principle, there are  $2^i \times 2^i$  ( $i = 2, \dots, N$ ) kinds of choices for image block. If the interest region occupies a relatively small area in an image, a larger digit will be a good choice for the number of blocks, which means that *i* is a bigger value.

In this paper, the background region is formed by the following rules: When  $i \leq [N/2]+1$ , we merge the outermost j=1 circles including  $(4 \times (2^i - 1))$  number of blocks as the background region; When  $i \geq [N/2]+1$ , we merge the outermost j=2 circles including  $(4 \times (2^i - 3) + 4 \times (2^i - 1))$  number of blocks as the background region. In this work, the background region is also regarded as the texture block.

Division of interest region and its color blocks

On the basis of image block, merging the outermost *j* circles will take the rest blocks as the interest region. However, it is conceivable that if the color histogram of interest region is calculated directly, it may bring a problem of large computation cost due to the large number of the color blocks. Therefore, the rest image blocks will be merged by a certain rule to form the color block and the concrete merging flowchart is shown in Fig. 1. Adopting this method, the number of color blocks is  $4 \times (2^{i-1} - j)$ 



Fig. 1 Flowchart of image unevenly merging

when the outermost j (j = 1 or 2) circles are merged as texture block. Figure 2 shows the process of the block division by taking 8×8 image blocks as an example.



Fig. 2 Division of the total 13 blocks by uneven merging of 8×8 blocks

*M*1: Merging from the second row and the second rank image block continuously, with a total of five blocks;

*M*2: Merging from the third row and the third rank image block continuously, with a total of three blocks

An example of image blocking by the above method is shown in Fig. 3, which includes one texture block and twelve color blocks of the image. Here, i = 3, which means that the unevenly merging is based on the  $2^3 \times 2^3$  blocks.

## 2 Color Feature Extraction of Interest Region

After the image is unevenly blocked, the color feature<sup>[9]</sup> of the separated color blocks of the interest region can be extracted by the following image retrieval method.

#### 2.1 Color Conversion Model

The common used color spaces are RGB, HSV, YUV, and so on. The HSV uses hue, brightness, and color saturation to express pixels. Since HSV color space has the advantage of naturality and visual consistency, it required the conversion of model RGB to  $\text{HSV}^{[3]}$ . A single pixel in the RGB model has the value of (r, g, b); the corresponding value in HSV space is (h, s, v). They have the following relationships:

$$v = \max(r, g, b), \quad s = \frac{v - \min(r, g, b)}{v}$$
  
Make  $r' = \frac{v - r}{v - \min(r, g, b)}, \quad g' = \frac{v - g}{v - \min(r, g, b)},$   
 $b' = \frac{v - b}{v - \min(r, g, b)},$ 

Fig. 3 Illustration of uneven image blocking

(a) The image to be blocked; (b) The texture block of the image; (c) The color blocks of the image

Then  

$$h' = \begin{cases}
5+b', & \text{if } r = \max(r, g, b) \text{ and } g = \min(r, g, b) \\
1-g', & \text{if } r = \max(r, g, b) \text{ and } g \neq \min(r, g, b) \\
1+r', & \text{if } g = \max(r, g, b) \text{ and } b = \min(r, g, b) \\
3-b', & \text{if } g = \max(r, g, b) \text{ and } b \neq \min(r, g, b) \\
3+b', & \text{if } b = \max(r, g, b) \text{ and } r = \min(r, g, b) \\
5-r', & \text{others} \\
h = h'/6 \times 360 
\end{cases}$$
(2)

 $h = h' / 6 \times 360$ 

### Hence $h \in [0, 360]$ , $s \in [0, 1]$ , $v \in [0, 1]$ .

#### 2.2 Color Quantified and Color Histogram

To reduce the computation cost, the HSV data should be nonlinearly quantized. The formulas are given as follows:

$$H = \begin{cases} 0, h \in [354, 15) \\ 1, h \in [15, 25) \\ 2, h \in [25, 45) \\ 3, h \in [45, 55) \\ 4, h \in [55, 80) \\ 5, h \in [80, 108) \\ 6, h \in [108, 140) \\ 7, h \in [140, 165) \\ 8, h \in [165, 190) \\ 9, h \in [190, 220) \\ 10, h \in [220, 255) \\ 11, h \in [255, 275) \\ 12, h \in [275, 290) \\ 13, h \in [316, 330) \\ 15, h \in [330, 345) \end{cases} S = \begin{cases} 0, s \in [0, 0.15) \\ 1, s \in [0.15, 0.40) \\ 2, s \in [0.40, 0.75) \\ 3, s \in [0.75, 1] \\ 0, v \in [0.15, 0.40) \\ 2, v \in [0.40, 0.75) \\ 3, v \in [0.75, 1] \end{cases}$$

Let l = 16H + 4S + V, then  $l \in [0, 255]$ . We take h(l) as the quantized histogram:

$$h(l) = \frac{n_l}{K} \tag{3}$$

which indicates 256 colors level after the quantization. Here,  $n_i$  is the number of pixels which have the color level l, K is the total number of the pixel in the image.

