New Method of Image Retrieval Using Fractal Code on the Compression Domain

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Abstract: - Image retrieval and indexing techniques are important for efficient management of visual database. Many techniques are generally developed based on the associated compression domain. In the fractal domain, a fractal code is a contractive affine mapping that represents a similarity relation between the range block and the domain block in an image. A new algorithm of IFS fractal code for image retrieval on the compression domain is presented in this paper. First,the inquired image and each image in the database are encoded by Jacquin fractal coding. Second, the image fractal feature vector and the distance of fractal code between two images are defined, and the distance between the inquired image and current image in the database are computed one by one. Finally, the preceding n frame images which are the smallest distance sum of fractal code are taken as the retrieval result. Experimental results show that compared with the direct image pixels similar matching strategy, our scheme shortens the retrieval time of compression domain greatly and guarantees the retrieval accuracy. Our proposed method is effective and feasible.

Key-Words: - Fractal code; Iterated function system; Image retrieval; Compression domain

1 Introduction

In recent years, more and more applications such as digital libraries, geographical map and medical image management, require effective and efficient means to access images. Up and now, there are two main image retrieval methods: the text-based image retrieval and the content-based image retrieval. Text-based image retrieval is based on key words. It is easy to be implemented. However, the more the attributes are abstracted, the more information the users need to input. To overcome the limitation of the traditional text-based image retrieval, the inquiring retrieval is based on the content of an image, including color, shape, texture and the object's special relationship[1-2]. However, It is limited by the development of correlated subjects, such as image procession, pattern recognition and computer visualization. Furthermore, it has higher complexity.

In this paper, we focus on fractal image compression and propose a novel image retrieval method of IFS fractal code for image retrieval on compression domain. First, each image in the database is compressed by Jacquin fractal coding and IFS fractal code is obtained, which cost much time in fractal coding. Second, the distance of query image and the image in the database is calculated using the distribution character of fractal code. Finally, the preceding n frame images which are the smallest distance sum of fractal code are taken as the retrieval result. Experimental results show that our scheme is effective and feasible.

The balance of the paper is organized as follows. Related work is stated in Section 2. CBIR techniques and system are described in Section 3. fractal Image coding is presented in Section 4. Our retrieval method is proposed in Section 5. Experimental results and discussions are given in Section 6. Finally, concluding remarks are drawn in Section 7.

2 Related Work

In the common scheme, the performance of the system greatly depends on the process of feature extraction from original image sets. Most current image search engines have treated the original image set for retrieval. It is indispensable to extract features from the images that are obtained from compression image data by decoding and to create the additional database of features for retrieval. However, the compression code is available for image retrieval, practical advantages can be obtained.

Given most images and videos stored in the compressed form, it is highly desirable to perform content-based visual retrieval directly in the compression domain. In other words, extraction of visual features, matching of images and videos, or even manipulations of search results can be implemented using the compression visual data without decompression (or sometimes with minimal decoding). The advantage of performing these tasks in the compression domain is obvious. The computational cost can be greatly reduced compared to the alternative which fully decodes the compression material and executes the above tasks in the uncompressed domain. Not only that the decoding process is avoided, the amount of data in the compression domain is also lower than in the uncompressed domain. There are many retrieval methods using compression techniques such as Wavelet, DCT, VQ, Fractal, and so on[3].

A fractal code of an image is a compression code generated by exploiting the self-similarity of the image. The original image can be decoded with an arbitrary resolution from the fractal coded image. These advantages make fractal coding an extremely promising compression method that is suitable for the development of image retrieval systems in the compression data domain. The prospects of fractal coding in the content-based image retrieval was first discovered by A.D.Sloan[4]. He proposed a method that directly coded the patched up images in the image database. For any range block, there exists a corresponding domain block in any image of the image database and the similarity between two images, say A and B, could be measured by the total domain numbers in image B for all the range blocks in image A. However the computational complexity of his approach is high. Further research can be referenced in Ref[4-15]. Joint fractal coding based image retrieval [4] and the retrieval method combining the ninth furcated tree decomposition and the fractal coding [5] are proposed. A.X.Hong [6] extended the fractal coding matching strategy in the polar coordinates and S.Y.Yang[7] put forward a content-based image retrieval method which can be executed in the fractal compression domain and does not need to do fractal coding of the iconic image. Z.Y.Wang [8] proposed a block-constrained fractal coding scheme and a matching strategy for content-based image retrieval. T.D.Chen[9-10] used image topology characteristic of Iterative Function System (IFS) to image deposit and retrieval. Y.Xu[11] proposed a new fractal coding based indexing technique using histogram of collage errors which is a quantitative measure of the similarity between range block and "best-match" domain block. Fractal dimension, vectors and distance distribution histogram [12-13] are used for image retrieval. According to the feature that the domain block is in one-to-one correspondence with the least mean square error, G.R.Jin[14] put forward a multi-pose-and-expression face retrieval method. Liangbin Zhang [15] uses the inquired image entropy to classify the image database and gives a novel fractal retrieval method of the same kind images.

