Image Retrieval Method Based on Entropy and Fractal Coding

LIANGBIN ZHANG, LIFENG XI
Computer Science and Information Technology College
Zhejiang Wanli University
Ningbo, Zhejiang, 315100
P.R. CHINA

BISHUI ZHOU
School of Computer Science
Hangzhou Dianzi University
Hangzhou, Zhejiang, 310018
P.R. CHINA

Abstract: - In content-based image retrieval system, describing and extracting image's feature is a key question. An image can be characterized by its fractal codes, and fractal codes can be used as the image's feature to retrieve the images effectively. This paper proposes a novel image retrieval method using information entropy and fractal coding. First, each image in the database is classified by computing information entropy which is compared with a given threshold estimated from the inquired image. Second, the inquired image's fractal codes are generated via Jacquin method, which is applied to the same kind of database images with fractal tenth iteration decoding. Finally, the image retrieval result is obtained by matching the similar Euclidean distance between the inquired image and the iterated decoded image. Experimental results show that compared with the direct image pixels similar matching strategy, our scheme not only reduces retrieval complexity and retrieval time, but also guarantees the retrieval rate. Thus our proposed method is effective and feasible.

Key-Words: - Fractal coding; Image information entropy; Image retrieval; Similar

1 Introduction

With the rapid development of the technology of image collection, storage, procession and display, digital images are widely used. However, it is difficult to manage a huge image database, so the study of the image database management system and the image inquire and retrieval system has become a hot subject. 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, and the image is expressed as a set of fixed attributes. 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.

The image indexing process consists in assigning a signature to each image, which will be used by the system in the matching phase to retrieve similar images to the inquired image. This signature, identifying description, consists of features extracted from images. Indexing technique is then similar to image compression technique which consists in coding image to eliminate the redundancy, and then represents it by a compact code. Indeed, code is used to identify and restore the corresponding image. In spite of this similarity, both techniques are rarely integrated. Fractal coding is a promising approach to represent image content with compact codes without extracting visual features explicitly.

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[2]. 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[3-15]. Joint fractal coding based image retrieval [3] and the retrieval method combining the ninth furcated tree decomposition and the fractal coding [4] are proposed. A.X.Hong [5] extended the fractal coding matching strategy in the polar coordinates and S.Y.Yang[6] 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 [7] proposed a block-constrained fractal coding scheme and a matching strategy for content-based image retrieval. T.D.Chen[8-9] used image topology characteristic of Iterative Function System (IFS) to image deposit and retrieval. Y.Xu[10] 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 [11-12] 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[13] put forward a multi-pose-and-expression face retrieval method. Y.Ma [14-15] proposed a novel image retrieval on IFS code, the distance of query image and the image in the database was calculated using the distribution character of fractal code. But it needed long retrieval time for IFS code of each image in the database should be obtained with fractal coding, this method was not feasible.

In this paper, we propose a novel image retrieval method based on image entropy and fractal coding. In our scheme, compared with the inquired image, each image in the database is classified by computing formation entropy. And we apply the fractal codes of the inquired image to be iterative decoded from the same kind of database images. Then the similarity is measured between the decoded image and the inquired image. Finally the image retrieval result is obtained. Experimental results show that compared with the direct pixels similar matching strategy, our retrieval scheme improves the retrieval time greatly and guarantees the retrieval accuracy.

The balance of the paper is organized as follows. CBIR techniques and systems are given in Section 2. Theoretical foundations of the image information entropy and fractal coding are described in Section 3. Our retrieval method using image entropy and fractal coding is presented in Section 4. Experimental results and discussions are given in Section 5. Finally, concluding remarks are drawn in Section 6.

2 CBIR Techniques and Systems

2.1 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.

2.2 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.

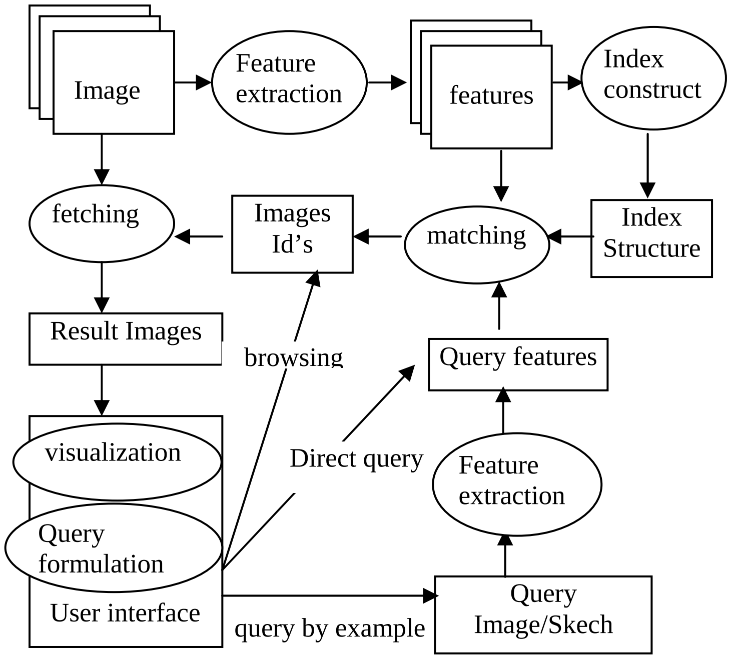


Fig.1 content based image retrieval framework

2.3 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.

