Fractal Face Representation and Recognition

A.Z. Kouzani, F. He, and K. Sammut
School of Engineering, Flinders University of SA
GPO Box 2100, Adelaide
SA 5001, Australia
e-mail: egazk, egfh, egks@eng.flinders.edu.au

Abstract— This paper presents a face representation and recognition scheme based on the theory of fractals. Each face image is represented by its fractal model which is a small collection of transformation parameters. The transformation is carried out once for known face images. For recognition, the input face image is transformed and its fractal model is then compared against the database of fractal models of known faces. Feedforward neural networks are utilised to implement the compression and recognition parts. Some experimental results are presented. The maximum compression ratio obtained for the successful recognition of known faces was observed to be 89:1 (for a compression threshold of 0.002).

I. Introduction

A fractal is a fragmented geometric shape that can be subdivided in parts, each of which is a reduced-size copy of the whole. Fractals model many real-world objects that do not correspond to simple geometric shapes, e.g. clouds, mountains, turbulence, and coastlines [9]. Fractals are generally self-similar and independent of scale.

Iterated function systems (IFSs) are linear fractal models that can describe complex objects using self-reference. An IFS consists of a set of maps from $\Re^n$ to itself. If the maps of an IFS are contractive, then the IFS converges to a unique fixed point called an *attractor*. *Partitioned iterated function systems* (PIFSs) are generalisations of IFSs. In PIFSs, the domains of the maps are restricted. The domain of a PIFS is a subset of the transformation space, not the whole space.

Fractal theory has recently found applications in image processing. Particularly, a part of the fractal approach, which is based on the theory of PIFSs, has received a great deal of attention in image compression [1][2][4][5]. This method assumes that image redundancy can be efficiently exploited through self-similarity on a blockwise basis. The basic idea is to approximate an image by the attractor of a set of PIFSs. The original image is therefore represented by copies of properly transformed parts of itself.

Important advances in face representation and recognition have employed forms of principal component analysis (PCA) which is an expansion of the Karhunen-Loève representation [3], [6], [10]-[11], [12]-[13]. In PCA, the optimal basis is given by the eigenvectors of the correlation matrix. However, the algorithm to calculate the eigenvectors of a correlation matrix has cubic complexity. Even in a simplified case [12], if more known faces are added to the database, then (i) the calculation of the basis becomes computationally expensive, (ii) the compression ratio declines, (iii) the basis must be recalculated, and (iv) all faces within the database must be re-compressed using the new basis.

This paper presents a face representation and recognition model based on the theory of fractals. Each input face image is represented by its fractal model which is a small collection of contractive transformation parameters. An input face image is partitioned into non-overlapping smaller blocks (*range* blocks) and overlapping larger blocks (*domain* blocks). For each range block, a search is done through the domain block pool to find a domain block whose contractive affine transformation best approximates the range block. Therefore, for each range block the parameters of the related transformations are stored. The union of these parameters represents the compressed image of a person's face. The input to the face recognition system are centred face images detected from an input image by a facial detection system [7]-[8]. The transformation is carried out once for all the face images in the database. For recognition, the input face image is transformed and its fractal model is then compared against the database of fractal models of known faces. Feedforward neural networks are employed to implement the proposed face representation and recognition system.

In Section II, a computational model of face recognition is described. The realisation method is then explained in Section III. In Section IV, simulation results are presented. The performance of the system is then discussed and compared with the performance obtained for PCA. Finally, concluding remarks are given in Section V.

0-7803-4053-1/97/$10.00 © 1997 IEEE

II. Representation and Recognition of Human Face Images

Fractal compression performs a vector quantisation of image blocks. The vector codebook is constructed from locally averaged and subsampled larger blocks of the image. The codebook is used for coding constant regions and edges of the image. The compression is done through contractive maps from the plane to itself. The coded image is the fixed point of the maps. The images are stored by saving the parameters of the maps and are decoded by iterating the maps to find the fixed point. In this section, the computational model of the face representation and recognition is explained. The model is based on the theory of IFSs.