3 CBIR Techniques and Systems

3.1 Image Retrieval and Information Retrieval

Recent technology development in various fields has made large digital image databases practical. Well organized database and efficient browsing, storing, and retrieval algorithms are very important in such systems. Image retrieval techniques were developed to aid these components.

Image Retrieval was originated from Information Retrieval[16], which has been very active research topic since 1940s. The question was simply stated: "We have huge amounts of information to which accurate and speedy access is becoming ever more difficult." In principle, Information Retrieval is simple. It can be illustrated by a scene of a store of documents and a person (user of the store). He formulates a question to which the answer is a set of documents satisfying his question. He can obtain the set by reading all the documents in the store, retaining the relevant documents and discarding all the others. In this scene, it is a "perfect" retrieval. But in practice, we need to model the "read" process in both syntactic and semantic to extract useful information. The target of Information Retrieval is not only "how to extract useful information", but also "how to measure relevance among documents". These challenges also exist in image retrieval.

Since the 1970s image retrieval has become a very active research topic, with two major research communities, database management and computer vision. One is text-based and another is visual-based. Text-based image retrieval has become very popular since 1970s, which involves annotating the image with keywords, and use text-based database management systems (DBMS) to retrieve the images. In text-based image retrieval system, keywords of semantic information are attached to the images. They can be typed manually or by extracting the captions of the images. It is very efficient for simple and small image databases, since the whole database can be described by just few hundreds of keywords. But in the 1990s, several large leaps in development of processor, memory and storage made the size of image databases grow dramatically. As the image database and image size grow, there will be more images having different contents and the images having rich contents cannot be described by only several semantic keywords. The demand of labor on annotating the images also rises dramatically. Also the keywords are very dependent on the observer's interest and they are subjective. Captions are not always precisely describing the picture. Indexing and searching a large image database via keywords are time-consuming and inefficient. Content Based Image Retrieval researches attempt to automate such complex process of retrieving images that are similar to the reference image or descriptions given.

3.2 Content Based Image Retrieval

The earliest use of the term Content Based Image Retrieval in the literature seems to be by Kato [17], was to describe his experiments in automatic retrieval of images from a database by color and shape features. The term has since been widely used to describe the process of retrieving desired images from a large collection on the basis of features that can be automatically extracted from the images themselves. The features used for retrieval can be either primitive or semantic, but the extraction process must be predominantly automatic. Retrieval of images by manually-assigned keywords is definitely not CBIR as the term is generally understood, even if the keywords describe image contents.

The ideal approach of querying an image database is using content semantics, which applies the human understanding about image. Unfortunately, extracting the semantic information in an image efficiently and accurately is still a question. Even with the most advanced implementation of computer vision, it is still not easy to identify an image of horses on a road. So, using low level features instead of semantics is still a more practical way. Until semantic extraction can be done automatically and accurately, image retrieval systems cannot be expected to find all correct images. They should select the most similar images to let the user choose the desired images. The number of images of retrieved set can be reduced by applying similarity measure that measures the perceptual similarity.

Content Based Image Retrieval (CBIR) is an automatic process to search relevant images based on user input. The input could be parameters, sketches or example images. A typical CBIR process first extracts the image features and store them efficiently. Then it compares with images from the database and returns the results. Fig.1 describes the flow of a typical CBIR process.

CBIR system consists of three major components and the variations of them depend on features used.

(1) Feature extraction–Analyse raw image data to extract feature specific information.

(2) Feature storage–Provide efficient storage for the extracted information, also help to improve searching speed.

(3) Similarity measure–Measure the difference between images for determining the relevance between images.