#### 3 Texture Feature Extraction of Image Background

In order to draw the texture characteristics of the image background that are separated out, we select the mean and variance of the image Gabor filter<sup>[10]</sup> results as texture features of background region.

Gabor transformation equation is shown as follows<sup>[11]</sup>:

Gabor(x, y) =  $\frac{1}{2\pi\sigma^2} e^{-\frac{x'^2+y'^2}{2\sigma^2}} (\cos 2\pi f x' + j \sin 2\pi f x')$  (4)

where  $x' = x \cos \theta + y \sin \theta$ ,  $y' = -x \sin \theta + y \cos \theta$ , f is the center frequency, and  $\theta$  is the direction angle to the Gabor filter.

To depict the texture information better to distinguish between two objectives, we need to extract information feature to the greatest extent. It is required that the design of filter on the frequency domain is not overlapping but covering almost all areas, which is a Gabor filter design problem. From the formula shown above, the position of Gabor filter is decided by the parameters of direction angle  $\theta$  and center frequency f.

Direction angle  $\theta$  is proposed to be defined as the following process. During the establishing procedure for Gabor filter, we determine six directions for choice:  $30^\circ$ ,  $60^\circ$ ,  $90^\circ$ ,  $120^\circ$ ,  $150^\circ$ , and  $180^\circ$ . Such selection can satisfy the analysis of the most of texture images.

For determination of the parameter f, Jain *et al* <sup>[12]</sup> gave a relatively simple algorithm. For an image with pixels length and width  $N_c$ , where  $N_c$  is the power of 2. The center frequency can take the numerical value:  $1\sqrt{2}, 2\sqrt{2}, 4\sqrt{2}, \cdots, (N_c/4)\sqrt{2}$ . The size of images in the Corel is  $384 \times 256$  or  $256 \times 384$ . The greatest common multiple of the length and width of these images is  $2^7$ . If  $N_c = 256$ , then  $f_{\text{max}} = 64\sqrt{2}$ . In this paper, we choose and use five center frequencies  $1\sqrt{2}$ ,  $2\sqrt{2}$ ,  $4\sqrt{2}$ ,  $8\sqrt{2}$ , and  $16\sqrt{2}$  during the Gabor filter.

The direction angle and center frequency are selected according to the above discussion, the process of texture retrieval will withdraw 30 (=6×5) groups of parameters from Gabor filter groups. Each group includes mean value M and variance value S. Therefore, the texture features of one picture can be expressed by 30 means and 30 variances, with a total of 60 variables.

#### **Results and Discussion** 4

According to the unevenly image block, more than one color blocks are separated from the interest image region. One texture block is also obtained as image background. Then, the color histograms, which are taken as the color features of each color block, are extracted. Meanwhile, we use results of Gabor filters as texture feature. Therefore, it can integrate the two characteristics to compare the similarities between images.

For the image q to be retrieved and the target image t, the total distance can be expressed as:

$$D(q,t) = \lambda \sum_{k=1}^{4 \times (2^{i-1}-j)} \frac{1}{4 \times (2^{i-1}-j)} D_k(q,t) + (1-\lambda)D'(q,t)$$

$$i \in \{2, 3, \cdots, 7\}; j = 1 \text{ or } 2$$
 (5)

where  $D_k(q, t) = (h_q(l) - h_t(l))^T A(h_q(l) - h_t(l))$ ,  $A = [A_{ij}]$ , in which  $A_{ij}$  means the similarity between  $h_q(i)$  and  $h_t(j)$ ,  $A_{ij} = A_{ji}$ ,  $A_{ii} = 1$ , and  $\sum D_k(q, t)$  is the general color histogram distance of each color block. The texture distance between the two images is:

$$D'(q,t) = \sqrt{\sum \left[\sum_{i=0}^{N-1} (M_{q,i} - M_{t,i})^2 + \sum_{j=0}^{N-1} (S_{q,j} - S_{t,j})^2\right]}$$

where *M* and *S* represented mean and variance value of the output of Gabor filter, respectively, and N = 30.

Parameter  $\lambda$  indicates the distance power-weight, and it can be adjusted with actual needs and circumstances. According to the formula, the similarity between the two images is inversely proportional to the distance, i.e., the smaller distance means the higher similarity. The retrieval system outputted 10 images with the lower distance than the other retrieved images.

All the experiments were performed with the standard Corel image database for image retrieval. One of the results is shown in Fig. 4.