- Random browsing
- Search by example
- Search by sketch or color layout
- Search by text (including key word or speech)
- Navigation with customized image categories
- 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.

3 Image Information Entropy and Fractal Image Coding

3.1 Image Information Entropy

3.1.1 Information Entropy

Shannon was a key figure in the development of information science. He proposed a measure of information content for messages in a message system. A message system is a collection of tokens that can be sent or used to record information. The idea is that in constructing content of longer records, these messages will appear with different frequencies and according to patterns. These patterns govern how much information each message actually carries. Let X be a discrete random variable taking a finite number of possible value $X_1, X_2 ......, X_n$ with probabilities $P_1, P_2, ...P_n$ respectively such that $\sum_{i=1}^{N} P_i = 1, 0 \le p_i \le 1, i = 1,2,......, N$ .We attempt to arrive at a number that will measure the amount of uncertainty. Let h be a function defined on the interval (0,1] and $h(p)$ be interpreted as the uncertainty associated with the event $X = x_i, i = 1,2,...,n$ or the information conveyed by revealing that X has taken on the value x_i in a given performance of the experiment. For each n, we shall define a function H_n of the n variables $p_1, p_2, ... p_n$. The function $H_n(p_1, p_2, ... p_n)$ is to be interpreted as the average uncertainty associated with the event $\{X = x_i, i = 1,2,...n\}$. Shannon's entropy is defined as form (1)

$$H_n(p_1, p_2, ..., p_n) = -\sum_{i=1}^{N} p_i \log_2 p_i \qquad (1)$$

Shannon's entropy is considered as the measure of the information uncertainty[23].

3.1.2 Image Entropy

Digital image is composed of pixels. Given $f(i,j)$ is the grey level of pixel (x,y), clearly $f(x,y) > 0$, for an image of dimension $M \times M$,defining the relationships

$$H(f) = -\sum_{i=1}^{M}\sum_{j=1}^{M} p_{ij} \log_2 p_{ij}, \quad p_{ij} = f(i,j) \Big/ \sum_{i=1}^{M}\sum_{j=1}^{M} f(i,j) \qquad (2)$$

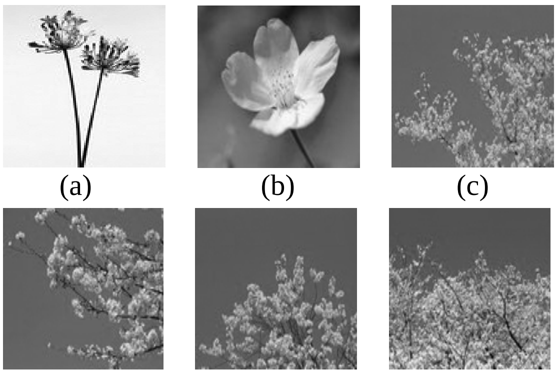
Where $H(f)$ is the image entropy, in which p_{ij} is the grey level probability distribution.

Because the entropy value corresponds to the distribution level of the image greyness, the greater the partial entropy, the better distribution the grey level. It does not influence its grey level itself, so we can make use of its partial entropy value to segment uniform objects. This segmentation method is not sensitive to a single pixel noise, because all its pixels contribute to the partial entropy in the window, which thus becomes a filter.

Equation (2) needs enormous calculation because it involves logarithm calculation, speed is low. From Equation (2) we can know, $P << 1$, therefore we can expand equation (2) using Taylor and rounding the higher terms to get an approximate equation as followers.

$$H(f) \approx -\sum_{i=1}^{M}\sum_{j=1}^{M} p_{ij}(p_{ij} - 1) = 1 - \sum_{(i,j)\in(M,M)} P_{ij}^2 \quad (3)$$

Equation (3) only includes $M \times M$ terms of multiplication addition and its calculation speed is faster than equation (2).