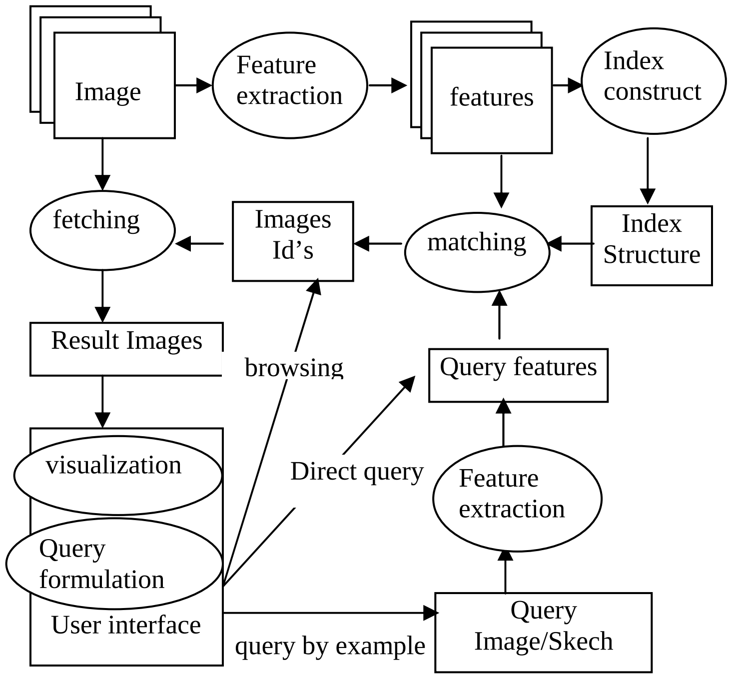

Fig.1 content based image retrieval framework

3.3 Image Retrieval Systems

Since the early 1990s, content-based image retrieval has become a very active research area. Many image retrieval systems for commercial or researches have been built. Most image retrieval systems support one or more of the following options.

(1)Random browsing
(2)Search by example
(3)Search by sketch or color layout
(4)Search by text (including key word or speech)
(5)Navigation with customized image categories
(6)Relevance feedback for interactive searching

We have seen a rich set of search options today, but systematic studies involving actual users in practical applications still need to be done to explore the trade-off among the different options mentioned above. Here, we selected representative systems in image retrieval and highlight their distinct characteristics.

(1)QBIC

QBIC (Query By Image Content)[18-19], is the first commercial CBIR system developed by IBM. Its structure and techniques used have made a great effect on most of the later image retrieval systems. QBIC supports queries based on example images, user-constructed sketches and drawings, and selected color and texture patterns, etc. QBIC also takes into account of the high dimensional feature indexing. In its indexing subsystem, KLT is first used to perform dimension reduction and then R*-tree is used as the multidimensional indexing structure. In the system, text-based keyword search can be combined with content-based similarity search. A QBIC-based system is available at: http://www.hermitagemuseum.org/fcgi-bin/db2www/qbicSearch.mac/qbic?selLang=English h.

(2)Photobook

Photobook [20] is a set of interactive tools for browsing and searching images developed at the MIT Media Lab. Photobook consists of three sub-books from which shape, texture, and face features are extracted, respectively. Users can then query, based on the corresponding features in each of the three sub-books. The Photobook implemented human perception in image annotation and retrieval. Since there was no single feature which can best model images from each and every domain, and a human's perception is subjective, they proposed a "society of model" approach to incorporate the human factor. Experimental results show that this approach is effective in interactive image annotation. Demo of Photobook can be found at: http://www-white.media.mit.edu/vismod/demos/facerec/basic.html.

(3) VisualSEEK and WebSEEK

VisualSEEK [21] is a visual feature search engine and WebSEEK[22] is a World Wide Web oriented text image search engine, both of which are developed at Columbia University. Main research features are spatial relationship query of image regions and visual feature extraction from compressed domain. The visual features used in their systems are color set and wavelet transform based texture feature. To speed up the retrieval process, binary tree based indexing algorithms is also developed. VisualSEEK supports queries based on both visual features and their spatial relationships.

We have also introduced some popular CBIR systems in this chapter, from classics like IBM's QBIC to other recently developed systems. All of them use low level features, one reason is image semantics still not practical for automatic searching. Among these CBIR systems, the datasets are different, and feature descriptions are also different. Also they are all isolated from each other; the data used in one system may not be able to use in other systems directly. It is difficult to compare these systems and methods. It is necessary to have a common environment for image feature interchange.

4 Fractal Image Coding

4.1 Self-affine and Self-similar Transformations

The fractal image compression algorithm is based on the fractal theory of self-similar and self-affine transformations [23]. Some basic definitions:

1. A self-affine transformation $w: R^n \to R^n$ is a transformation of the form $w(x) = T(x) + b$, where T is a linear transformation on R^n and $b \in R^n$ is a vector.

2. A mapping $w: D \to D,\ D \subseteq R^n$ is called a contraction on D if there is a real number c, $0 < c < 1$, such that $d(w(x), w(y)) \le cd(x, y)$ for $x, y \in D$ and for a metric d on R^n. The real number c is called the contractility of *w*.

