Image Retrieval Algorithm Based on Fractal Coding

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Abstract. A traditional fractal image retrieval system needs to code all the images before the retrieval, and thus real-time retrieval cannot be realized. Focusing on this problem, this study puts forward an image retrieval algorithm based on image entropy and fractal blocks. In the algorithm, images are screened at first according to comparison of image entropies. Therefore, the screened images in an image library are similar to a query image to some extent. In this way, the number of images requiring to be matched with the query image in the image library can be reduced. In the meanwhile, the time for image retrieval can be greatly shortened. Then, the retrieval function is realized based on the characteristic computation structure similarity of fractal blocks of images. As shown by the experimental results, the algorithm does not need to extract fractal code documents at first when images are put into the library. Thus, defects in offline retrieval of the traditional fractal image retrieval can be overcome. In addition, a precision ratio and a recall ratio of checking results can be ensured.

Keywords: Image retrieval · Fractal coding · Image entropy · Online retrieval

1 Introduction

Image retrieval has always drawn the joint attention from numerous researchers. In the field of Content Based Image Retrieval (CBIR), people have tried a semantic-based retrieval model and proposed a retrieval model based on image feature sets (e.g. color and layout of images). However, complicated contents of a whole image could not be completely described by the above image features. With the occurrence of the fractal theory and its application in the image retrieval field, solutions have been proposed for solving the above problems. In this technology, a fractal encoding algorithm is used for extracting fractal features of images, namely image fractal codes. Fractal codes are employed for describing trans-scale similarity redundancy information in an image and can uniquely denote the original image. Therefore, by recording image features by fractal codes and applying them to similarity judgment and retrieval of images, the recall ratio and accuracy of image retrieval technology can be increased effectively.

In the end of 1990s, A.D. Sloan [1] took the initiative to apply the fractal technology in image retrieval, since various fractal-based image retrieval algorithms have come up

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with one after another. However, the complicated course of fractal image encoding led to excessive time spent on encoding and the failure to realize the rapid retrieval in image retrieval. Therefore, a lot of method have been proposed to increase the encoding speed. Literature [2] proposed a wavelet-fractal based image encoding algorithm and made full use of correlations of sub-bands to improve the quality of reconstructed images, turning global search to neighbor search and thus reducing the encoding time. As proposed in Literature [3], a quad tree partition method was applied iteratively during encoding and a median filter was used after encoding to removal noise in images, aiming to increase encoding efficiency. Literature [4] proposed a method for presenting image blocks by orthogonal sparse encoding and texture feature extraction, by which image reconstruction quality is better and encoding becomes quicker. Till the present, a lot of methods have been proposed for increasing retrieval efficiency. In Literature [5], an improved Hu invariant moment characteristic quantity was extracted from fractal codes as the retrieval index, which can thus obtain good retrieval effects. Literature [6] proposed a fractal image retrieval algorithm based on adjacent matching and proposed a new distance formula capable of quickly judging similar blocks between images, which manage to shorten the encoding time and enhance the accuracy of image similarity judgment. Literature [7] came up with an improved rapid fractal image retrieval algorithm based on HV partition to accelerate encoding. In order to increase the accuracy of image retrieval, a new weighting parameter based on partitioning block sizes was proposed, which could significantly improve the precision ratio of algorithm.

By the above-mentioned methods, the encoding time is reduced through various improvements during fractal encoding, for the purpose of speeding up the retrieval. However, these methods need to conduct fractal encoding of a to-be-retrieved image and images in an image library at first before image retrieval, while fractal codes are adopted for retrieval after obtaining their encoding files. As a result, online real-time retrieval cannot be realized. Aiming at above problems, the paper proposes a rapid image retrieval algorithm based on image entropies and fractal blocks. At first, an image 2D entropy is used to screen an image library so as to decrease the retrieval scope. Then, the to-be-retrieved image is rapidly matched with fractal block parameters of the images in the library. The method does not request pre-encoding of the image, and directly takes the image fractal block, namely R block, as the basis to judge the similarity between images. Therefore, an online real-time retrieval function based on fractal encoding is realized.

