Application of Fractal Codes as Similarity Measure for Compressed Image Databases

K. Faez
Department of Electrical Engineering
Amirkabir University of Technology
Hafez Ave, Tehran
IRAN, 15914

A.N. Venetsanopoulos
Department of Electrical and Computer Engineering
University of Toronto
10 King's College Rd. Toronto, Ont.
CANADA, M5S-3G4

Abstract: In image database applications, it is desirable that functions such as searching, browsing, and partial recall be done without totally decompressing the images. Using wavelet-compressed images is becoming increasingly popular. Image databases, and edge images derived from such compressed images can be viewed as indexes that can be queried by examples. In this research, a fractional code generated by a neural fractal memory [1] with four neurons was used as a distance-measure for the index edge image, and the query sketch image. This distance measure was compared with the central and Zernik moments being used by other researcher [2].

Key Words: image databases,fractal codes,similarity measure,fractal memory, edge images. *CSCC'99* Proceed. pp.7381-7384

1-Introduction

Daily increasing popularity of Internet in the world and the vast amount of available multimedia data in it poses some problems regarding multimedia resource discovery. A lot of users want to access the network using a low bit-rate communication link. Images have huge storage requirements in multimedia databases applications. So to decrease their memory requirements, they will be stored being compressed by one of the well-known methods.

Browsing is one of the key functions in these databases, and doing this function using full resolution images over the network is very time consuming and it may degrade the network performance noticeably. The search time in image databases relates directly to the format of the images being stored. Therefore it is highly desirable to compress the images such that we can search for an image without a requirement to decompress all the searched images completely.

Using the wavelet transform to compress the images enables us to derive an edge image from a detailed subband image without the need for a complete decompression. This edge image can be used as an index for searching an image database. Using this method eliminates the need for a separate index, which might otherwise occupy a large storage space. As well, this method allows us to have the functions, such as a "query by visual example" [3].

Similarity measure is one of the key issues in searching image databases. Some users may apply a query with detailed knowledge of the image they are looking for, while others may do not have enough detailed information regarding their target. Therefore, similarity measures rather than the exact match is a suitable search criterion for image databases. This search should be human initiative and allows for the inexact way in which human submit queries.

In some cases, a user query may lack entire knowledge of the target image and the search engine needs to cope with a low-resolution query with possibly some scale change, rotation, translation, and some degrees of deformity. To search an image effectively, the search engine should be robust, and capable of a partial similarity measure.

In this paper, we define a new similarity measure based on the fractal code. A recurrent fractal neural network having only four neurons finds this fractal code. This similarity measure is compared against the central and Zernike moments introduced in [2].

In Section two, the fractal code derived from an edge image is introduced and the architecture of a recurrent neural network to derive the fractal code is investigated. In Section 3, similarity measure to compare any two images is discussed and some other distance functions are introduced. Section 4 is devoted to the experimental results and Section 5 concludes the discussion.

2- Fractal Code

To compare two different images, some features should be extracted from each image, and their extracted features will be compared to measure their degree of similarity. To discriminate between different images, the extracted features should have the highest degree of discrimination between the images.

So far, different features have been introduced for similarity measure, including color histogram, object shape, transform coefficient, texture, image edge, and spatial relationship of objects in an image, moment invariant, and their combinations. In [2], the Zernike moments are introduced for this purpose, and the corresponding results of simulation are tabulated.

In this paper, we introduce the fractal code derived by a four neurons recurrent network to be used as the similarity measure. For this purpose, an edge image is generated from a compressed representation of the image and used as input to the recurrent neural network. The neural network will generate the corresponding fractal code, which is used as an index for the database queries. The user will be required to draw a sketch of some object in the target image. It is shown that the fractal code can be a good feature in describing the image index and the sketch presented by the user.

2-1 Fractal Neural Code

So far, the neural networks have been used in a variety of applications. In this research, we treated a recurrent neural network as an Iterated Function System that is coding for its underlying fractal attractor [4]. The fractal attractor used in this work are two dimensional, hence the network is in effect coding for fractal images, and may be acting as a form of visual memory.

Iterated Function Systems (IFS's) are a set of simple functions. Each function receives as input a coordinate from a space and returns a new coordinate, which is usually a simple transformation of the input coordinate. When these functions are applied iteratively to points in a space, they converge on a set of points, called the IFS's attractor. This attractor is a fractal, a set with similar structure at different resolutions. The connection between IFS's and recurrent neural networks comes from the thinking of a network's neurons as the functions or transformations of an IFS. As such, these neurons receive (X,Y) coordinates as input and return new ones in a recurrent manner.