3. If $d(w(x), w(y)) = cd(x, y)$, then w is called a similarity.

A family $\{w_1, \ldots, w_m\}$ of contractions is known as a local iterated function system (LIFS). If there is a subset $F \subseteq D$ such that for a LIFS $\{w_1, \ldots\ldots, w_m\}$,

$$F = \bigcup_{i=1}^{m} w_i(F) \tag{4}$$

then F is said to be invariant for that LIFS. If F is invariant under a collection of similarities, F is known as a self-similar set.

Let S denote the class of all non-empty compact subsets of *D*. The $\delta-$parallel body of $A \in S$ is the set of points within distance δ of A, i.e.

$$A_\delta = \{x \in D : |x - a| \le \delta, a \in A\}. \tag{5}$$

Let us define the distance $d(A,B)$ between two sets A, B to be

$$d(A,B) = inf\{\delta : A \subset B_\delta \wedge B \subset A_\delta\} \tag{6}$$

The distance function is known as the Hausdorff metric on S (other distance functions can also be used).

Given a LIFS $\{w_1,......,w_m\}$, there exists an unique compact invariant set *F*, such that

$$F = \bigcup_{i=1}^{m} w_i(F) \tag{7}$$

This *F* is known as the attractor of the system.

If E is a compact non-empty subset such that $w_i(E) \subset E$ and

$$w(E) = \bigcup_{i=1}^{m} w_i(E) \tag{8}$$

We define the k-th iteration of w, $w^k(E)$, to be

$$w^0(E) = E, w^k(E) = w(w^{k-1}(E)) \tag{9}$$

for $k \geq 1$, then we have

$$F = \bigcap_{i=1}^{\infty} w^k(E) \tag{10}$$

The sequence of iteration $w^k(E)$ converges to the attractor of the system for any set E. This means that we can have a family of contractions that approximate complex images and, using the family of contractions, the images can be stored and transmitted in a very efficient way. Once we have a LIFS, it is straightforward to obtain the encoded image.

If we want to encode an arbitrary image in this way, we will have to find a family of contractions so that its attractor is an approximation to the given image. Barnsley's Collage Theorem states how well the attractor of a LIFS can approximate the given image.

4.2 Collage Theorem

Let $\{w_1,......,w_m\}$ be contractions on R^n so that

$$| w_i(x) - w_i(y) | \leq c \, | x - y |, \forall x, y \in R^n \wedge \forall i \tag{11}$$

where $c < 1$. Let $E \subset R^n$ be any non-empty compact set. Then

$$d(E,F) \leq \frac{1}{(1-c)} d(E, \bigcup_{i=1}^{m} w_i(E)) \tag{12}$$

where *F* is the invariant set for the w_i, and *d* is the Hausdorff metric [23].

As a consequence of this theorem, any subset of R^n can be approximated within an arbitrarily tolerance by a self-similar set, i.e., given $\delta > 0$, there exist contracting similarities $\{w_1,......,w_m\}$ with invariant set F satisfying $d(E,F) < \delta$. Therefore, the problem of finding a LIFS $\{w_1,......,w_m\}$ whose attractor *F* is arbitrary close to a given image I is equivalent to minimize the distance $d(I, \bigcup_{i=1}^{m} w_i(I))$.

4.3 Jacquin Image Coding

Fractal image coding makes good uses of image self-similarity in space by ablating image geometric redundant. Fractal coding process is quite complicated but decoding process is very simple, which makes use of potentials in high compression ratio. The main theory of fractal image coding is based on iterated function system, attractor theorem, and collage theorem. Regard original compressible image as attractor, how to get LIFS parameters is main problem of fractal coding.

We explain the basic procedure for the fractal image coding which is namely Jacquin coding[23].

1. A given image I is divided into non-overlapping M range blocks of size $B \times B$ and into arbitrarily located N domain blocks of size $2B \times 2B$. The range blocks are numbered from 1 to M, and represented by $R_i (1 \leq i \leq M)$. Similarly, the domain blocks are from 1 to N, and represented by $D_j (1 \leq j \leq N)$.

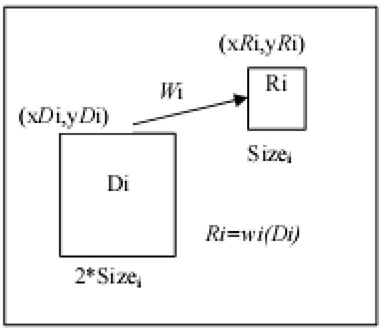

Fig.2 w_i represents the similarity relation between the range R_i and its similar domain D_i