2 Basic Fractal Coding Algorithm

At the very beginning, fractal image coding was proposed by Barnsley [8] and Jacquin [9], and then developed. Fractal image compression essentially indicates that real images have high affine redundancy, namely, the images contain a lot of self-reference substances and a lot of parts are self-similar. Besides, each area of the image can be used to express each other through proper conversion. Theoretically, fractal coding means that fractal codes are constructed by self-similarity of images, and image features are extracted by fractal codes. In terms of extraction of fractal codes, the images need to be segmented at first. The image I is divided into n non-intersected sub-blocks Ri (i = 1, 2…n). The set

R_i constitutes an R pol, and the union set of R_i is the image to be coded. According to the specific algorithm rules, the image I is further divided into D_i (i = 1, 2…n) blocks which constitute the D pool. Based on the overall and local similarity of the image, the D_i similar to Ri is searched. The through affine transformation, contrast control and brightness control, a mapping relation ωi, is established, of which the general form is expressed as follows:

$$\omega_i : D_i \to R_i, \mathrm{i} \neq \mathrm{j}, I, j = 1, 2 \ldots, n \tag{1}$$

$$\omega_i(D_i) = \lambda_i(\gamma_i D_i) = s_i t_k(\gamma_i D_i) + o_i \tag{2}$$

where Mapping γi translates D_i to R_i and shrinks to a size consistent with R_i. t_k is an equidistant affine transformation parameter, which can be used for pixel re-arrangement and thus strengthen matching quality. s_i and o_i respectively stand for adjustment of brightness and contrast ratio. In order to find the D block best matched with the R block in the D pool (codebook), it is of necessity to calculate the fractal parameters s_i and o_i. Therefore, according to the collage theory, it is necessary to minimize the following errors:

$$\min\|R_i - (s \cdot D_i + o \cdot 1)\|^2 \tag{3}$$

The first-order partial derivatives of s and o in Eq. (3) are calculated based on differential geometry. The obtained equations are respectively equal to 0, and thus the linear system of equations of parameters s and o can be obtained. Then, s and o can be obtained through solution of the equation system, namely:

$$\begin{cases} s = \frac{\langle R - \overline{R} \cdot 1, D - \overline{D} \cdot 1 \rangle}{\|D - \overline{D} \cdot 1\|^2} \\ o = \overline{R} - s \cdot \overline{D} \end{cases} \tag{4}$$

The s and o of each D block in the codebook, corresponding to the R block, are quantified by a consistent quantification device. The error *E(R, D)* is calculated:

$$E(R_i, D) = \|R - (s \cdot D + o \cdot 1)\|^2 \tag{5}$$

Equation (4) is substituted into Eq. (5), and thus the following results are obtained in the end:

$$E(R_i, D) = \left\|R - \overline{R} \cdot 1\right\|^2 - s^2\left\|D - \overline{D} \cdot 1\right\|^2 \tag{6}$$

D_i is treated by 8 types of isometric transformation and t_k satisfying Eq. (6) is calculated:

$$E\left(R_i, t_k\left(D_{M(i)}\right)\right) = \min_{0 \leq k \leq 7} E\left(R_i, t_k\left(D_{M(i)}\right)\right) \tag{7}$$

At this moment, the optimum similar approach of a R_i can be obtained:

$$R_i = s_i \cdot t_k\left(D_{M(i)}\right) + o_i \cdot 1 \tag{8}$$

After following the above steps, the fractal coding parameters of the current R_i block can be obtained, including the quantified brightness control parameter s_i, the contrast control parameter o_i, the subscript M(i) of De block best matching the R_i block as well as the sequence number t_k of isometric transformation. The above steps are repeated for the rest R blocks till all the R blocks obtain fractal coding parameters of their iterative functions.

It can be found from the above introduction to the fractal coding algorithm that the to-be-coded initial image can be selected randomly during coding of the fractal coding algorithm. Meanwhile, the same reconstructed attractor image can be obtained after different times of iterations. Actually, the significance of the fractal coding algorithm is to seek for a more compact piece of digital information to uniquely characterize the original image. In this way, redundancy in the image can be reduced or eliminated.