So far, the coding of fractals by Iterated Function Systems was mostly used in compressing the images [5]. As such, this interpretation of network dynamics may form the basis of a highly efficient method for storing visual information and other related memories. In almost all of those applications, the fractal code was extracted by searching for local similarity between two different segments of an image. This search imposes a highly burden on the processing time. Here we use a neural network introduced by [1], for which a global self-similarity was used to find the fractal code.

2-2 Recurrent Network Architecture

A neural network based IFS can have an arbitrary number of transforms. The neural network used in this research was constrained to two transformations. This is since the corresponding extracted fractal code has enough discrimination power.

In Fig.1, the corresponding architecture is shown. Each transform is a mapping from one X,Y coordinate to another. Therefore, each transform consists of two scalar functions, one for each output component, either X, or Y. So, the neural network used here consists of four neurons, operating as a two transform IFS, where all neurons receive an X,Y coordinate as input and return either the X, or Y component of a transform finally. The coordinates derived by the two transforms are ORed together to produce two points in the output image.

The activation function of each neuron is the standard sigmoid function of the weighted sum of the inputs, with a basis term:

$$F(x,y)=1/(1+\exp(-w1*x-w2*y-w3))$$

Since each neuron has three modifiable weights, thus the network will have totally twelve training weights.

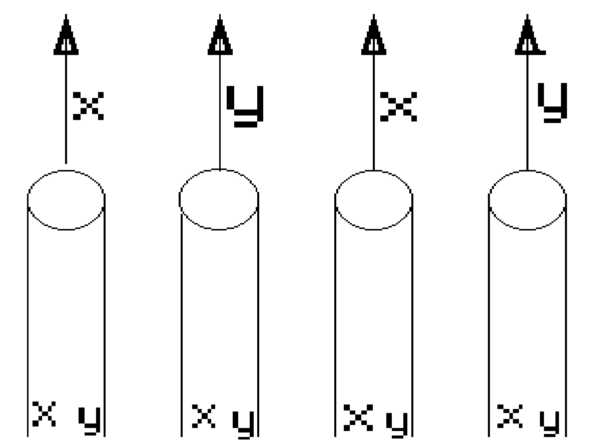

Fig 1. The neural network architecture Consisting of four neurons

To train the network, an extension of the Hausdorff distance developed in [5] was used. This method tries to train the network for a given attractor, such that the error between a given input image as an attractor and the corresponding output image will be minimized. This is the direct application of the collage theorem which states that in order to find an IFS for a given fractal attractor, it is necessary to find a transformation which maps the attractor to itself. As such, the error function will be minimized when the desired attractor and the transformed desired attractor mutually overlap. Since the network transformations are pseudo conctractive due to the sigmoid nonlinearity, it follows from the collage theorem that this is equivalent to the network coded attractor being equal to the desired attractor.

3- Similarity Measure

As it was mentioned before, different functions have been used as the similarity measure between the images. In [2], they used Zernike moment to find the distance between any two images. Here, we are using the fractal code of the images to evaluate their distance. Since for each image, the fractal code consists of a vector of twelve components (the twelve weighting factors), to find the distance between any two images, we measure the distance between the two vectors. The distance function used in this paper is the sum of squares of the differences between the corresponding components of the two-fractal code vectors, derived for any two images. This distance measure is denoted by D1 (General) in the given table.

Among the twelve components, four components correspond to the biases in the corresponding neurons. To make the distance function invariant with respect to the translation of the image, we modified the D1 distance function. In the new distance function denoted by D2 (modified), we discarded the bias components and only considered the other eight components in the fractal code. Experimental results show that the two distance functions have the same performance.

4-Simulation Results

The performance of the proposed distance function was tested by a simulation. To be able to compare the results with those given in [2], we used the same artificially generated images used in [2]. The images labeled Img1 through Img10 consists of edge images of both geometrical and arbitrary shapes. These images are shown in Fig2. The query images are formed from affine transformed versions of the original images. For example, the edge image Img3 is a 90 degrees rotated version of Img1, the image Img4 is a scaled version of Img1, and the image Img5 is a scaled and –90 degrees rotated version of Img1. Similarly, the edge images Img7 through Img10 are the distorted versions of the images Img1, Img3, Img4, and Img5, respectively. Image Img2 is a free hand drawing of Img1, as a realistic query that has suffered some deformation

Table 1 shows the results of the simulation for the ten images. In this table, the distance function is shown for the central moment, Zernike moment, the D1 (General) Distance, and the D2 (modified) Distance. As it is seen, the fractal code distances (both D1 and D2) have a better power of discrimination than the central and Zernike moments.