A. Image Representation

An image can be represented as a collection of discrete pixels. Each pixel takes a discrete value (typically between 0 to 255) representing a gray level. A function $f : \Re^2 \to \Re$ can be thought of as an image of infinite resolution. Because real images are finite in extent, and for simplicity, the domain of f is assumed to be the square $(x, y) \in \{(u, v) : -1 \leq u \leq 1, -1 \leq v \leq 1\}$ and the range to be $f(x, y) \in [0, 1]$. The function $f(x, y)$ gives the gray level z at each point (x, y).

B. Contractive Transformations

A transform w of the form

$$w\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} a_i & b_i & 0 \\ c_i & d_i & 0 \\ 0 & 0 & s_i \end{bmatrix}\begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} e_i \\ f_i \\ o_i \end{bmatrix} \quad (1)$$

takes an input image and produces an output image. The transform w can scale, stretch, skew, and rotate. Combinations of these transformations can map in a variety of ways. A transformation is *contractive* if it brings points closer together. Figure 1 illustrates a contractive transformation of a face image in the plane.

C. Iterated Function Systems

An IFS consists of a set of maps $\{w_i\}_{i=1}^{N}$ from $\Re^n$ to itself. If the maps of an IFS are contractive, then the IFS converges to an unique fixed point called an attractor. Given any initial nonempty bounded input image, the attractor is obtained after a finite number of iterations. Figure 2 shows different iterations of an IFS with three maps for an initial input face image. The final image represents the attractor of the IFS.

D. Partitioned Iterated Function Systems

PIFSs are generalisations of IFSs. In PIFSs, the domains of w_i are restricted. The domain of a PIFS is a subset of the transformation space, not the whole space. However, the transformations w_i are still of the form given in equation 1. Figure 3 displays two PIFSs with their domains.

E. Fractal Model of Face Images

The fractal model of a face image is a collection of maps w_is with $W = \bigcap_{i=1}^{N} w_i$. To achieve a good approximation of a face image, it is required that the face image f be close to the attractor of W. In order to obtain a fractal model of a face image, the image is partitioned into non-overlapping smaller blocks (range blocks) R_i and overlapping larger blocks (domain blocks) D_i. A domain pool is prepared from the available domain blocks. For each range block, a search is done through the domain pool to find a domain block whose contractive transformation best approximates the range block. A distance metric such as *root mean square* (RMS) can find the approximation error. A *threshold* value can be considered so that when the calculated error falls below the threshold, the related domain block is accepted as the reference block for the current range block. Therefore, for each range block the parameters of the related transformations are stored. The union of these parameters represent the compressed image of a person's face. Since the aim of this work is to recognise a face image rather than to reconstruct it, a simplification is applied to the compression process to reduce the number of parameters needed to model a face image. Hence, for each map w, only the following parameters e_i and f_i which specify the position of the related domain block are stored. The domain blocks' size is chosen to be twice that of the range blocks. Figure 4 displays the mapping of some domain blocks onto range blocks.

As an example, Figure 5 illustrates the decomposition of a face image using the fractal technique. The original image, and the first, third, and fifth iterates of the reconstructed image are demonstrated for 8x8 range blocks and 16x16 domain blocks.

III. System Realisation

Neural networks are trained to carry out different stages of face compression and recognition. The main reason for employing neural networks is to take advantage of the highly parallel architecture of neural networks in order to achieve real-time recognition. Two different feedforward networks are designed. The first network implements the search process in which the best approximation of a range block is found among the domain pool. The network accepts two groups of inputs, a domain block and a range block, and calculates the RMS error between the range block and the transformed domain block. Only one network is sufficient to perform the search process. However to speed up the search, more networks with the same architecture can be used in parallel.

The second network has also a feedforward architecture and has been trained to recognise faces. It receives two group of inputs, the fractal model of an input image and the fractal model of a known face from the fractal database. It calculates the degree of similarity between the two fractal face models. If the output is below a threshold, the input face is considered as a known face whose fractal is currently under examination. Similar to the compression stage, more networks with the same architecture can be used to speed up the recognition process.

IV. Experimental Results

Experiments were carried out on a database of known face images to verify the performance of the system. The database consists of 150 front-view face images of 64x64, 256 gray levels. Simulations were done in two steps: compression and recognition.

In the compression stage, the fractal model of all known faces are found and stored. The domain and range block sizes were set to 16x16 and 8x8 pixels, respectively. The compression threshold was selected as 0.002.

