OPTIMIZATION OF FRACTAL IMAGE COMPRESSION BASED ON KOHONEN NEURAL NETWORKS

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Abstract-**Fractal image compression is a bloc based image compression , detecting and coding the existing similarities between different regions in the image. It allows interesting compression ratios; however it presents the disadvantage of the long compression time, whereas the decompression is fast. The time consuming part of the encoding step is the search for an appropriate domain for each range .Most of time required in the fractal compression is spent in the matching of a large number of blocks in the image [16, 17]. To speed up the fractal coding time, several methods have been devised to accelerate the search and reduce the encoding complexity, such as the Fisher classification method. Other methods consist in using Artificial Intelligence techniques such as Genetic Algorithms and Artificial Neural Networks. In this paper the method of artificial neural networks is used to speed up the fractal compression phase. Self Organizing Map (SOM) neuron networks were used.**

Keywords- Fractal compression, inverse problem, neural networks, Kohonen neural networks.

I. INTRODUCTION

To accelerate the fractal compression phase with the Self Organizing Maps (SOM) , we reduced the input size .Character vectors are independent of the size and shape of the blocks. The learning process is done only once and the time consumed in the learning process won't be counted with the coding time.

Another improvement consists in applying the coding algorithm on measurements calculated on a set of block pixels rather than directly on pixels themselves , based on a small number of characters of block texture and style. he search field is reduced with the introduction of neuron networks.

II. FRACTAL IMAGE COMPRESSION

The fractal image compression consists of detecting the similarities between blocks in different resolutions of the image, and reducing them into a set of factors of simple geometric transformations creating what's called PIFS [1].

The fractal compression method can be summarized as follows: A library of domain blocks will be made of a set of blocks which can overlap in the image in a low resolution. Another set of range blocks will be formed by subdividing the original image into non-overlapping blocks by applying one of the partitioning methods [10]. Thus for each range block r_i a domain block d_i is matched according to a distance (generally Euclidean), i.e. the best domain block with its affine transformation w_i having as parameters a and o such as $w_i(d_i)$ is an approximation with the r_i block ; in other words: $w_i(d_i)= a.\mathrm{d}_\mathrm{j} + o \approx r_i$

Thus only the parameters of the contracting affine transformations and positions of domain blocks will be recorded [2,3].

III. SELF-ORGANIZING MAPS

Self-organizing maps are a kind of artificial neural networks witch inspire from the learning neural networks. This kind of neural network allows to project an entry space on a one or two dimensional map called topological map. It's composed of two layers, an entry vector, and a map where all elements are of the same dimension as for the entry.

The training of Kohnen networks [11, 12 ,13] is competitive: when an entry vector is presented to neural network, all neurons get in completion to determine the winner neuron which is the one with the weight vector i closest to the entry vector according to a distance measure (generally the Euclidean distance). Thus the winner neuron and his neighbour get closer to the vector entry by adjusting their weight vectors according to the distance between them and the winner following this rule,

$$w_g (t+1) = w_g (t) + \alpha(t) (X(t) - w_g (t))$$

where t is the iteration index, and $\alpha(t)$ is the updating factor inversely proportional to the distance between the winner and its neighbours; during the training it decreases towards the minimum. This process is to be iterated until the convergence of the map (when the distortion of the map between two consecutive iterations is smaller).

By the end of the training ,the map is ready to be used .Thus when a new entry vector is presented to the map ; the distance between this vector and each neuron is calculated to determine the winner which is the closest to the new vector, and hence it will be affected to the class which corresponds to the winner [4].

III.1 SELF-ORGANIZING MAPS IN FRACTAL COMPRESSION OF IMAGES

The self organizing maps are used just before the matching of the domain blocks and the range blocks. Each bloc will be coded upon some feature measures: standard deviation, skewness, neighbour contrast, beta, horizontal gradient, vertical gradient [5].

Feature vectors have to be normalized before being used in the neural networks.

III.2-LEARNING

For the self-organizing map, the training could be done once, and then the map is ready to be used for any other image. For the training , the map could be initialized with random values, or could be a map already used .The training set is the feature vectors calculated upon domain blocks. After training each domain block is assigned to a class which corresponds to the winner neuron [6,7,8].