In view of the feature that a fractal coding document can uniquely characterize the original image, and the document also contains position information of image sub-blocks, it is deemed that the fractal coding documents can be applied to an image retrieval system, which is characterized in following aspects;

1. More similar images will have similar fractal coding documents.
2. It can be considered that the closer the fractal coding documents between images are, the more similar the images will be.

A.D. Sloan [1] took the initiative to employ the fractal coding algorithm in image retrieval. Fractal coding should be conducted when images are put into a library. The obtained fractal coding documents are stored in a feature database, and thus only offline retrieval can be realized. The so-called offline retrieval suggests that, before image matching, the image retrieval system has completed feature extraction of all the images in the database. This retrieval algorithm is poor in feasibility. Therefore, this paper puts forward an online real-time retrieval algorithm which does not need to perform feature extraction of all the images of a database in advance.

3 Improvement of Rapid Image Retrieval Algorithm Based on Fractal Coding

3.1 Image Retrieval Algorithm Based on Fractal Blocks

In the fractal coding algorithm, we are required to divide the image into $B * B$ non-overlapping value domain R blocks and overlapping $2B * 2B$ definition domain D blocks, and find the best matching block $D_{M_{(i)}}$ of the value domain block R_i, as well as calculate the collage error of the best matching block $D_{M_{(i)}}$ of R_i:

$$E\big(R_{i,}t_i\big(D_{M\,(i)}\big)\big) = \sqrt{\sum\nolimits_{a=1}^{n}\sum\nolimits_{b=1}^{n}\left(r_{ab} - S(R_i)d_{ab} - o(R_i)\right)^2/n} \tag{9}$$

where the pixel value at the position (a, b) of the R block is r_{ab}, and the pixel value at the (a, b) position of the $D_{M\,(i)}$ block (a, b) is d_{ab}.

The size of the matrix composed of the collage errors of all R blocks is 1/(n * n) of the original image size. The use of collage error histogram as the basis for fractal coded image retrieval has been verified in the Literature [10]. Although a collage error is affected by the parameters of the fractal coding document, it cannot completely represent the original image. Besides, the algorithm also needs to generate a fractal coding document index when the image is input into the library, and it is not online retrieval. Therefore, this study proposes a rapid fractal retrieval algorithm based on fractal block R blocks.

For an R block of size N × N, the standard variance:

$$\sigma_R = \frac{1}{N}\left\|R - \overline{R} \cdot 1\right\| = \left(\frac{1}{N \cdot N}\sum_{i=1}^{N \cdot N}(r_i - \overline{R})^2\right)^{1/2} \tag{10}$$

By combining the standard variance with the J.M. Beaumont fractal coding scheme [11], the R block and the matching D block conform to:

$$R_i = \frac{\sigma_r}{\sigma_d}(t_k(r_i(D_{M(i)}))) + \overline{R_i} - \frac{\sigma_r}{\sigma_d}\overline{M}(t_k(S_i(D_{M(i)}))) \tag{11}$$

where: σ_r represents the standard variance of R_i, σ_d is the $D_{M_{(i)}}$ standard variance of the transformed best matching block, $\overline{M}$ means taking the mean. Formulas (2) and (11) are combined, then:

$$s_i t_k\left(\gamma_i\left(D_{m(i)}\right)\right) + o_{i=}\frac{\sigma_r}{\sigma_d}\left(t_k\left(\gamma_i\left(D_{m(i)}\right)\right)\right) + \overline{R_i} - \frac{\sigma_r}{\sigma_d}\overline{M}\left[t_k\left(\gamma_i\left(D_{m(i)}\right)\right)\right] \tag{12}$$

If the value domain block R_i and the best matching $D_{M_{(i)}}$ block satisfy the equation $s = \frac{\sigma_r}{\sigma_d}$, it is substituted into Eq. (12):

$$\mathrm{o}(R_i) = \overline{R_i} - s_i\overline{M}\left[t_k\left(\gamma_i\left(D_{m(i)}\right)\right)\right] \tag{13}$$

From Eq. (13), it can be seen that the grey scale adjustment is not performed on the $D_{M_{(i)}}$ block, then:

$$\overline{M}\left[t_k\left(\gamma_i\left(D_{m(i)}\right)\right)\right] = \overline{M}\left[D_{m(i)}\right] \tag{14}$$