In the recognition stage, two groups of experiments were performed. In the first experiment, the known face images were presented to the system and the recognition process was carried out. 100% recognition was achieved in this step. The maximum compression ratio obtained for successful recognition of all known faces was 89:1. Figure 6 demonstrates recognition of the known face number 100. In the second experiment, 50 unknown face images were directed to the system and the recognition process was carried out. None of the input images were recognised by the system. Figure 7 shows the recognition result for an unknown input face image.

The proposed system is less computationally expensive than that for PCA. Moreover, when a new face is added to the database, recalculation of eigenfaces and re-compression of known faces are not necessary.

V. Conclusions

Feedforward neural networks have been employed to implement a fractal based human face representation and recognition system. An input image is transformed into its fractal model and compared with fractal models of known faces. Simulation results show that the proposed system overcomes the shortcomings of PCA. The maximum compression ratio obtained for the successful recognition of the known faces was observed to be 89:1. A comprehensive face image database is currently being constructed by the authors. This will allow future experiments to be conducted with larger numbers of face images.

Acknowledgements

The first author would like to thank DEET, Australia, and FUSA, for providing him with scholarships to undertake this research.

References

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

[2] M.F. Barnsley and L.P. Hurd, *Fractal Image Compression*. AK Peters Ltd., 1993.

[3] R. Chellappa, C.L. Wilson, and S. Sirohey, "Human and machine recognition of faces: A survey," *Proceedings of the IEEE*, vol. 83, no. 5, pp. 705-740, May, 1995.

[4] Y. Fisher (Ed.), *Fractal Image Compression: Theory and Application*. Springer-Verlag New York, Inc., 1995.

[5] A.E. Jacquin, "Fractal image coding: A review," *Proceedings of the IEEE*, vol. 81, no. 10, pp. 1451-1465, October, 1993.

[6] M. Kirby and L. Sirovich, "Application of the Karhunen-Loeve procedure for the characterization of human faces," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 12, no. 1, pp. 103-108, January, 1990.

[7] A.Z. Kouzani, F. He, and K. Sammut, "Commonsense knowledge representation and reasoning with fuzzy neural networks," *Proc. 1996 Australian and New Zealand Conference on Intelligent Information Processing Systems*, Adelaide, Australia, pp. 237-240, November, 1996.

[8] A.Z. Kouzani, F. He, and K. Sammut, "Commonsense knowledge-based face detection," To be presented at *1997 IEEE International Conference on Intelligent Engineering Systems*, Budapest, Hungary, 15-17 September 1997.

[9] B.B. Mandelbrot, *The Fractal Geometry of Nature*. New York: Freeman and Company, 1983.

[10] A.J. O'Toole, H. Abdi, K.A. Deffenbacher, and D. Valentin, "Low-dimensional representation of faces in higher dimensions of the face space," *Optical Society of America*, vol. 10, no. 3, pp. 405-411, March, 1993.

[11] A. Samal and P.A. Iyengar, "Automatic recognition and analysis of human faces and facial expressions: A survey," *Pattern Recognition*, vol. 25, no. 1, pp. 65-77, 1992.

[12] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal of Cognitive Neuroscience*, vol. 3, no. 1, pp. 71-86, 1991.

[13] D. Valentin, H. Abdi, A.J. O'Toole, and G.W. Cottrell, "Connectionist models of face processing: A survey," *Pattern Recognition*, vol. 27, pp. 1209-1230, 1994.

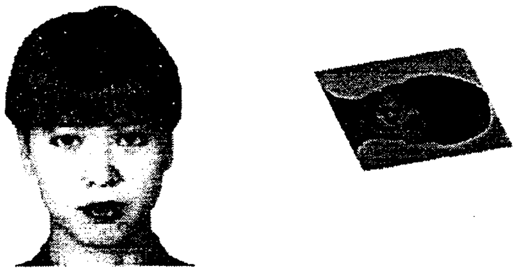

Fig. 1. A contractive transformation of a face image in a plane.