5-Conclusion

In this research, a new distance function based on the fractal code of an image was introduced. To extract the fractal code from an image, a recurrent fractal memory with four neurons was used. This fractal code can be used in an image database as for the index edge image, and for the query sketch image. It is shown that the new distance function has a better power of discrimination than the central and Zernike moments.

References

[1] O. Melnike, and J.P. Pollack, A Gradient Descent Method for a Neural Fractal Memory, *Proceedings of IJCNN'98 Conference*, 1998, USA, pp. 1069-1073.

[2] P. Sangassapaviriya, and P.O. Ogunbona, Similarity Measure for Compressed Image Database, proceedings of TENCON-97, 1997, Australia, pp. 203-206

[3] K. Hirata, and T. Kata, Query by Visual Example: Content-based Image Retrieval in Advances in Database Technology, *EDBT'92, Third International Conference on Extending Database Technology*, 1992, Vienna, Austria.

[4] M.F. Barnsley, *Fractals Every Where*, Academic Press, San Diego, 1988.

[5] M.F. Barnsley, and L.P. *Hurt, Fractal Image Compression*, A.K. Peters, Wellesley, 1992.

[6] P.O.Ogunbona, and P. Sangassapaviriya, Content-based Retrieval from Compressed-Image databases, IEEE Data Compression Conference, 1997, USA.

Table 1. Comparing the Fractal Code Distances with Central and Zernike Moments

Image	*Central Moment*	*Zernike Moment*	*D1 Distance*	*D2 Distance*
Img1	*0.00000*	*0.00000*	*0.00000*	*0.000000*
Img2	*2.94063*	*1.37405*	*26870.0*	*26855.70*
Img3	*0.09087*	*0.00293*	*13.0797*	*13.0636*
Img4	*2.44818*	*0.07428*	*16.2892*	*15.1673*
Img5	*16.5035*	*0.11638*	*14.5660*	*14.1026*
Img6	*4.17946*	*0.55602*	*14.9969*	*14.8399*
Img7	*15.6431*	*0.81793*	*6.1324*	*6.1291*
Img8	*15.6431*	*0.81706*	*13.0797*	*13.0636*
Img9	*16.0681*	*0.77964*	*713.348*	*276.8289*
Img10	*16.0681*	*0.77947*	*12.6960*	*12.6789*

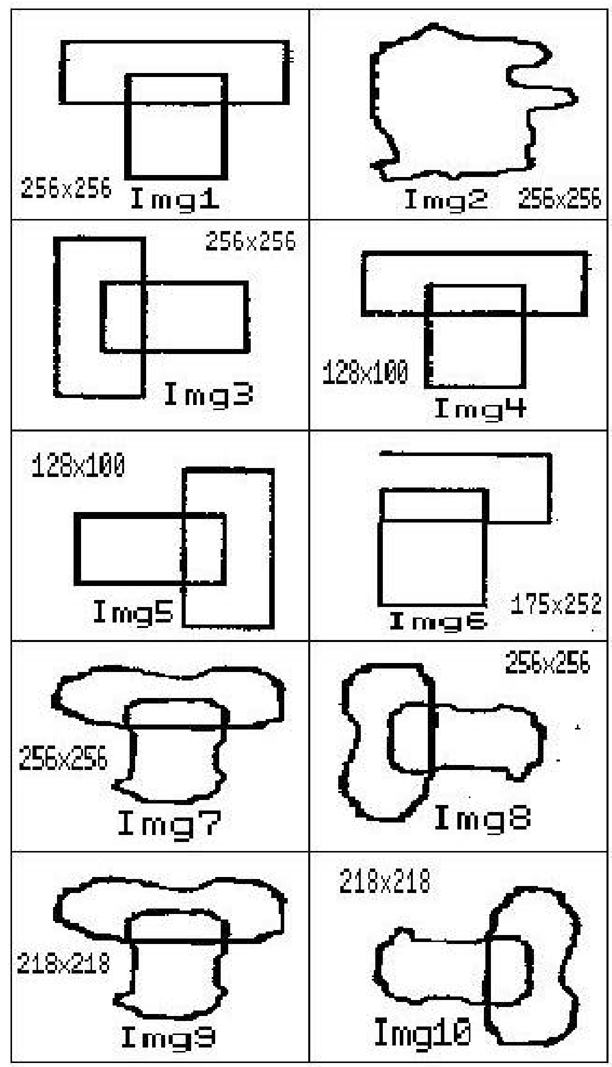

Fig2. The artificially generated images for simulation