Fig. 4 The result of retrieving a picture belongs to the kind of sea (a) Image to be retrieved; (b) Results of image retrieval

Figure 5 shows the comparison results of recall and precision of image retrieval on the basis of uneven blocks for ten different categories of images, i.e., African, sea, building, buses, dinosaurs, elephants, flowers, horses, food, and mountain. We can find that, for the image categories which can be segmented into interest image region and the background clearly, such as elephant, and pictures with distant view, such as sea, mountains, etc, our image retrieval method will achieve a better effect; however, for some kinds of images whose regions of interest are single and almost occupy all areas of the graphics, such as bus and flowers, to avoid taking the part of interest area as background during retrieving, the number of blocks should be set as large as possible to obtain the satisfied result. This conclusion can also be derived from that in Fig. 6. It shows the comparison of recall and precision statistical results of Corel images retrieval for three different kinds of image evenly blocks:  $4 \times 4$  (*i* = 2),  $8 \times 8$  (*i* = 3), and  $16 \times 16$  (*i* = 4), which have 4, 12, and 28 uneven color blocks and extra one texture block, respectively. It is shown that both the retrieval recall and precision increase with increasing the number of image blocks.

Meanwhile, for the distant-view images in the Corel, we conduct the image retrievals by using four different



for 10 different categories of images

methods. The results are shown in Fig. 7, which demonstrate the image retrieval efficiency comparison among the methods of color histogram, Gabor texture, color histogram integrated with Gabor texture, and our proposed method of block color histogram integrated with Gabor texture based on 13 image blocks. The results indicate that the new method shows higher retrieval precision than all the other methods without loss of the recall, and especially, the retrieval precision is improved by about 10% compared with the third method. It is shown that the proposed method is very effective for searching the image with the visible texture region and color region.



Fig. 6 Comparison of retrieval effect among three kinds of the total image blocks



Fig. 7 Comparison of retrieval effect among the different methods

### 5 Conclusion

In this paper, we establish the image block model of interest region (the main partition of image) and the image background. Moreover, on this basis, for the interest region, we carry out the uneven blocks and extracted color histogram of each block and withdraw texture information of the background part. Then, both the color and texture features are synthesized to conduct image retrieval. The experimental results show that this method performs effectively and accurately, especially for the distant-view images that can be separated with interest image region and the background clearly.

#### References

- Liao Hancheng. Image Retrieval Based on MD5 [C]// International Conference on Advanced Computer Theory and Engineering 2008. Phuket: IEEE Press, 2008: 989-991.
- [2] Haralick R M, Shanmugam K, Dinstein I. Textural features for image classification Systems [J]. *IEEE Trans System*, *Man and Cybernetics*, 1973, 3(6): 610-621.
- [3] Zhou Mingquan, Geng Guohua, Wei Na. Content-Based Image Retrieval Techniques[M]. Beijing: Tsinghua University Press, 2007(Ch).
- [4] Song Yan, Liu Fang'ai. Image retrieval based on color and texture [J]. *Computer Engineering and Design*, 2007, 28(17): 4180-4182.
- [5] Xu Huiying, Yuan Jie, Zhao Jianmin. Image retrieval based on color and texture [J]. *Computer Science*, 2009, 36(5): 282-286(Ch).
- [6] Xu Xiangli, Zhang Libiao, Liu Xiangdong, et al. Image retrieval using multi-granularity features of color and texture [C]//Fifth International Conference on Fuzzy Systems and Knowledge Discovery. Jinan: IEEE Press, 2008: 54-58.
- [7] Meng Fanjie, Guo Baolong, Li Xinwei, et al. New image retrieval method based on convex hull of interest points [J]. Journal of Optoelectronics Laser, 2010, 21(6): 936-939(Ch).
- [8] Zhang Wubin. Image Retrieval Based on the Color Feature [D]//Chengdu: School of Information and Software Engineering, University of Electronic Science and Technology of China, 2009.
- [9] Wang Xiangyang, Lu Tingting. A robust content-based color image retrieval using multiple features[J]. *Journal of Image* and Graphics, 2007, 12(10): 1748-1760(Ch).
- [10] Su Xiaohong, Ding Jin, Ma Peijun. Image retrieval by convex hulls of interest points and SVM-based weighted feedback [J]. *Chinese Journal of Computers*, 2009, **32**(11): 2221-2228(Ch).
- [11] Sastry C S, Ravindranath M, Pujari A K, et al. A modified Gabor function for content based image retrieval[J]. Pattern Recognition Letters, 2007, 28: 293-300.
- [12] Jain A K, Farrokhnia F. Unsupervised texture segmentation using gabor filter [J]. *Pattern Recognition*, 1991, 24(12): 1167-1186.