2. As is shown in Fig.2, for each range block R_i, the best matched domain $D_k (1 \leq K \leq N)$ and an appropriate contractive affine transformation τ_{ik} which satisfy the following equation are found as

$$d(R_i, \tau_{ik}(D_k)) = \min d(R_i, \tau_{ij}(D_j)) \tag{13}$$

Where τ_{ij} is an contractive affine transformation from the domain block D_j to the range block R_i; the distortion measure $d(R_i, \tau_{ij}(D_j))$ is the mean square error (MSE) between the range block R_i and the contractive domain block $\tau_{ij}(D_j)$. The contractive affine transformation τ_{ij} is composed of two mappings ϕ_j and θ_{ij} as follows:

$$\tau_{ij} = \theta_{ij} \circ \phi_j \qquad (14)$$

The first mapping ϕ_j is the transformation of domain-block size to the same size as range blocks. This transformation can be described as follows: The domain block D_j is divided into non-overlapping unit blocks of size 2×2; and each pixel value of the transformed block $\phi_j(D_j)$ is an average value of four pixels in each unit block in D_j. The second mapping θ_{ij} consists of two steps: The first step transforms the block $\phi_j(D_j)$ by one of the following eight transformations: rotation around the center of the block $\phi_j(D_j)$, through 0^0,$+90^0$,$+180^0$, and $+270^0$ and each rotation after orthogonal reflection about mid-vertical axis of the block $\phi_j(D_j)$ .Those eight transformations are called isometries. The second step is the transformation p_{ij} of pixel values of a block obtained by the first step. This transformation p_{ij} is defined as

$$p_{ij}(v) = s_{ij}v + h_{ij} \qquad (15)$$

where v is a pixel value of the block obtained by the first step, and the parameters s_{ij} and h_{ij} are computed by the least square analysis of pixel values of the range block R_i and the block obtained by the first step. We call the parameters s_{ij} and h_{ij} a scaling coefficient and an offset, respectively. The LIFS parameters listed below are encoded:

- Parameters to indicate a location of the best matched domain block;
- A parameter to indicate an isometric on the best matched domain block;
- A scaling coefficient and an offset.

The proposed method quantizes these LIFS parameters [23].

Fig.3 shows the similar region in classical image with lena. Small regions are called range blocks and large regions are called domain blocks.

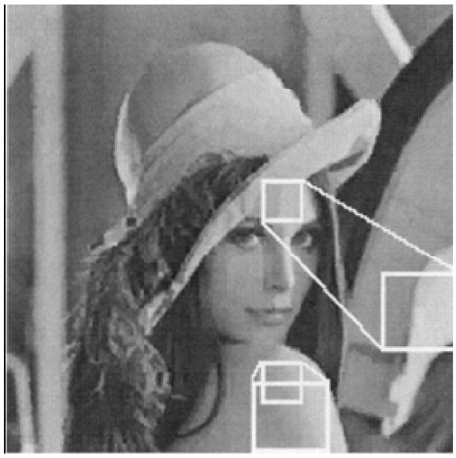

Fig.3 similar regions with image lena

5 Retrieval Method Using Fractal Code on the Compression Domain

5.1 Improved Relative Parameters of IFS Code

IFS fractal code of image compression can be indicated as given above. We can see that parameters (x_i, y_i) indicates the absolute position of the match domain and has nothing to do with the current range position. Fig.4 and Fig.5 show while the range block position has moved a little, the match domain block position has correspondingly moved and we get different IFS fractal code.

To solve this problem, parameter (x_i, y_i) is replaced with (d_i, θ_i) which indicate the relative position and direction coefficient between the range block and the domain block. Fig.4 and Fig.5 show the relation of the absolute parameters (x_i, y_i) and the relative parameters (d_i, θ_i).

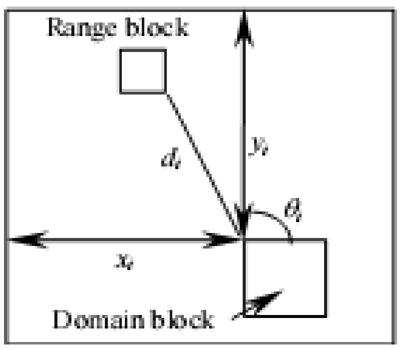

Fig.4 the absolute parameters (x_i, y_i)

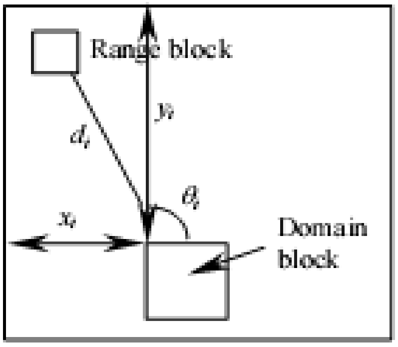

Fig.5 the relative parameters (d_i, θ_i)

When the value of *di* is small, the match domain block is arround the current range block nearby. Otherwise, the match domain block position is far away from the current range block. When most of the parameter θ_i has the approximate value, image texture feature has the same direction.