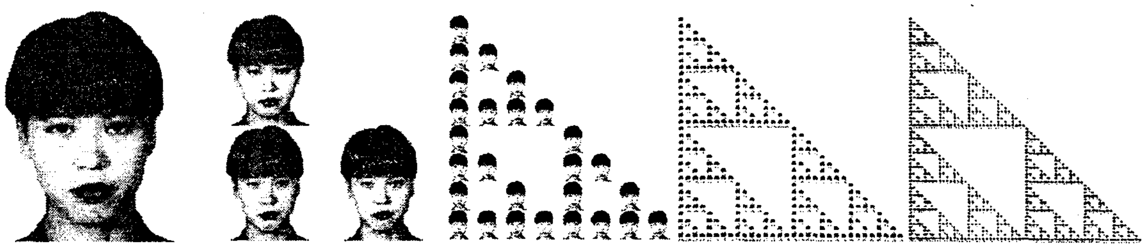

Fig. 2. An attractor of an IFS with three maps.

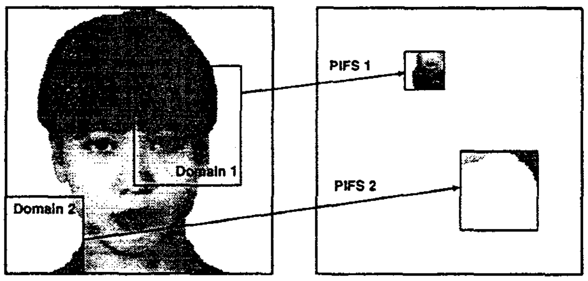

Fig. 3. Partitioned iterated function systems.

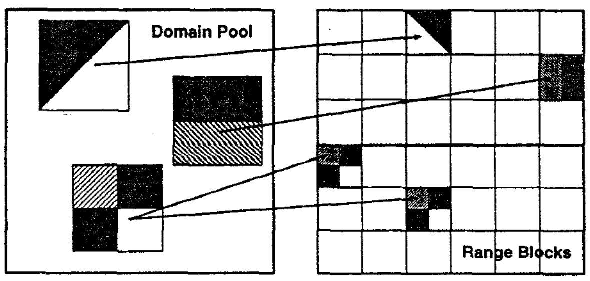

Fig. 4. Mapping of some domain blocks onto range blocks.

Fig. 5. Fractal decomposition of a sample face image. a) Original image, b) first, c) third, d) fifth iterates of reconstructed image for 8x8 range blocks & 16x16 domain blocks.

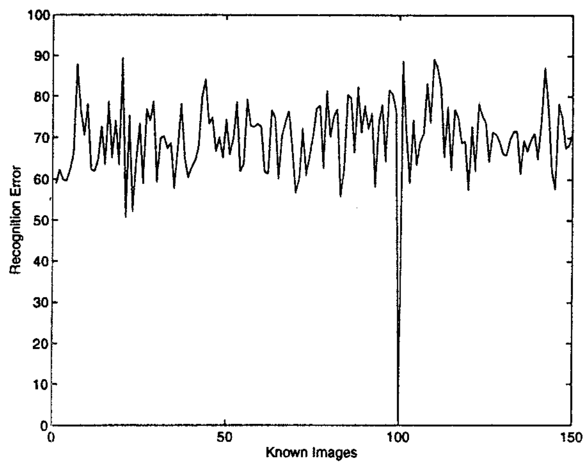

Fig. 6. Recognition result for a known input face image (number 100).

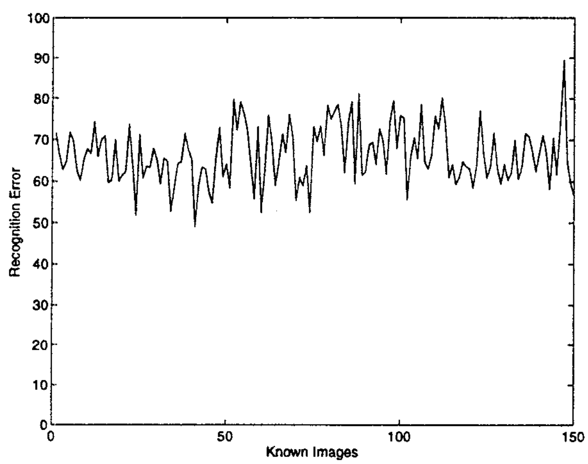

Fig. 7. Recognition result for an unknown input face image.