Using Fractal Coding to Index Image Content for a Digital Library

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Abstract

Efficiently storing and retrieving images in a digital library have recently become active topics. Due to the limitation of traditional keyword-based retrieval approach, content-based image retrieval becomes increasingly demanding in today's digital library applications. Using fractal image compression technique, we have observed that its self-transformation property to compress images can be utilized to automatically index images by content. In this paper, we investigate the effect of fractal image coding on content-based image indexing. The initial experiments conducted on biomedical images demonstrate that this approach not only greatly reduces image storage but also is effective on indexing images by content. We thus believe that fractal coding provides a promising indexing approach to digital libraries.

1 Introduction

The need to store and retrieve image data in computer is growing rapidly in many fields, including business, manufacturing, education, Computer Aided Design (CAD), and medicine [HLHC92, PLSM94, SC94, GS, PLSFK94]. For example, in radiation oncology, diagnostic imaging procedure is important in defining the nature and extent of disease and planning the best approach to treatment of the patient's tumor. This procedure is usually involved in a large volumes of images. As current computer technology has made feasible to electronically generate and process digital images, it becomes increasingly demanding that such a diagnostic imaging procedure is computerized. Thus, a medical image digital library needs to be built for doctors and nurses for easy access. Main operations performed on such an image digital library are efficient retrievals and processing of images.

The main characteristic that differentiates an image digital library from the conventional data processing in database management systems is the profound features embedded in images, such as shape, color, texture, layout, and position of objects in an image. People are interested in retrieving images based on these features. Keyword-based retrieval approaches are not sufficient in this situation. A keyword-based retrieval approach in general uses a set of keywords to describe the subject of images. Thus, when an image is added to the library, a set of keywords to represent the image must also be provided. Although keyword-based approaches offer a great degree of simplicity, it obviously cannot support the interesting retrievals based on the features of images.

The concept of content-based image retrieval has been proposed which allows various retrievals to be performed on the content of images. For example, a common retrieval request would be to find all images that are similar to a given image. The purpose of content-based indexing techniques is to provide a vehicle of implementing efficient content-based retrievals. Various semantic-based models [CIT94] have been proposed to organize such indices. In these models, the features of an image is extracted from its content. Such features may include format descriptors, intrinsic and spatial relationships among image components, etc. This profound information is then used to form indices which represent the image.

Filling a given semantic-based model with image content is a challenging task. Existing approaches either assume that indices are filled manually or use pattern recognition techniques to automatically extract relevant features from images. The former approach seems neither interesting nor acceptable in practice; and the latter approach is an on-going research topic in Computer Vision and Pattern Recognition, which is not yet completely solved. Rabitti and Savino [RS91] have developed an integrated approach to image indexation and retrieval using the results generated in the image recognition analysis process. However, the investigation in this direction is still in its infancy. Another promising research direction is to automatically index image content based on image coding. It has been observed that fractal coding may play an important role in developing such indexing techniques [Slo94]. However, this research direction has not been deeply pursued.

In this paper, we propose a novel automatic indexing approach based on fractal image compression technique. Fractal coding technique has been proposed to perform image compression and its result has been shown to be very effective. The main characteristics of this approach are that it assumes that image redundancy can be captured and exploited through piecewise self-transformability [Jac93]. The method approximates an original image by obtaining from a finite number of iterations of an image transformation called a *fractal code*. We observed that this self-transformativity property of fractal compression coding can be utilized for indexing images. we will investigate the effect of fractal image coding on content-based image indexing. The initial experiments conducted on biomedical images demonstrate that this approach not only greatly reduces image storage but also is effective on indexing images by content. We thus believe that fractal coding provides a promising indexing approach to digital libraries.

The remainder of this paper is organized as follows. Section 2 introduces the main characteristics of Fractal coding technique for image compression and the reasons why we believe that this technique can be utilized to index image content while building a digital library with a large volume of images. Section 3 explains the detailed description of our approach to indexing image content. Section 4 demonstrates our initial experimental results conducted on biomedical images. Concluding remarks and future directions are offered in Section 5.

2 Fractal Coding

This section will first introduce the central ideas of fractal coding method for image compression. We will then present our observations on using fractal codes to automatically index image content.

2.1 Overview of Fractal Image Coding

Different image compression methods targeting great massive storage reduction and efficient transmission have been studied for a long time among which a novel promising approach called *fractal image coding* has drawn much attention recently. This approach is based on the concepts and mathematical results of iterated function systems (IFS). Barnsley and his coworkers at Georgia Institute of Technology first noticed the potential of IFS on applications in computer graphics.

