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Novel Approach for Face Recognition Using Fractals

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Abstract — **Biometrics has been used for person identification since long time. Till today, researchers, neuroscientists and engineers working on the how human brain works for identification of the person. Hence it is a very interesting topic to do the work on it.**

Every individual has unique fingerprint and it does not changes throughout the lifetime. So it is the most widely used technique. But the face is most natural, non intrusive biometric and the cost of the system is low as compared with the other biometric system.

Fractals are popular because of their ability to create complex images using only several simple codes. This is possible by capturing image redundancy and presenting the image in compressed form using the self similarity feature. In this paper we present new fractal method for human face recognition. Many conventional methods of face recognition depend solely on appearance and model based. But there is inbuilt degree of self similarity in the image of faces which can be efficiently utilized through representation exploiting self-transformations, known as Iterated Function System (IFS).

Interestingly, virtually all images of natural or man-made objects, show region wise self similarity although they may not be globally self similar. Such objects can be represented by Partitioned Iterated Function System (PIFS) very compactly.

I. INTRODUCTION

Fractal code of an arbitrary grey-scale image can be divided in two parts - geometrical parameters and luminancce parameters. Fractal code of an image is a set of contractive mappings each of which transfer a domain block to its corresponding range block. Given a library of reference images: $I_1, I_2, \cdots, I_n$ and a query image Q, we want to preprocess the reference images to produce indices such that we can find the 'closest' image I_i to Q.

In this paper, we consider the indexing problem for a class of images where it is possible to state fairly accurately the notion of a background and a foreground. Our experiments revolve around an important subset of this class, namely, photographs of humans (such as those used in corporate identity cards, or those clicked by an automatic teller machine camera). Unlike images generated under structured lighting conditions (such as those of nuts and bolts in factory plants), faces with facial and tonsural hair growth have a predominant texture. Traditional segmentation based techniques do not work well in such cases, and many interesting [2, 12] approaches fail.

Fractals are important mathematical entities that have the ability to represent natural unstructured entities such as face, hair, and trees against the background in a photograph. Fractal descriptors are also compact, and therefore, have been used for compression. Indeed, the fractal subdivision method of chopping an image may be viewed as an automatic segmentation algorithm.

The biggest impediment in using fractal descriptors for indexing is the one-to-many relationship between an image and fractal descriptors. Many descriptors can converge (using the fractal paradigm) to the same image. In this paper, we study the use of fractal indices for general image indexing, and exemplify it with faces as the domain. Note that no assumption is made of "zeroing background" unlike approaches such as the venerable eigenfaces [11].

II. RELATED WORK

Although the Iterated Function System (IFS) structure of fractal object representation has been utilized by many researchers for the purpose of image compression, there have been very few attempts directed towards object indexing or recognition. In [4] the authors have presented a somewhat restricted recognition scheme applicable to the specific domain of L-System fractals and tested their technique on binary synthetic plant images generated by the L-System.

In [8] a recognition method is suggested which (i) works on binary images, and (ii) which is based on applying the reference set of Partitioned Iterated Function System (PIFS) codes on the query object and finding out the code which produces minimum change. The query is then recognized to be the object corresponding to that PIFS code, if the change found out is less than a threshold. This technique is not very interesting for the indexing problem because the comparison happens in the image domain, and not in the domain of indices.

In [7] the authors present a technique of indexing and content-based retrieval by a set of PIFS fractal parameters without dealing with the theory of proximity of PIFS codes for visually similar images as established in this paper. In addition, the time required for indexing and retrieval of an image by the method suggested in [7] is larger as compared to that of our method.

The system proposed in [3] has the interesting property of being invariant under two classes of pixel intensity transformations: illumination or color alterations. The system can be used both by sketches, and the query by example paradigms. As seen in Section 4 and Figure 4, our system is more tolerant to semantic content changes.

In [13], a joint fractal coding technique is used for image retrieval, and compared with wavelet coding. They conclude that wavelet transform approach performs more effectively in content-based similarity comparison on those images which contain strong texture features, whereas fractal coding approach performs relatively more uniformly well for various type of images. Unlike our experiments on faces, the conclusions are drawn on synthetic Broadatz texture images. The use of a joint fractal coding is different from our canonical coding.

III. MATHEMATICAL FOUNDATIONS

This section provides basic notation and definitions related to fractal image coding. The notion of complete and compact metric spaces, and the Hausdorff metric *h* are as formulated in [1]. These are presented in the context of any set, and therefore are applicable to images when viewed as sets.

