FACE RECOGNITION USING FRACTAL CODES

Hossein Ebrahimpour-Komleh, Vinod Chandran, Sridha Sridharan

RCSAVT, QUT, Brisbane, QLD 4001, Australia

ABSTRACT

In this paper we propose a new method for face recognition using fractal codes. Fractal codes represent local contractive, affine transformations which when iteratively applied to range-domain pairs in an arbitrary initial image result in a fixed point close to a given image. The transformation parameters such as brightness offset, contrast factor, orientation and the address of the corresponding domain for each range are used directly as features in our method. Features of an unknown face image are compared with those pre-computed for images in a database. There is no need to iterate, use fractal neighbor distances or fractal dimensions for comparison in the proposed method. This method is robust to scale change, frame size change and rotations as well as to some noise, facial expressions and blur distortion in the image.

1. INTRODUCTION

Fractal theory of iterated contractive transformation has been used in several areas of image processing and computer vision. In this method, similarity between different parts of an image is used for representing of an image by a set of contractive transforms on the space of images, for which the fixed point is close to the original image. This concept was first proposed by Barnsley [1], [2]. Jacquin was the first to publish an implementation of fractal image coding in [3]. In this paper we use fractal image coding using a quadtree partitioning as described in [4], [5].

Face recognition in this context refers to the automatic identification of an individual, represented in a database, based on the information contained in a digital gray scale image. Many strategies have been developed to solve this, such as Dynamic Link Matching [6], Feature Recognition using Neural Networks [7] and Principal component Analysis (PCA) [8].

Neil *et al* introduced some applications of fractal transformations in shape recognition and object recognition for use on binary images [9]. Kouzani *et al* used this method in conjunction with neural networks [10] and fractal dimension [11] for face recognition. Recently some use of fractal neighbor distance (FND) [12] in face recognition [13] and content-based image retrieval [14] have been reported. In this paper, we will present a new method of feature extraction from fractal-coded images and its applications in face recognition.

2. FRACTAL FACE RECOGNITION

2.1. Overview of fractal image coding

Different image compression methods targeting 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). The first fully automated algorithm for fractal image compression, proposed by Jacquin [3], was based on partitioned iterated function systems (PIFS) and affine transformation acting locally rather than globally. An image to be encoded is partitioned into non-overlapping range blocks R. The task of a fractal encoder is to find a domain block D of the same image 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. 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:

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

Where ***s*** is the contrast and ***o*** is the brightness offset.

2.2 Quadtree partitioning

Various other schemes of fractal image compression were proposed after Jacquin's work, which differ in the partitioning method, composition of the domain blocks pool, class of transformation or type of search used in locating suitable domain blocks. The fractal coding method used in this paper is based on quadtree partitioning. Quadtree partitioning employs the well known image processing technique based on recursive splitting of selected image quadrants, enabling the resulting partition be represented by a tree structure in which each non-terminal node has four descendants. The usual top-down construction starts by selecting an initial level in the tree, corresponding to some maximum range block size, and recursively partitioning any block for which a match better than some preselected threshold is not found [4]. In figure1 a sample of quadtree partitioning is shown. Note that a region containing detail is split into smaller domains in the process of finding a sufficiently good match.

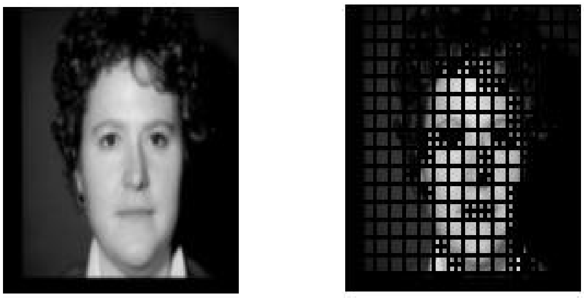

Figure 1. Quadtree partitioning.

2.3 Mapping domains to ranges

The dominant computational step in fractal image encoding is the domain-range comparison. For each range block, the algorithm compares transformed versions of all the domain blocks and eight orientations of each domain block to the selected range block. The transformations are affine and the orientations consist of four 90^0 rotations and the reflected version of each. Domain-range comparison is a three-step process. One of the eight basic orientations is applied to the selected domain block. Next, the rotated domain is shrunk to match the size of the range. 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. To find the optimum contrast ***s*** and brightness ***o***, we want to find the values for ***s*** and ***o*** that minimize:

$$\sum_i \sum_j (s.d_{ij} + o - r_{ij})^2$$

Here, d_{ij} and r_{ij} are the domain and range pixel values, respectively. These pixels form a rectangular array of M rows and N columns each since the domain size has already been shrunk to match the range at this point. The solution is:

$$s = \alpha / \beta$$

$$o = \bar{r} - \left(\frac{\alpha}{\beta}\right)\bar{d}$$

$$\alpha = \sum_i \sum_j (d_{ij} - \bar{d})(r_{ij} - \bar{r})$$

$$\beta = \sum_i \sum_j (d_{ij} - \bar{d})^2$$

$$\bar{d} = \frac{1}{NM}\sum_i \sum_j d_{ij}$$

$$\bar{r} = \frac{1}{NM}\sum_i \sum_j r_{ij}$$

Fisher [4] examined whether there is some form of local self-similarity in a typical image, which can be exploited to restrict the domain pool. His conclusion was that although it appears as if there was a preference for local domains from the probability density function of domain-range distances, this was just an artifact because there are a large number of closer domain positions overall and not because of self-similarity. We have re-examined this question of local self-similarity in images by looking for closed sets of domain pools. We choose one range block and find the corresponding domain. Every range block within this domain is then similarly mapped to other domains and the process continued until the set of domains no longer increases. We found that in a typical face-background type of image there is indeed such a closed partition, which contains most of the face and shoulder (as shown by the highlighted area in figure 2). Thus, images tend to show segment self-similarities (not necessarily local) and this can be exploited in compression and robust recognition using fractal techniques.

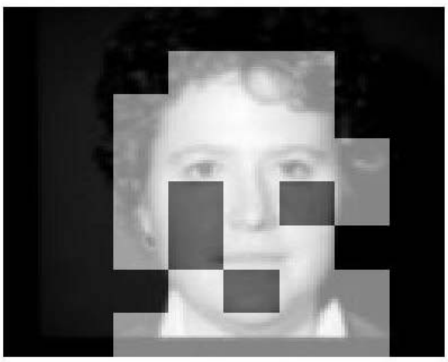

Figure 2- Facial image segmentation by closed Domain-Range relationships.

2.4 Fractal codes as features

Using fractal codes as features for object recognition and human identifications was proposed in [15] by the first author. This method assumes that image redundancy can be efficiently reduced using these features. We observe these features contain significant information about edges and textures that can be exploited for recognition. In figure 3 these features are shown using a gray values for each value of the corresponding feature.

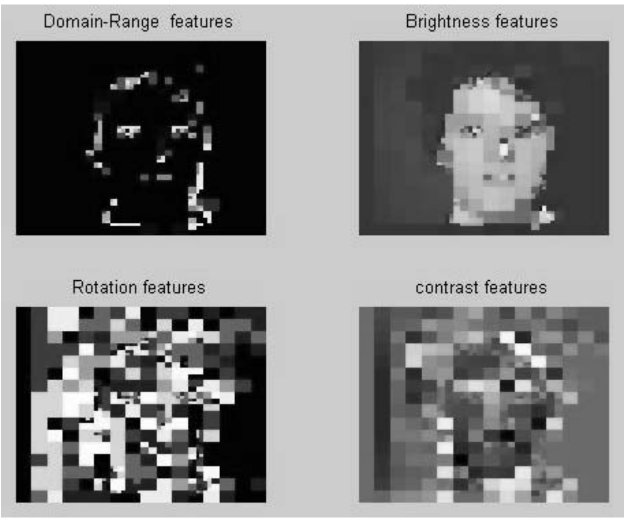

Figure 3-Fractal features of an image**.**

3. CLASSIFICATION

We used each fractal feature as a vector such that each image has 4 feature vectors of same size. The size of each vector, however, varies from one image to another and it depends on the size of image, image complexity and the minimum size of range and domain blocks. In order to normalize the size of each vector we use the quad-tree partitioning geometry and apply each feature value at its geometrical position (as can be seen from figure 3). Because quad-tree partitioning can be applied to an image of any arbitrary size, we can resize all feature vectors to the size of the query image. This makes our method robust to size and scale changes. For classification we used the Peak Signal-to-Noise ratio (PSNR) between feature vectors of the query image and feature vectors of all image in the database as a measure of distance and a minimum distance classifier.

4. ACCURACY TESTS

To initially test our system, we have used a subset of the M.I.T (Media Lab) face database. This subset of M.I.T face database consists of 2 face images from 90 subjects for a total of 180 images, with some variation in the illumination, and the scale and head orientation. In figure 4 some examples from this face database are shown.

Figure 4- Typical images from the MIT face database. Two different frontal views of each person are included.

We used each feature separately for classification, first, to obtain some idea of their information content or ability to discriminate between faces. Classification accuracy was plotted as a function of the number of images as the size of the number of images tested grew from 1 to 180, the size of the database. It was found that the orientation parameter yielded an accuracy of about 72% and the domain-range address relationship yielded an accuracy of about 64% separately on this data. The other two features yielded lower accuracy (as can be seen from figure 5). The use of all four features resulted in a total accuracy of close to 88.5% accuracy for a small database size. The accuracy tended to level off around 85%. Further tests are necessary to establish whether such accuracy will be sustained when the database size is increased to 1000 or more.

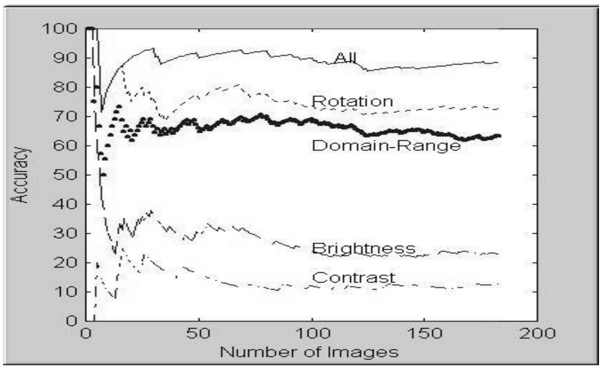

Figure 5- Recognition accuracy using Rotation, Domain-Range, brightness and contrast features, independently, and total accuracy achieved using all features, plotted against the number of the images in the database as this is progressively increased.