Hence, IFS fractal code of Image I can be stored as vector *IFS(I)* with form (16)

$$IFS(I) = \{d_i, \theta_i, l_i, s_i, g_i\}, i = 1,2.....N \qquad (16)$$

here, parameters are proceeded with normalized way. Parameter (d_i, θ_i) indicates relative position and direction coefficient between the range block i and the domain block i. Parameter (s_i, g_i) indicates a scaling coefficient and an offset between the range block i and the domain block i respectively. Parameter (l_i) indicates an isometric on the best matched domain block i. N is the number of the image range blocks.

5.2 Image Representative Feature Vector of IFS Code

As mentioned above, IFS fractal code describes the relations of similar regions in an image. Here, we can characterize an image by focusing on the mapping vectors from the range to the domain. We extract a new feature out of IFS code as follows. Image I representative features vector is defined with form (17) from the IFS fractal code.

$$F(I) = \{\bar{d}, \bar{\theta}, \bar{l}, \bar{s}, \bar{g}\} \qquad (17)$$

here, $\{\bar{d}, \bar{\theta}, \bar{l}, \bar{s}, \bar{g}\}$ is mean of $\{d, \theta, l, s, g\}$ respectively and $\{d, \theta, l, s, g\}$ is the fractal IFS codes of all the corresponding range blocks.

5.3 Similarity Between Representative Feature Vectors

The similarity as for distance between two images is calculated by the following process. Here, we denote two images as *A* and *B*, and denote representative vector sets of them as *F(A)* and *F(B)*.

$$distance(A,B) = \| F(A) - F(B) \| \qquad (18)$$

$$= \sqrt{(\bar{d}_A - \bar{d}_B)^2 + (\bar{\theta}_A - \bar{\theta}_B)^2 + (\bar{l}_A - \bar{l}_B)^2 + (\bar{S}_A - \bar{S}_B)^2 + (\bar{g}_A - \bar{g}_B)^2}$$

5.4 Our Proposed Algorithm

Combined with Image features vector and IFS fractal code on compression domain, our proposed image retrieval algorithm is as follow.

Step1. The inquired image is encoded by Jacquin fractal coding with 4×4 fixed child block, and then IFS code of the inquired image's is obtained. Moreover, we use equation (17) to calculate the inquired image features vectors.

Step2. Each image of the database is encoded by Jacquin fractal coding with 4×4 fixed child block, and each image fractal features vector is obtained with fractal code and equation (17) which cost so much compression and calculation time.

Step3. Consumed the inquired image is p and current image in the database is q, their image distance $D(p,q)$ is computed with as equation (18)

$$D(p,q) = \sqrt{(\bar{d}_p - \bar{d}_q)^2 + (\bar{\theta}_p - \bar{\theta}_q)^2 + (\bar{I}_p - \bar{I}_q)^2 + (\bar{s}_p - \bar{s}_q)^2 + (\bar{g}_p - \bar{g}_q)^2}$$

Hence the similarity between image p and image q is directly calculable from representative vectors.

Step4. These computed distances are descending sorted and the smallest or the smaller distance of the first N number images are as the inquired image's same or the similar images. Thus, our retrieval process is done. The structure of the system is shown in Fig.6.

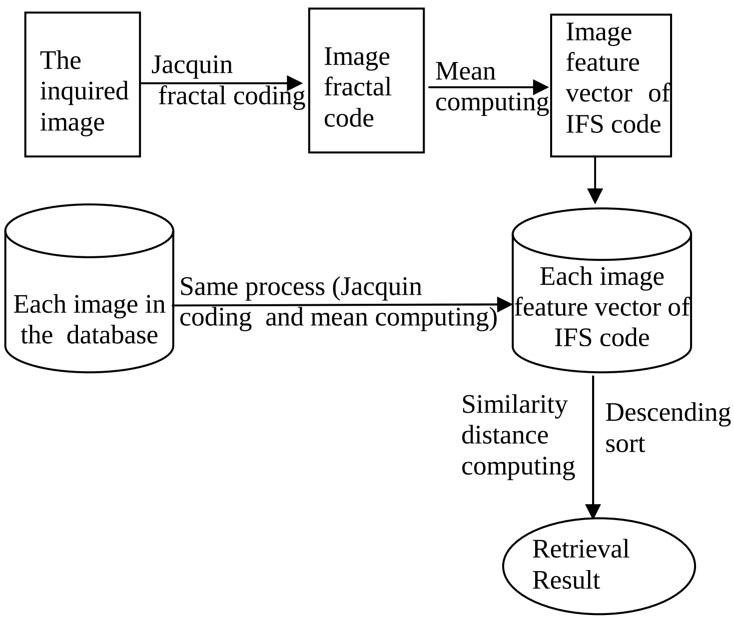

Fig.6 the structure of the system

6 Experimental Results and Discussion

All the experiments are carried out on a computer with Intel 2.5Ghz and 1GB RAM in the Win2000 professional operating system and Matlab7.0 language is used.