Equation (14) is substituted into Eq. (13), then:

$$o(R_i) = \overline{R_i} - s_i \cdot \overline{M}[(D_{M(i)})] \tag{15}$$

It can be found that the pixel average value $\overline{R_i}$ of the value domain block R_i, the pixel average value of the best matching block $D_{M(i)}$, and the brightness adjustment factor s_i determine the offset o_i. All the o_i are combined into an offset image in the form of a matrix, and it is similar with the collage error matrix in Literature [10]. Compared with the use of the collage error as the similarity measurement, eight equidistant transformations t_k need to be calculated. Using the offset o_i as the similarity measurement significantly reduces the amount of calculation.

In fact, fractal coding is a lossy compression algorithm. The main reason is that in the process of fractal coding, a block D adjusts the image brightness through affine transformation, changes the frequency domain information of the original image, and is distorted to the original image. The D block overlapping and segmented in the same image is composed of R blocks that do not overlap each other. Therefore, it can be concluded that the D block is composed of R blocks that are collaged into the block. Then, the image R block can be used as the basis for judging the similarity between the images.

At present, the indicators for calculating graphic similarity include mean square error, Euclidean distance and peak signal-to-noise ratio. However, due to the different sensitivity of the human eyes to color, this calculation method often fails to meet the visual quality standard of the human eye. Therefore, the concept of structural similarity (SSIM) is proposed. This similarity calculation can obtain image structure information from the visual area, which is more in line with the human visual system (HSV). The calculation method is as follows:

$$SSIM = \frac{4\sigma_{xy}\overline{XY}}{(\sigma_X^2 + \sigma_Y^2)(\overline{X}^2 + \overline{Y}^2)} \tag{16}$$

The value range of SSIM is [−1, 1], where the gray-scale mean values of images X and Y are expressed as $\overline{X}$, $\overline{Y}$ and the standard variances are σ_X, σ_Y; σ_{XY} represents the covariance of images X and Y. It indicates the larger the SSIM value is, the more similar the images X and Y are. When the SSIM value is 1, it suggests that the brightness, contrast, and structure of the two images exactly remain the same.

From the above analysis, we can obtain an image retrieval algorithm based on fractal blocks for image X and images in the image library.

(1) According to the fractal coding method, the query image X is divided into value domains of size B × B, which are not intersected with each other. The pixel mean $\overline{R}(i)$ and variance $\sigma_R(i)$ of each R_i block are calculated;
(2) An image Y is extracted in turn from the image library, and then segmented according to step 1. The pixel mean $\overline{R'}(i)$ and variance $\sigma_{R'}(i)$ of each R_i block are calculated;
(3) The gray-level covariance $\sigma_{RR'}$ (i) of R_i of all query images and image-library images $R_i^{'}$ is calculated and all the SSIM (R_i, $R_i^{'}$) is calculated. Finally, the similarity S of two images is obtained:

$$S = \sum SSIM\left(R_i, R_i^{'}\right)/N \tag{17}$$

N is the total number of R blocks;
(4) The similarity S between the images in the image library and the query image X are calculated in sequence according to steps (2) and (3), and sorted in a large-to-small sequence. Meanwhile, the image with a high ranking and large structural similarity is selected as the search result.

Most image retrieval methods cover each image in the entire image database. Although this can ensure the accuracy of the retrieval results, it still consumes a certain amount of time for matching. In order to further improve the time-consuming retrieval of the retrieval system, this paper considers introducing the image entropy for simple and rapid screening of the image library in order to ensure that the re-screened database image and the image to be retrieved are similar to a certain extent as much as possible.

3.2 Image Entropy

In 1865, the German physicist Clausius first proposed the concept of entropy. Zachary J M applied entropy to image retrieval in 2000. Shannon's information theory defines the probability of a certain kind of information as entropy, that is, entropy can be expressed as the degree of disorder of the measured information. The digital image studied in this article is composed of pixels, and each pixel corresponds to a gray value. The data of the image has a non-negative value. The aggregation of pixels with different brightness makes the image display different shapes. Therefore, the concept of image entropy is introduced in line with the definition of information entropy.