Jacquin [Jac92, Jac93] proposed the first fully automated algorithm for fractal image compression. It was based on affine transformations acting locally rather than globally. An image to be encoded is partitioned into nonoverlapping range blocks R. The task of a fractal encoder is to find a larger block of the same image (a domain block D) for every range block such that a transformation of this block W(D) is a good approximation of the range block.

The transformation W is a combination of a geometrical transformation and luminance transformation. In matrix form W can be expressed as follows:

$$W \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} a & b & 0 \\ c & d & 0 \\ 0 & 0 & s \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} e \\ f \\ o \end{bmatrix}$$

where z denotes the pixel intensity at the position (x, y), s is the contrast, and o is the luminance offset.

Only the transformation of each range block need to be transmitted to the decoder. This transformation code, iteratively applied to any initial image, will generate a simulated version of the original image. To ensure the convergence at the decoder, the union of all transformations W have to be contractive. Thus, the fractal compression approach is lossy [MAH94].

Since Jacquin's initial work in fractal block image coding, there are lots of extensions which enhance the initial work in one way or another. Worth of mention is that Fisher, Jacob and Boss [FJB91] introduced adaptive methods in the encoding. They used quadtree, rectangular and triangular partitions of the range blocks to improve the image fidelity. Other researchers improved to targeting the complexity reduction of encoding and faster way of decoding [LQR94].

Fractal coding is a promising approach to image compression. Within a short period of development, fractal coding has yielded results which rival the best examples of data compression by other methods. It's a lossy method and usually takes time to encode. However, decoding process is simple, fast, and is independent of resolution. With the fractal codes (transformations), you can get images of any resolution you want. Thus, fractal codes are efficient for image representation in databases. Images can always be encoded off-line, and then the fractal codes are decoded in real-time.

2.2 Significance of Fractal Image Coding in Indexing

We will now discuss the significance of fractal coding in indexing images by content. We will demonstrate that images can be differentiated based on their fractal codes (or transformations). Consequently, the characteristics of an image can be identified by its fractal codes.

Consider the following three transformations that are given in [FL92]:

$$W_1 \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$W_2 \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} 0 \\ 0.5 \\ 0 \end{bmatrix}$$

$$W_3 \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} 0.5 \\ 0 \\ 0 \end{bmatrix}$$

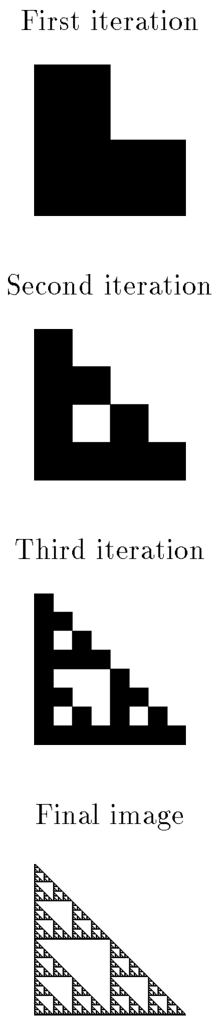

Figure 1: Image reconstruction.

Let us choose an initial image with the square $\{(x,y) : 0 \leq x \leq 1, 0 \leq y \leq 1\}$. The images generated from the first three iterations of the above transformations and the final converged image are shown in Figure 1 [FL92].

We now slightly change the coefficients in the above transformations to the following:

$$W_1 \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0.51 & 0 & 0 \\ 0 & 0.51 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$W_2 \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0.51 & 0 & 0 \\ 0 & 0.51 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} 0 \\ 0.5 \\ 0 \end{bmatrix}$$

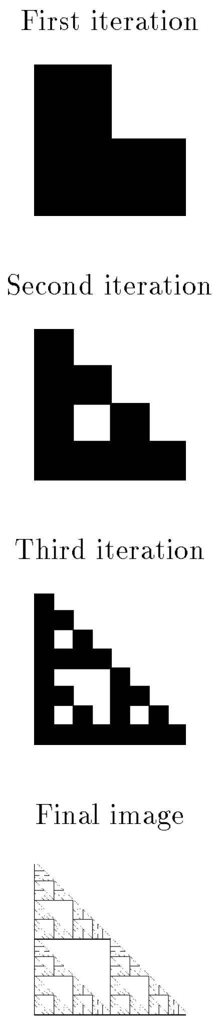

Figure 2: Image reconstruction.

$$W_3 \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0.51 & 0 & 0 \\ 0 & 0.51 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} 0.5 \\ 0 \\ 0 \end{bmatrix}$$

After repeating the same steps as those in Figure 1, we then obtain a different image which is shown in Figure 2. As a result, we observe that the fractal codes of images somehow indicate the semantics of the images which can be used to identify these images.