(a) (b) (c)

(d) (e) (f)

Fig.2 flowers images entropy

Computing with equation (3), we can easily get image entropy of six sequent flowers (Fig.2) as 2.2337, 2.4197, 3.3162, 3.4761, 3.2481, 3.5932. We can see that in vision the more similar two images are, in computing the closer image entropy two images have. Image entropy is represented image colorful statistics information, and it can also be describing and extracting image attribution feature [24].

3.2 Fractal Image coding

3.2.1Self-affine and Self-similar Transformations

The fractal image compression algorithm is based on the fractal theory of self-similar and self-affine transformations [25]. 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 $\{w_1, ..., w_m\}$ of contractions is known as a local iterated function system (LIFS). If there is a subset $F \subseteq D$ such that for a LIFS $\{w_1, ..., w_m\}$,

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

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.

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

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

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

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

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

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

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

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

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

for $k \ge 1$, 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.

3.2.2 Collage Theorem

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

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

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

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

where *F* is the invariant set for the w_i, and *d* is the Hausdorff metric [25].

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 $\{w_1, \ldots\ldots, w_m\}$ with invariant set F satisfying $d(E, F) < \delta$. Therefore, the problem of finding a LIFS $\{w_1, \ldots\ldots, w_m\}$ whose attractor *F* is arbitrary close to a given image I is equivalent to minimize the distance $d(I, \bigcup_{i=1}^{m} w_i(I))$.

3.2.3 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[26].

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 $R_i (1 \le i \le M)$. Similarly, the domain blocks are from 1 to N, and represented by $D_j (1 \le j \le N)$.

2. For each range block R_i, the best matched domain $D_k (1 \le K \le N)$ 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:

$$\tau_{ij} = \theta_{ij} \circ \phi_j \tag{14}$$

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

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

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 [27].

4 Our Proposed Algorithm

Combined with image entropy and fractal coding, 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 (3) to calculate the information entropy of the inquired image and the fixed setup threshold is got.

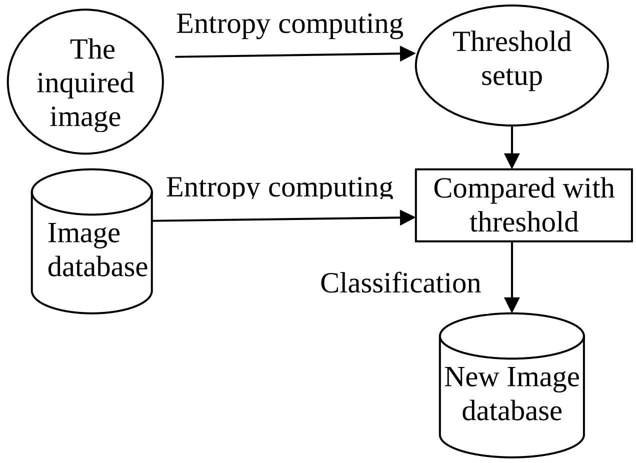
Step2. compared with the inquired image entropy, if current database image entropy computed by equation (3) exceeds the fixed setup threshold, they are not of the same kind and current database image does not satisfy with the retrieval require, thus we choose next image in the database. Otherwise goto Step 3 until the database image is ended.

Step3. current database image is as original image for the inquired image IFS code to be decoded with tenth fractal iteration, and fractal decoded image is obtained. The Euclidean distance computed between the decode image and the inquired image is measure of two image similar metric. We choose next image in the database then goto Step 2.

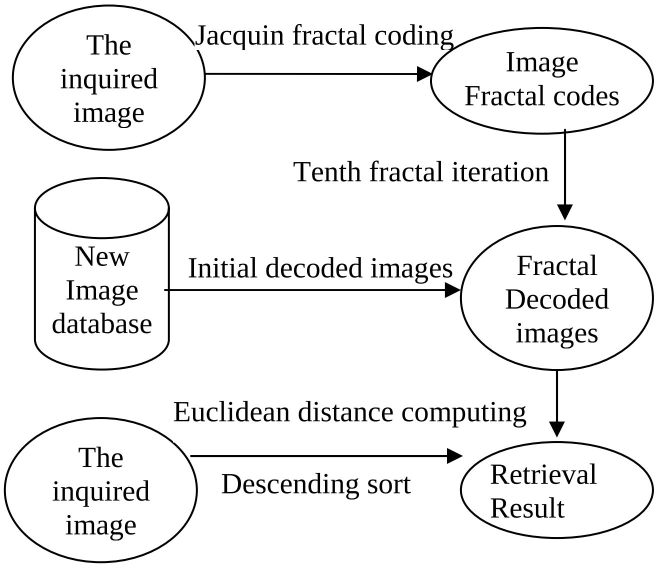
Here, consumed the inquired image is I_q with the fixed size $M \times M$, the decoded image is I_P with the same size, P is the number of the database images. Their image Euclidean distance is defined as

$$D(p,q)=\sum_{i=1}^{M}\sum_{j=1}^{M}\sqrt{(I_p(i,j)-I_q(i,j))^2} \qquad (16)$$

Step4. These computed Euclidean 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. Retrieval process is done. The structure of the system is shown in Fig.3.