The probability and statistics theory is used for calculation. The value of the random variable X is x_i $(1 \leq i \leq n)$, suggesting the amount of signal generated by the signal source, and the corresponding prior probability p_i, $\sum_{i=1}^{n} p_i = 1$. Due to the uncertainty of the information source, information entropy is defined as follows:

$$H(p_1, \ldots, p_n) = -k \sum_{i=1}^{n} p_i \log p_i \tag{18}$$

where: k is 1, and the base of the logarithm is generally e. According to the above Eq. (18) that introduces information entropy, the concept of one-dimensional entropy of an image [12] can be defined. For an image with the size of $M \times N$, the one-dimension entropy $H(f)$ is defined as:

$$H(f) = -\sum_{i=0}^{255} p_i \log p_i \tag{19}$$

where: $p_i = \frac{f(i)}{M \times N}$, f(i) is the statistical number of occurrences of the gray value pixel $i(0 \leq i \leq 255)$ in the image, and p_i is the frequency of occurrence of the pixel value i in the entire image.

Based on the image one-dimensional entropy Eq. (19), the image entropy of the four images in Fig. 1 is calculated, finding that the more similar the images are, the corresponding image entropy is also more similar. Therefore, the image entropy can be considered as the basis for dividing the image database.

Although the one-dimensional entropy of an image reflects the distribution of pixel values in the entire image, as for images with completely different gray-scale histograms, in case of the same probability distribution, they have the same information entropy but fail to reflect the spatial position distribution of the image pixel value in the whole image. Therefore, the spatial position distribution information is introduced, and the gray average value of the pixel neighborhood is added on the basis of the one-dimensional entropy. Both of them constitute the two-dimensional entropy of the image.

Fig. 1. One-dimensional entropy of 4 images

For an image of $X \times Y$ size, the 4-neighbor pixel average value of the image pixel and the corresponding pixel gray value are combined into a binary feature group (i, j), $i(i \in [0, 255])$ represents the pixel gray value of the image space position (a, b) and $j(j \in [0, 255])$ is the average gray value of 4-neighborhood pixels. Then:

$$H = -\sum_{i=0}^{255} \sum_{j=0}^{255} p_{ij} \log p_{ij} \tag{20}$$

where: $p_{ij} = \frac{f(i,j)}{X \times Y}$, $f(i, j)$ is the number of occurrences of the pixel gray value feature group (i, j).

Fig. 2. Two-dimensional entropy of 4 images

Formula (20) was used to calculate image 2D entropies of four images in Fig. 1 with the application of Matlab as well, as shown in Fig. 2. It is found through the comparison of experimental data in Fig. 1 and Fig. 2 that the 2D entropy difference between similar images was smaller than that of 1D entropies. However, the 2D entropy difference between dissimilar images was more obvious. For example, the difference between H(A1) and H(A2) was 0.282, and the difference between H(A1) and H(B1) was 0.95. Nevertheless, the difference between H'(A1) and H'(A2) was 0.181, and the difference between H'(A1) and H'(B1) was 1.833. Therefore, compared with 1D entropies of images, 2D entropies can more accurately classify and screen out similar images accurately, significantly promoting the acceleration of image retrieval.

3.3 Rapid Image Retrieval Method Based on Two-Dimensional Image Entropy and Fractal Blocks

By comparing the image entropy, each image in the image library in the image library is screened, and thus the number of images in the image database that need to be matched with the query image can be reduced. Consequently, the total image retrieval time is reduced, and the precision ratio and recall ratio of the retrieval results are taken into account. It is of note that the following two situations will occur when image entropy is combined with image matching strategies based on fractal blocks for image retrieval.

(1) There are images that are exactly the same as the query image in the image library. When the image library is sorted and sequenced, the image entropy of the two can be obtained and must be completely equal. Then, it is feasible to use Eqs. (16) and (17) to calculate the structural similarity between the two, which is equal to 1. If the above two conditions are satisfied, the same image can be deemed to have been retrieved.
(2) When there are only similar images in the image library, the image entropy of the two is definitely different. Besides, the obtained structural similarity is also different. Therefore, it is feasible to use the two-dimensional entropy of the image to screen the images in the image library, and subsequently calculate the structural similarity of the two according to Eqs. (16) and (17) as well as sequence them in descending order, wherein those ranking first can be used as retrieval images.