The inquired image is classical 256*256 grey-level image coded with 8 bits per pixel. This image database has 100 images, classified into four categories including landscapes, building, animals and texture to verify our retrieval scheme credible and wide application. Each image in database is first tailored to the size for 256*256 for evaluating our retrieval approach. They were preproessed and were described by fractal representative vectors, which cost much compression and computing time.

Fig.7 shows that the inquired image is a landscape map. Fig.8 shows that our retrieval output with the first nine images and corresponding calculation distance.

Fig.7 the inquired image


(1)distance= 0


(2)distance=18.8


(3)distance=19.6


(4)distance=24.5


(5)distance=27.1


(6)distance=29.5


(7)distance= 32.2


(8)distance=34.3

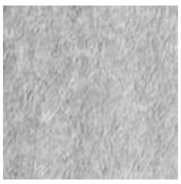
(9)distance=45.8

Fig.8 our scheme retrieval result

We can see from Fig.8 that the smaller distance between the retrieval image and the inquired image, the more similar two images are. Among nine retrieval images, there are first four images of the same landscape kinds and their average distance value is 15.725. The average distance value of the rest five images of different kinds is 33.78. The distance of the same kind images is much smaller than the distance of the different kind images. With our retrieval method, we can retrieval out the same kind or the same contend-based image from the inquired image, thus our retrieval method is stabilized.

Estimation way of retrieval result is shown in Ref[24] as follows. Assume the total number of the image database is P, according to each image i in database, we list out $N_i(1 \le i \le P)$ images similar with the inquired image artificially. According to each input inquired image q, we retrieval out $N_q + t$ images which are similar to the image q, here t is setup retrieval allowance in advance. If there are n_q similar retrieval images, so retrieval efficiency N_r is defined as

$$N_r = \frac{\sum_{q=0}^{p} n_q}{\sum_{q=0}^{p} N_q} \qquad (19)$$

The value of N_r is directly represented image retrieval efficiency. Table.1 gives the experimental data our retrieval scheme comparison with the direct pixel similar matching strategy (directly standard deviation of the two original images is computed as their image Euclidean distance).

Table 1. Retrieval performance comparison with two methods

Method / performance	the direct pixel similar matching strategy	our retrieval strategy
Retrieval time	120 S	78 S
Retrieval efficiency	79%	72%

Experimental results show that our retrieval scheme mainly guarantees the retrieval accuracy and can significantly reduce the computing retrieval time. Each image computing time is 2 seconds with the direct pixel similar matching strategy while in our scheme each image computing time is 1.1 seconds on average, which improves retrieval speed evidently.

Moreover, we try to valid different image fractal coding to compression, such as Fisher fractal coding, and we get different two IFS fractal code. From the approximate retrieval results, our scheme has little influence on different fractal coding.

However, our scheme is based on the compression domain of IFS fractal code which cost much time to compression each image in the database. Retrieval time in Table1 does not include the database images compression time, so fast image fractal coding should be researched further more.

7 Conclusion

In this paper, we proposed a novel image retrieval method using IFS fractal code on compression domain. Based on the image fractal feature vector, the distance of query image and the image in the database is calculated using the distribution character of fractal code. Compared with the direct pixel similar matching strategy, our retrieval scheme on compression domain mainly guarantees the retrieval accuracy and reduces the computing retrieval time significantly.

However, Our scheme on the image compression domain cost much time to compression each image in the database. Many issues remain to be addressed, and we plan to continue this research in the following directions:

(1) Shorten fractal compression time greatly with many improved method, such as combined with genetic algorithms, neighbourhood domain block nearby searching, classified domain block searching and so on.

(2) Compare variants of the fractal image compression and select an approach that offers the best similarity matching of identical images.

(3) Build a comprehensive indexing system for image database based on the features offered in the image fractal codes.

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References:

[1] Yujin Zhang, *Content-based Vision Information Retrieval*, Beijing: Science press, 2003. 5.

[2] Yan Hang, Yubin Yang and Zhaoqian Chen, A Survey of Content-based Image Retrieval, *Computer Application and Research*, Vol.11, No.9, 2002, pp.9-13.