III.3- COMPRESSION

The compression will be performed through these steps:

1- *Domain blocks classification*: on each domain block a feature vector is calculated, then affected to the class which corresponds to the winner neuron [14].

2- *Range blocks classification*: each block will be coded in the same way, and affected to the class that corresponds to the winner neuron.

3- *Matching of domain blocks and range blocks*: each range block will be matched with domain blocks belonging to the class to which it belongs and its neighbour classes (in a 3×3 neighbourhood according to the map topology), reducing thus the matching space.

The decompression does not need the map; it will be done by applying the affine transformations on an arbitrary image for a number of iterations.

IV. ADAPTIVE ALGORITHM

Kohonen network is used in fractal compression using the adaptive algorithm which searches the best range block d_i for a source block r_i with the affine transformation w_i, having the contrast parameter s_i and brightness parameter o_i, such as $w_i(d_i)$ is closer to the block r_i,. In other words the distance d($w_i(d_i)$, r_i) is minimized . When the distortion between blocks is higher than a predefined threshold , we subdivide the source block into four sub blocks and keep repeating the division until , either the difference is lower than the threshold or the minimal block size is reached.

V. APPLICATION RESULTS:

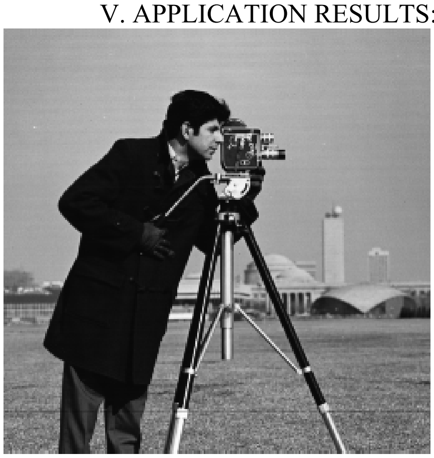

Fig.1- Cameraman image reconstructed after fractal compression with adaptive algorithm using Kohonen neural networks, to the left the original image, to the right the reconstructed image at a PSNR of 29.1537

Fig.2 - House image reconstructed after a fractal compression with adaptive algorithm using Kohonen neural networks, to the left the original image, to the right the reconstructed image at a PSNR of 22.585

For the application, the self-organizing maps have been applied in the fractal compression using the adaptive quad tree algorithm.

The following table describe the results of the application of fractal compression on still images in two parts, the first without neural networks, the second with the neural networks (self-organizing networks [9]).

Threshold	**Number de blocks**		**Execution time**		**PSNR**		**Ratio**	
	Classic Fractal algorithm	**Neuro fractal algorithm**	**Classic Fractal algorithm**	**Neuro fractal algorithm**	**Classic Fractal algorithm**	**Neuro fractal algorithm**	**Classic Fractal algorithm**	**Neuro fractal algorithm**
2	2752	2938	25 min 12 sec	10 min 43 sec	29.4596	29.3353	4.7:1	4.4:1
5	2065	2116	19 min 47 sec	8 min 13 sec	29.4347	29.3535	6.3:1	6.1:1
10	1645	1744	15 min 49 sec	7 min 9 sec	29.3158	29.1537	7.9:1	7.5:1
30	517	571	4 min 58 sec	2 min 60 sec	28.3795	28.4064	25.3:1	22.9:1
50	79	79	0 min 46 seco	1 min 11 sec	26.8663	26.7265	165.9:1	165.9:1

Table 1- Results of the classic algorithm (without neural networks) vs the neurofractal for the cameraman image

We observe a speeding of the compression time with a slight decrease of the quality. This was observed for all 5 tested images *(Cameraman , House , Roses , Lena and trees)*.

VI CONCLUSION

In our neuron fractal method compression time was speed up without severely affecting the image quality .
The coding time is improved by one third ccompared to the standard methods whjch dont use neuron networks.
The method proposed by A.Bogdan et H.Meadows [1] has disadvantages : it is slow since one iteration takes 30 minutes because of the large input dimension and its inability to adapt to a variable partitioning.

Other classification techniques to be investigated are multi dimensional topological maps and the human visual system based methods.

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