Briefly, the two-dimensional entropy of the image and the similarity of the image structure based on the fractal block jointly determine the retrieval result. In order to balance the weight between the two, the research considers introducing a linear weighted sum, which can also be called an evaluation function. It is believed in statistics that the average or other values need to be calculated in the statistical process of a group of data and the weight of one piece of data is equivalent to judging its importance in this group of data. In addition, it is believed that the smaller the two-dimensional entropy difference between the two images and the greater the structural similarity between the two images are, the higher the similarity between the two images will be. Therefore, an evaluation function of the retrieval system is constructed. This function is a measurable output concerning the similarity between images:

$$\text{score} = \lceil s_x - s_y \rceil \cdot P_s + \left(1 - S_{xy}\right) \cdot Q_S \tag{21}$$

wherein, P_s is $\lceil s_x - s_y \rceil$ the ranking after sequencing of the two-dimensional entropy difference between the image X to be retrieved and the image library Y, and Q_S denotes the ranking of the structural similarity S_{xy} between the image X to be retrieved and the image Y in the image library.

Then, the paper will introduce the implementation process of the rapid image retrieval algorithm based on two-dimensional image entropy and fractal blocks proposed in this study:

1. Input the image X to be retrieved, and process the image from color to grayscale.
2. Perform a spatial filtering operation on the image X to create a mask window average_kernel of the average value of the four-neighborhood pixels.
3. Use the mask to perform the linear filtering calculation of the two-dimensional convolution of the image.
4. Use Eq. (20) of the two-dimensional entropy of the image to calculate the entropy value of the query image X and all images in the image library.
5. Calculate the absolute value of the difference between the two-dimensional entropy of the query image X and the image-library image and sequence them in a small-to-large sequence, and select the top N/2 images as the next round of image retrieval library, wherein N is the number of original image-library images.
6. According to the fractal coding method, the query image X and the screened image-library image are divided into 8×8-size R blocks. A matching algorithm based on fractal blocks is used to calculate the pixel mean $\overline{R}(i)$ and variance $\sigma_R(i)$ of each R_i block of the query image and the image-library image.
7. Use Eqs. (16) and (17) to calculate the structural similarity $S.$ between the query image and all the screened images in the image library and sequence them from large to small.
8. Calculate the ranking of the query image and the filtered image-library image by the difference of the two-dimensional entropy and the structural similarity ranking.
9. Calculate all the scores according to the evaluation function Eq. (21) of linear weighted sum and sequence from small to large; select the top ten as the search result.

4 Experimental Results and Analysis

The experimental running environment is: processor Intel(R) Core(TM) i5-7200U, memory RAM) is 4.00 GB, and the simulation software Matlab 2016a.

In order to test the effectiveness of the retrieval algorithm based on image two-dimensional entropy and fractal block, 30 texture images are used here. The size of the images is 256×256, and each image is divided into 4 blocks according to the "ten" character. Four of the texture images are taken as an example, as illustrated in Fig. 3. If the uncut original image is used as the image to be detected, and if the four sub-block images that have been cut can be detected and all of them rank first, the effectiveness of the algorithm can thus be verified.

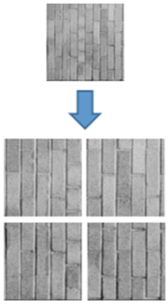

Fig. 3. Segmented texture image

The results retrieved by simulation are shown in Fig. 4 below. Obviously, when any uncut texture image is used as the retrieval image, the image retrieval algorithm based on the two-dimensional entropy fractal block can not only retrieve 4 images completely. The sub-images are segmented, which are placed at the top of the similar images. The same experiment is continued on 30 texture images, and 4 sub-images with the similarity ranking top can be retrieved. The current experiment fully demonstrates the effectiveness and feasibility of the image retrieval algorithm based on two-dimensional entropy and fractal technology.