[3] Mandal MK, Idris F and Panchanathan S, A Critical Evaluation of Image and Video Indexing Techniques in the Compression Domain, *image vision computer*,Vol.10, No.7,1999,pp.513-529.

[4] A.D.Sloan, Retrieving Database Contents by Image Recognition: New Fractal Power, *Advanced Imaging*, Vol.9, No.5, 1994, pp.5-10.

[5] Aidong Zhang, Diao Cheng and Raj Acharya, An Approach to Query-by-texture in Image Database Systems, *Proceedings of the SPIE Conference on Digital Image Storage and Achieving Systems*, Philadelphia, USA, 1995, pp.338-349.

[6] Anxiang Hong, Gang Chen, Jiongfeng Wu and LiJun Li, Image Matching Based on Fractal Image Coding, *Electronic Journal*,Vol.30, No.5, 2002, pp.624-627.

[7] Shouyi Yang and Weixiong Luo, Content-based Image Retrieval in Fractal Domain, *Journal of Electronics and Information Technology*, Vol.25, No.3, 2003, pp. 419-423.

[8] Zhiyong Wang, Zheru Chi and Yinglin Yu, Fractal Coding for Image Retrieval, *Acta Electronica Sinica*, Vol.28, No.6, 2000, pp. 19-23.

[9] Tianding Chen and Jilin Liu, A New Method of Fractal IFS Image Database Retrieval Combining Discriminate Function, *Journal of Electronics & Information Technology*, Vol.25, No.12, 2003, pp.1598-1601.

[10] Tianding Chen, Jinlin Liu and Weijin Lou, A Image Retrieval Model of Fractal-based Encoding Topological Characteristic, *Journal of Image and Graphics*, Vol.9, No.1, 2004, pp. 56-61.

[11] Yan Xu and Jiajun Wang, Fractal Coding based Image Retrieval Using Histogram of Collage Errors, *Journal of electronics& Information Technology*, Vol.28, No.4,2006,pp.603-605.

[12] Jinshan Jiang, Yueqing Li and Guoqiang Wang, Multi-clue Retrieval System for Trademark Images based on the Fractal Dimension, *Journal of South China University of Technology (Natural Science Edition)*, Vol.32, No.4, 2004, pp.37-42.

[13] Min Yao, Wensheng Yi, Bin Shen and Honghua Dai, An Image Retrieval System based on Fractal Dimension, *Journal of zhejiang University Science*, Vol.4, No.4, 2003, pp. 421-425.

[14] Guangrong Ji, Cuilu Qu and Wencang Zhao, Multi-pose-and-expression Face Image Retrieval Based on Partitioned Fractal coding, *Periodical of Ocean University of China*, Vol.35, No.5, 2004, pp.826-830.

[15] Liangbin Zhang, Lifeng Xi and Bishui Zhou, Image Retrieval Method based on Entropy and Fractal Coding, *WSEAS Transaction on Systems*, Vol.7, No.4, pp.232-241.

[16] F.W.Lancaster, *Information Retrieval Systems: Characteristics, Testing and Evaluation*, Wiley, New York, 1968.

[17] K. Hirata and T. Kato, Query by Visual Example, Content Based Image Retrieval, *Advances in Database Technology-EDBT'1992*, Vol.580, 1992, pp. 56-71.

[18] M. Flicker, and etc., Query by Image and Video Content: the QBIC System, *IEEE Computer*, Vol.28, No.9, 1995, pp. 23-32.

[19] W.Niblack, and etc., The QBIC Project: Querying Images by Content Using Color, Texture and Shape, *Proceedings of SPIE Storage and Retrieval for Image and Video Databases*, Vol.1908, 1994, pp. 173-187.

[20] A. Pentland, and etc., Photobook: Tools for Content-based Manipulation of Image Databases, *International Journal of Computer Vision*, Vol.18, No.3, 1996, pp. 233-254.

[21] J. R. Smith and S.F. Chang, Visualseek: A fully Automated Content-based Image Query System, *Proceedings of ACM Multimedia*, 1996, pp. 87-98.

[22] J.R. Smith and S.F. Chang, Visually Searching the Web for Content, *IEEE Multimedia Magazine*, Vol. 4, No.3, 1997, pp.12-20.

[23] Shouji Chen and Liming Zhang, *Fractal and Image Compression*, Shanghai Science nd Technology Education Publishing House, 1998.

[24] Hai Wei, Lansun Shen and Xiaohua Li, Image Compression and Indexing Methods Based on Iterate Function System, *China Image and Graphics Journal*, Vol.7(A), No.11, 2002, pp.1198-1203.