This suggests that in a fractal representation of the face, the information about which parts are self similar to which other parts and the orientation differences between these parts is more useful for recognition than the transformations between 'averaged' pixel gray level descriptions such as brightness and contrast from domain to range. Lighting variations are also more likely to affect brightness and contrast more significantly than the other two features, although we have not formally studied this yet. We are also interested in closed-set relationships between addresses of domains and ranges for application to region-of-interest segmentation (such as eyes or lips) and robustness to partial occlusion.

In figure 6 robustness of this method to rotation is demonstrated. In this test, a rotated version was used as the query image. The method, using only the orientation feature vector, was able to pick the correct identity as the closest match and the second view of the same person as the next close match in this test. It is interesting to note that the third and fourth best matches are similar to the query image from a human visual point of view, subjectively. The other matches are of the wrong gender but share some similarities in overall appearance and shape.

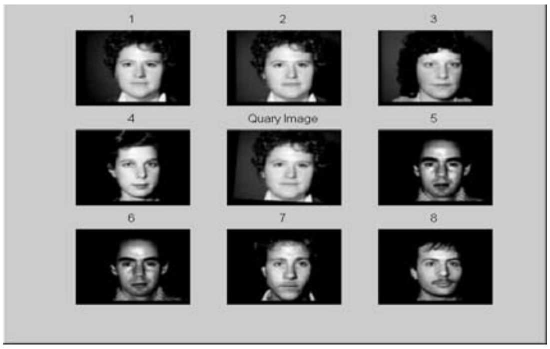

Figure 6- A rotated query image and the first 8 closest matches using the orientation feature.

5. CONCLUSION

This paper presents a new method for face recognition by using fractal code parameters directly as features. Although the accuracy of recognition is not as high as those reported by methods which rely on iterative reconstruction, this method can be developed further to recognize from parts of a face rather than the whole without a need for segmentation. The realization of this potential requires further study into domain-range relationships in the fractal representation and the formation of identifiable and consistent sub-pools of domains for important information-bearing regions of a face such as eyes, nose, lips etc.

6. REFERENCES

[1] M. Barnsley, "Fractals Everywhere," *Academic Press, San Diego*, 1988.

[2] A. E. Jacquin, "Fractal image coding: A review," *Proc. of the IEEE*, vol. 81, pp. 1451-1465, 1993.

[3] A. E. Jacquin, "A Fractal Theory of Iterated Markov Operators with Applications to Digital Image Coding," *PhD thesis, Georgia Tech*, 1989.

[4] Y. Fisher, "Fractal Image Compression: Theory and Application," *Springer-Verlag Inc.*, 1995.

[5] S. Welstead, "Fractal and Wavelet Image Compression Techniques," *SPIE Press*, 1999.

[6] L. Wiskott and C. v. d. Malsburg, "Recognizing Faces by Dynamic Link Matching," *Proc. Int'l Conf. on Artificial Neural Networks, ICANN'95*, pp. 347-352, 1995.

[7] P. Debevec, "A Neural Network for Facial Feature Location," *UC Berkeley CS283 Project Report*, December 1992.

[8] M. Turk and A. Pentland, "Face Recognition Using Eigenfaces," *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 586-591, 1991.

[9] G. Neil and K. M. Curtis, "Scale and Rotationally Invariant Object Recognition Using Fractal Transformations," *In Proceedings of ICASSP-96*, vol. 6, pp. 3458-3461, 1996.

[10] A. Z. Kouzani, F. He, and K. Sammut, "Fractal Face Representation and Recognition," *IEEE Int'l Conf. on Systems, Man and Cybernetics*, vol. 2, pp. 1609-1613, 1997.

[11] A. Z. Kouzani, F.He, and K. Sammut, "Face Image Matching Using Fractal Dimension," *IEEE Int'l Conf. on Image Processing*, pp. 642-646, 1999.

[12] T. Tan and H. Yan, "Analysis of the Contractivity Factor in Fractal Based Face Recognition," *IEEE Int'l Conf. on Image Processing*, vol. 3, pp. 637-641, 1999.

[13] T. Tan and H. Yan, "Face recognition by fractal transformations," *In Proceedings of ICASSP-99 (IEEE Int'l Conf. on Acoustics, Speech and Signal Processing)*, pp. 3537--3540, 1999.

[14] A. Lasfar, S. Mouline, D. Aboutajdine, and H. Cherifi, "Content-Based Retrieval in Fractal Coded Image Databases," *IEEE Int'l Conf. on Pattern Recognition*, vol. 1, pp. 1031-1035, 2000.

[15] H. Ebrahimpour-komleh, "Fractal Image Coding and Compression [Persian]," *Master thesis, Amir-Kabir University of Technology, Tehran, IRAN*, Feb. 1996.