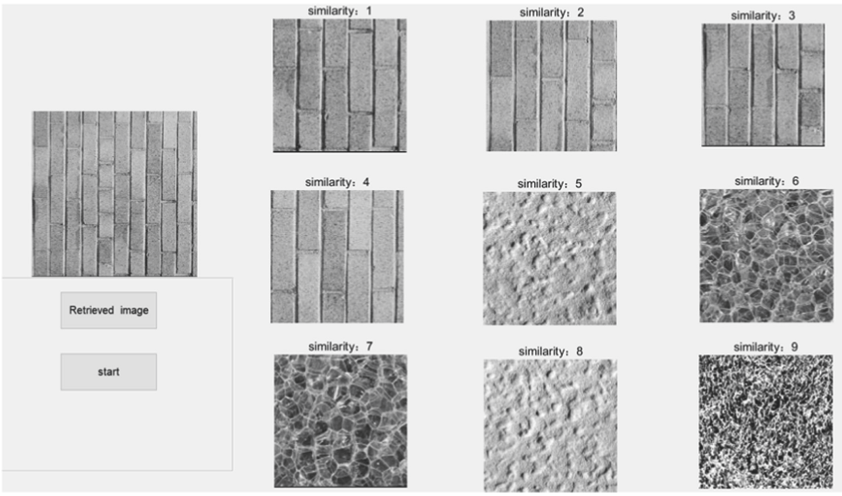

Fig. 4. Retrieval results of segmented texture images

Subsequently, the research tests 300 standard ORL face libraries. There are 30 people in the library, with different facial expressions. There are 10 face images for each, and there are totally 300 face images. This article uses color histogram-based image retrieval algorithms and performs experiments on image retrieval algorithms based on two-dimensional entropy and fractal technology, retrieves the top 20 images with output similarity, and compares and analyzes the experimental results in accordance with the precision ratio and recall ratio performance indicators. For the fairness of the experiment, the two algorithms are tested by the same retrieved image and the detected image is shown in Fig. 5. Test results are displayed in Fig. 6 and Fig. 7.

Fig. 5. Image to be detected

Fig. 6. Detection results of image retrieval algorithm based on color histogram

The precision ratio and recall ratio curves of the two image retrieval algorithms in the ORL face image library are shown in Fig. 8. It can be observed from the diagram that under the same recall rate, the precision ratio of the algorithm in this paper is obviously higher compared with that of the color histogram retrieval algorithm.

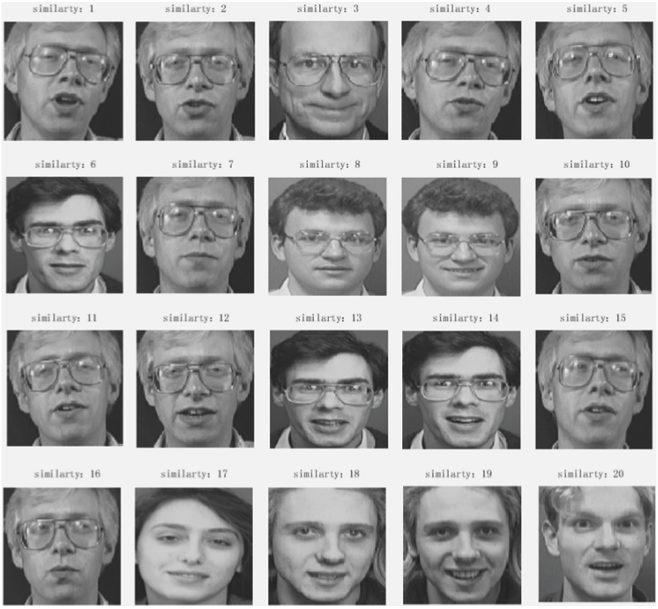

Fig. 7. Test results of retrieval algorithm based on two-dimensional entropy and fractal technology