A. Definitions

Metric Space

A space M is a metric space if for any of its two elements x and y, there exists a real number d(x , y) called distance, that satisfies the following properties:

(1) d(x , y) >= 0 (non-negativity)

(2) d(x , y) = 0 if and only if x = y (Identity)

(3) d(x , y) = d(y , x) (Symmetry)

(4) d(x ,z) <= d(x, y) + d(y , z) (Triangle inequality)

Contractive Transformation

A Transformation w : M → M is said to be contractive with contractivity factor *s* if for any two points $x , y \in M$,the distance

d(w(x) , w(y)) < s . d(x , y)

This formula says the application of a contractive map always brings points close together by some factor less than one. Contractive transformation have the property that when they are repeatedly applied, they converge to a point which remains fixed upon further iteration.

Affine Transformation

For a gray scale image *I*, if *z* denotes the pixel intensity at the position (*x, y*), then affine transformation W can be expressed in matrix form 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 *a, b, c, d, e* and *f* are geometrical parameters, *s* is the contrast and *o* is the brightness offset (luminance parameters).

This transformation also can be shown in linear form $W(X) = AX + B$, where *A* is *n X n* matrix and *B* is an offset vector of size *1 X n.* Using an affine transformation, we can scale, rotate an image, contrast scale or translate pixel intensities.

B. Iterated Function Systems(IFS)

An iterated function system $\{W : w_i , i = 1, 2, ., N\}$ consists of contractive affine transformation $w_i : M \rightarrow M$ with respective contractivity factor s_i together with a complete metric space *(M, d).*

This collection of transformation defines a contractive transformation W with contractivity factor $s = max(\ s_i , i = 1, 2, ..., N\}$.

The contractive transformation W on the complete metric space (*M, d*) will have a unique fixed point X_f which is also called the attractor of the IFS. Figure 1 shows an example of attractor of an IFS with 3 simple contractive transformation w_1, w_2, w_3 as:

Table 1. The IFS code for Serpinski triangle

w_i	a	b	c	d	e	f
w_1	0.5	0	0	0.5	0	0
w_2	0.5	0	0	0.5	0.5	0
w_3	0.5	0	0	0.5	0.25	0.5

where W_i is in the following form:

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

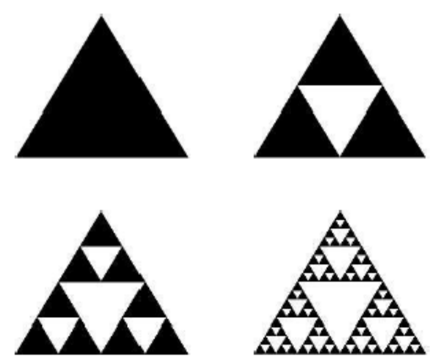

Figure 1. Serpinski triangle, attractor of an IFS containing 3

contractive transformation.

C. Partitioned Iterated Function System(PIFS)

Partitioned Iterated function systems(PIFS) is a more general type of transformation which exploits the fact that a part of an image can be approximated by a transformed version of another part of the same image, this property is called piecewise self-similarity. A PIFS consists of a complete metric space *X*, a collection of sub-domains $Di \subset X$, $i = 1, 2, \ldots n$ and a collection of contractive mappings $W_i : D_i \rightarrow X$, $i = 1, 2, \ldots n$. It works in steps as follows :

Range Blocks:

An image to be encoded is partitoned into non-overlapping range blocks R_i.

Domain Blocks:

An image is also partitioned into larger blocks D_j called domain blocks which can be overlapped.

Transformation:

The task is to find a domain block D_i of the same image for every range block R_i such that a transformed version of this block $W(D_{R_i})$ is a good approximation. *W* is a combination of a general transformation and luminance transformation.

The parameters of transformation along with brightness and contrast factor is called the PIFS code. Distance *dw* is a metric to compute the distance between two PIFS codes by summing-up the term-wise absolute differences between the parameters of the two codes.

The transformed version of the domain block can be rotated, mirrored, contrast scaled or translated to fit the range block. To keep the transformation contractive, the size of a domain block is always larger than range block so the scale factor is always less than one. The luminance part consists a few simple functions, such as a luminance shift and contrast scaling with contrast factor is less than one.

D. Partitioning

The decision to be made when designing this system is in the choice of the type of image partition used for the domain and rage blocks.