(a) image database preprocessing



(b) image retrieval processing

Fig.3 the structure of the system

5 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.

Experiments have been conducted on selected natural images in a image database. The inquired image is classical 128×128 grey-level flying eagle image coded with 8 bits per pixel. The image database has 500 images, classified into four categories including birds, insect, domestic animals and scene to verify our retrieval scheme credible and wide application. Each image in database is first tailored to the size for 128×128 for evaluating our retrieval approach.

Estimation way of retrieval result is shown in Ref[28] 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 redundance in advance. If there are n_q similar retrieval images, so retrieval efficiency N_r is defined as

$$N_r = \frac{\sum_{q=0}^{p} n_q}{\sum_{q=0}^{p} N_q} \tag{17}$$

The value of N_r is directly represented image retrieval efficiency. Fig.4 shows that the inquired image is a flying eagle. Fig.5 shows that our retrieval output with the first twelve images.

Fig.4 the inquired image

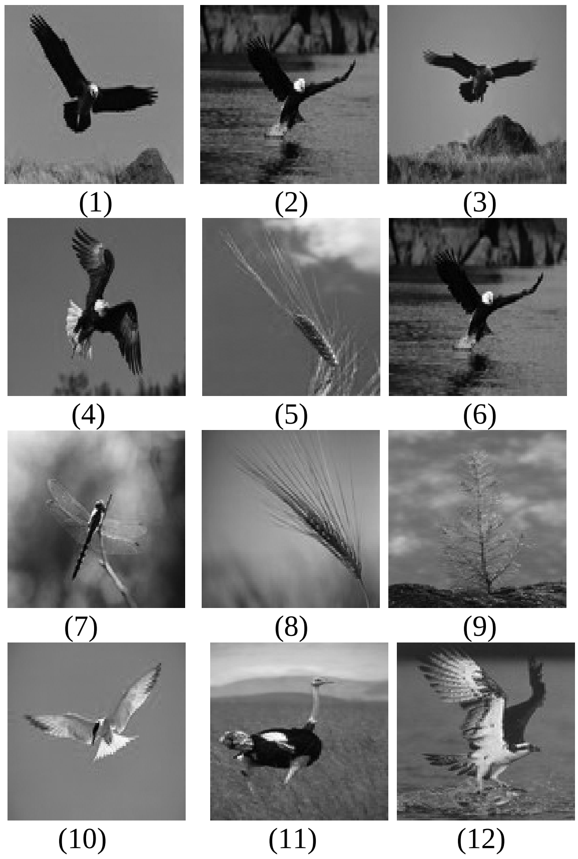


Fig. 5 our retrieval result

We can see from Fig.5 that the smaller Euclidean distance between the retrieval image and the inquired image, the more similar two images are. Among twelve retrieval images, there are seven images of the same bird kinds. 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.

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	**150 S**	**82 S**
Retrieval efficiency	**82%**	**75%**

Here, experimental performance parameter is stated in advance as follows:

(1)Retrieval time of both two methods include the image database preprocessing time.

(2)In the direct pixel similar matching strategy, the inquired image is not compressed image but the initial image itself.

(3)Our retrieval strategy time includes fractal encoding time of the inquired image.

(4)Retrieval efficiency is computed by form (17) and retrieval redundancy t=5, $N_q = 10$, p=500.

Experimental results show that our retrieval scheme mainly guarantees the retrieval accuracy and can significantly reduce the computing retrieval time. The image database is classified in advance by matching the image entropy between the current database image and the inquired image. Moreover, the inquired image is encoded with fractal coding only once, matched parent block definition lies in the inquired image itself, and image tenth iteration decoding process is fast. Each image computing time is 2 seconds with the direct pixel similar matching strategy while in our scheme each image computing time is 1.2 seconds on average, which improves retrieval speed evidently.

6 Conclusion

In this paper, we proposed a novel image retrieval method using image entropy and fractal coding.

Each image in database is classified by computing its image entropy compared with the inquired image entropy, and the same kind of images is as the original image to be fractal iteration decoded with the inquired image fractal IFS coding, and final similar matching lies in the decoded image and the inquired image. Compared with the direct pixel similar matching strategy, our retrieval scheme mainly guarantees the retrieval accuracy and reduces the computing retrieval time significantly.

However, many issues remain to be addressed, and we plan to continue this research in the following directions:

(1) The adaptive matching threshlod value is obtained instead of manual experimental experience acccoridng to the query image entropy.

(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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