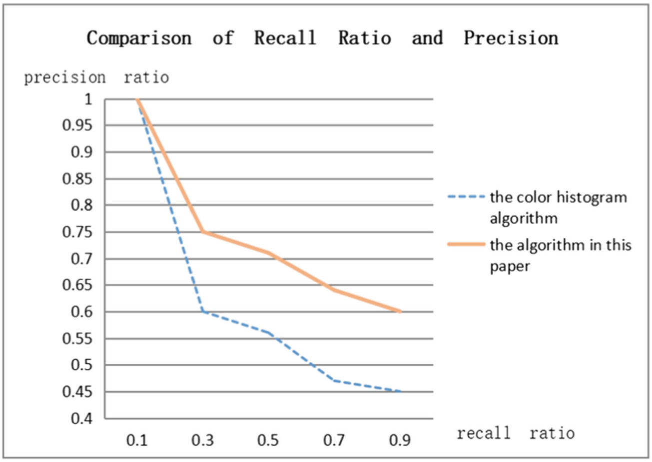

Fig. 8. Comparison of recall ratio and precision ratio between proposed algorithm and histogram algorithm

Finally, the comprehensive image library is tested. The current experiment uses five types of images libraries containing landscape architectural drawings, potted plant drawings, human activity drawings, fruit drawings, and animal drawings. There are 100 images for each category with 500 images in total. Color histogram retrieval method and the retrieval method based on the two-dimensional entropy and fractal technology are used for testing respectively. The following presents a list of the test results of the figure activity diagram of Fig. 9. As shown in Fig. 10 and Fig. 11, among the 9 retrieved approximate images, the color histogram algorithm only retrieves 5 similar images, and the proposed algorithm can retrieve 8 images of the same type. It can be found that the accuracy of the algorithm in this paper is much higher than that of the color histogram algorithm.

Fig. 9. Image to be detected

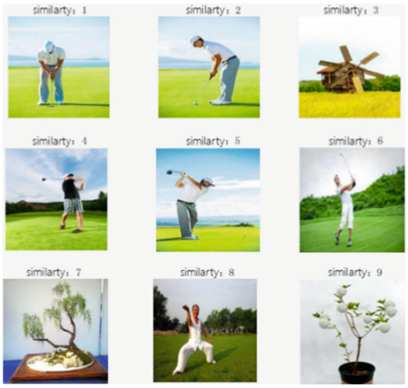

Fig. 10. Color histogram retrieval results

Fig. 11. Retrieval results of algorithm in this paper

According to the above test results, Table 1 shows the retrieval performance of the two image retrieval methods such as precision rate and recall rate:

According to the test results, the image retrieval algorithm based on two-dimensional entropy and fractal blocks proposed in this paper has higher precision ratio and recall ratio than the color histogram retrieval algorithm in the comprehensive image library retrieval testing. Besides, the retrieval time of the algorithm in this paper is less, further verifying the advantages of the retrieval algorithm proposed in this chapter.

Table 1. Comparison of comprehensive image library test of two retrieval algorithms

Detected image	Color histogram retrieval			Two-dimensional entropy and fractal technology retrieval		
	Recall ratio	Precision ratio	Time(s)	Recall ratio	Precisionratio	Time(s)
Castle	15.4%	44.4%	9.86	30.76%	88.9%	8.72
Pot plant	30.0%	66.7%	10.42	40.0%	88.9%	8.87
Figure	25.0%	55.6%	8.53	40.0%	88.9%	7.23
Fruits	25.0%	33.3%	11.04	41.7%	55.5%	9.51
Rabbit	33.3%	55.6%	10.63	60.0%	100%	10.03

5 Conclusion

To conclude, image retrieval is a hot issue commonly concerned by numerous researchers. The application of fractal technology in image retrieval has been further developed through the research in recent years. However, the extraction speed of fractal codes still needs to be improved continuously. Fractal codes pay more attention to the spatial structure of images, and are not sensitive to the occurrence frequency of the color gray value of an image. It indicates the fractal coding algorithm examines the image from another angle (structure) and is then applied to image retrieval. However, the traditional fractal image retrieval technology must code and store the images in the gallery before retrieval, and cannot be retrieved online in real time. As a result, the fractal image retrieval method proposed in this paper combines the image two-dimensional entropy for screening an image library, and adopts the improved fractal technology to quickly match and find similar images. Experiments show that this improved fractal technology introduces the principle of structural similarity, and calculates the similarity value by calculating the pixel mean and variance of each R block, which can be conducive to realizing rapid matching and effectively reducing the retrieval time.

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