The simplest possible range partition consists of the fixed size square blocks. Quadtree partitioning employs the well known image processing technique based on recursive splitting of selected image quadrants, enabling the resultant partition be represented by a tree structure in which each non-terminal node has four descendants.

A horizontal-vertical (HV) partition like the quadtree, produces a tree-structured partition of the image. Instead of recursively splitting quadrants, however, each image block is split into two by a horizontal or vertical line and a finally number of different constructions of a triangular partitions have been investigated.

IV. PROPOSED WORK

Using fractals for face recognition is a relatively new application of fractal image encoding. The goal of the fractal image encoding algorithms is to be able to create a series of mathematical processes which would produce an accurate reproduction of an image. Fractal codes have this ability to reproduce an image or at least a good approximation of it by a set of contractive transformations. These transformations can be shown in simple affine form and can be recorded by a several simple parameters.

In proposed system, the code for an image *X* is an efficient binary representation of a set of contractive affine transformation *W* whose unique fixed point is a good approximation to *X*. The algorithm used in this system can be described as follows:

A. Algorithm

1. Partition the image to be encoded into non-overlapping range blocks R_i using quadtree partitioning.
2. Partition the image with a sequence of possibly overlapping domain blocks D_j.
3. For each range block, find the domain block and transformation that best match the range block.
4. Save the geometrical positions of range block and matched domain block as well as the matching transformation parameters as fractal code of images.

B. Mapping domains to range blocks

The main computational step in the algorithm is the mapping of domains to range blocks. For each range block, the algorithm compares transformed version of domain block to the range block. The transformation *W* is a combination of a geometrical transformation and luminance transformation. For a gray scale image I, if *z* denotes the pixel intensity at the position *(x, y)*, then *W* can be expressed in matrix form as follows:

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

Coefficients a, b, c, d, e and f control the geometrical aspects of the transformation (skewing, rotation, scaling and translation), while the coefficients *s* and *o* determines the contrast and brightness of the transformation and together make the luminance parameters. The geometrical parameters of the transformation limited to rigid translation, a contractive size-matching and one of eight orientations. The orientation consists of four 90^0 rotations and a reflection followed by four 90^0 rotations.

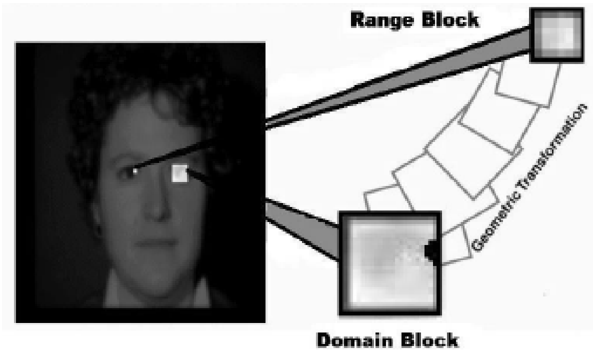

Figure 2: Mapping of domain to range blocks

Domain-range comparison is a three-step process. One of the eight orientations is applied to the selected domain block D_j . Next, the rotated domain is shrunk to match the size of the range block R_k. The range must be smaller than the domain in order for the overall mapping to be a contraction. Finally, optimal contrast and brightness parameters are computed using least squares fitting. Representing the image as a set of transformed blocks does not form an exact copy of the original image but a close approximation of it. Minimizing the error between $W(D_j)$ and R_k will minimize the error between the original image and the approximation.

Fractal codes of an image are having following parameters. The first parameters shows the geometrical positions of range blocks, the next column is the domain index number which uniquely locate the position of domain block using some preset parameters such as size of domain blocks, number of different domain sizes and overlapping factors. Third parameter contains the orientation index which is a number between o to 7, the last two parameters brightness and contrast factor *o* and *s* respectively. For recognition purpose last four parameters are used as fractal features.

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CONCLUSION

It is shown that the fractal parameters of an image have a self similarity based representation of that image and can be used as features for face recognition. Since the parameters of the fractal code of reference database image and query image matches, we can recognize the query image.

It is important to note that the PIFS code for an image, and the image itself do not have one to one correspondence. It is enough to be able to extract a canonical PIFS for a given image. This method can index objects which are unstructured in general. For faces, this means that we do not need to know the background unlike the eigenfaces approach which uses, for example in FERET database, the location of eyes. This approach of recognition is less computational intensive as compared to many other methods like PCA, LDA based, HMM, etc.

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