3 Fractal Codes for Indexing Image Content

As shown in Section 2, once we have a set of contractive transformations, we can iterate the process of mapping domain images into range images, and eventually converge to an image. Fractal image coding method can also generate a set of contractive transformations for any given image. Using these transformations, the original image can be approximately reconstructed. Thus, each image can be represented by its fractal codes in the database.

Let us now consider an image database in which all images are represented by their fractal codes. Let I be an iconic image (a piece of image or image portion which represents an object, e.g. an anomaly in a medical image). An interesting retrieval is to find all images which are relevant to iconic image I in content. To perform such a retrieval, the images in the database must be indexed based on their content. If we can relate the image content to their fractal codes, the retrieval can then be done by exploring the relationship between the fractal codes and iconic image I. If we can perform this, we will be able to index according to image content. Consequently, from a large image database, we will be able to locate images which contain similar iconic images (to some degree, certain criteria can be set), and browse them.

We propose to compute a measure for each transformation and a set of such measures for each image is used to index the image. These measures are then organized as indices which will be used for retrieving relevant images. Suppose a large set of icons is available to the user. Each icon represents an object. According to a selected icon, we can compare the icon to the fractal codes that we obtained from the fractal encoder, and decide the feature of the icon and the portion of each image in the image database, compare them and order those images for browsing.

Note that we do not need exact match between iconic images and different portions of images in the image database. We choose similarity measure, and can set different criteria of similarity.

Another approach given in [Slo94] is to juxtapose an iconic image and each image in the image database. Synthetic images are then generated and each of which is coded using the fractal coding method. The generated codes are then analyzed. The fractal encoder will describe the synthetic image in terms of itself. In particular, the system will compute a score which measures how much the example image is described in terms of itself versus how much it is described in terms of the image in the database. This approach needs special hardware (That is, fractal compression accelerator board based on their fractal compression chip) in order to generate synthetic images and compute scores efficiently.

Figure 3: MRI iconic image.

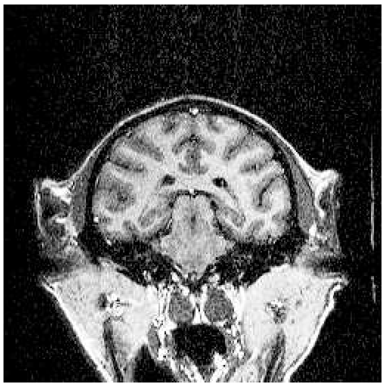

Figure 4: MRI slice image.

4 Implementation and Results

We have conducted initial experiments on some natural images as well as biomedical images. All images are converted to fractal codes before adding to the database. Thus, our image database consists of the fractal codes of the images, each of which represents an original image. We then compute the measures on the fractal codes and organize them into indices.

For example, given an iconic image in Figure 3, we analyze its fractal codes and look through the fractal codes and their measures in the database (One of such images is shown in Figure 4) using the built indices. We then evaluate measures, order them with top 15% (this is the parameter for image retrieval), and show them in the screen for browsing.

We have implemented this system under SUN Sparc workstations using the POSTGRES, an object oriented database system (or extented relational database management system) developed by UC at Berkeley, and HIPS Image Processing system developed by New York University. The initial results are quite encouraging. Because of the very quick nature of decoding and independent scaling property of fractal image compression, we have found that this method is very promising. With all these functionalities, we can access massive repositories of medical image data with the capability of indexing the visual information, creating visual browse data, and facilitating query by image content.

5 Conclusions and Future Research

We have developed a novel approach to automatically indexing images based on fractal image compression technique. As we have shown, the self-transformation property of fractal image compression technique offers the opportunity to distinguish one image from another based on their fractal codes. Consequently, the fractal codes of images can be used to index the images.

The initial experimental results conducted on biomedical images have demonstrated that this approach is effective. We plan to continue this research in the following directions:

- Compare different variants of the fractal image compression method and select an approach that offers the best similarity measure on identical images.
- Build a comprehensive index system for image databases based on the features offered in fractal codes.
- Build an interactive query language to support content-based retrievals following the index on the fractal codes of images.

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