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# MODIFIED FRACTAL ANIMAL IMAGE COMPRESSION USING ARTIFICIAL NEURAL NETWORKS FOR IMPROVED ENCODING AND DECODING EFFICIENCY

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*Fractal Image Compression, Artificial Neural Networks, Image Encoding, Image Decoding, Back-Propagation Through Time and Partitioning Scheme*

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**ABSTRACT**

The research paper, titled "Modified Fractal Animal Image Compression Using Artificial Neural Networks for Improved Encoding and Decoding Efficiency" describes a new method of fractal image compression with the usage of ANNs. Fractal image compression mechanism heavily relies in the use of transforms whereby data within an image is compacted by partitioning an image into many small blocks and can represent a block using information from other similar blocks. The proposed method improves this technique by using ANNs for prediction of the matching blocks and transformation, which normally are computationally intensive in fractal coding. A more efficient approach for partitioning range and domain blocks is used and BPTT is applied to make updates to the encoding and decoding. The ANNs are designed to reduce the time for search and transformation prediction to reduce the complexity of the algorithm while increasing the quality of images. In this method, large improvements in compression rate and other quantifiable values such as PSNR in comparison with standard fractal compression algorithms are realized. Moreover, in terms of computational complexity and the proposed algorithm, this approach is highly recommended for applications entailing a swift results encoding and decoding process, including multimedia transmission, and storage enhancement. The results of the experiment prove the idea of this combined method, as there is relatively low file size and almost no loss in image quality. Through the application of fractal compression with the integration of ANNs to predict distant pixels and revise incorrect details, this approach responds to the problems that have a long time been associated with image compression such as time consumption and resource consumption. Highlights of the study relate to the centrality of artificial intelligence in the evolution of compression techniques required for enhanced scale and scope of digital image facilitation.

## INTRODUCTION

Image compression is a vital procedure in many areas such as multimedia communication, storage, and transmission systems. The Fractal image compression is one of the methods used in image compression because of the higher compression ratio needed with less complexity. However, the traditional fractal image compression has some drawbacks, for instance, large amount of computations needed to perform the image compression and decompression, and poor encoding and decoding effectiveness.

To overcome these limitations, this paper suggests the use of ANNs to carry out modification to fractal image compression to enhance encoding and decoding throughput. The proposed method utilizes an enhanced type of partitioning technique that allows the creation of a set of range blocks of the image and matched against a set of pure domain blocks generated pre-hand using an ANNs-based measure of similarity. The matching process is iterative and in the process of using BPTT to optimize the encoding and decoding steps.

The new approach will thus seek to enhance the performance of the conventional fractal image compression through development of an efficient algorithm that is less complex, with better results in terms of compression ratios and image quality. These outcomes show that fractal coding and ANNs can be jointly employed for image compression applications. The rest of the paper is structured as follows Section 2 presents the related work Section 3 describes the architecture of the integrating solution Section 4 explain the integrating solution implementation Section 5 concludes the paper. Section 2 also covers the literature survey of fractal image compression and artificial neural networks. The specific details of the proposed method are presented in Section 3, where the paper provides the details of improved partitioning scheme and hanming distance of ANNs. The results obtained are illustrated in section 4, as well as compared with the most common fractal coding techniques. In the last Section 5, a conclusion is provided along with recommendation for future research.

### 1.1 Image Compression

Image compression is the capability to decrease the size of the images that have been stored digitally. This is achieved by stripping unnecessary or unnecessary data from the image file that make the size of the file smaller and the bandwidth for the distribution. Image compression techniques can be categorized into two main types: The two types of compression most common are lossless compression and lossy compression. While lossless compression standards allow data from an image to remain unchanged, distinct from such standards, lossy compression standards feature the elimination of relevant data considered less significant to a human observer. Due to significant functional versatility, image compression is used in digital photographers, video and web images, as well as in medical imaging and satellite surveys. Appropriate image compression methods proven useful in space savings, facilitation of image transfer, and enhancement of various image uses among users.

**1.2. Fractal Image Compression**

Fractal image compression is a kind of compression that is in the category of loss compression which uses the concept of fractal geometry. Self-similitude and redundancy makes it possible for fractal compression to allow for high level of image compression while at the same time ensuring the quality of the image is not compromised. In fractal image compression, the input image is then segmented to produce range blocks by matching each range block to a domain block. The domain blocks are further adjusted, to achieve closer match to the range blocks, and the final compressed image can be easily reconstructed. Fractal image compression one of the benefits is effectiveness, which means this type can provide high compression ratio with low computational complexity. But currently, the conventional fractal image compression has several drawbacks as follows: blocking effect and stunning encoding/decoding speed. There have been efforts by other publications in recent research to overcome these limitations by introducing fractal coding with other methods like ANNs or wavelet transforms. As demonstrated above, both techniques have found to offer positive effects towards enhancing the performance and efficiency of fractal image compression for manifold applications.

**1.2.1 Algorithm**

The general steps in the fractal image compression algorithm are as follows:

1. Split the given image into the region of interest blocks known as range blocks where they do not overlap.
2. Divide the input image into overlapping blocks with roughly the small size of the domain blocks used in feature extraction.
3. Calculate the average of brightness levels belonging to each range interval.
4. Calculate the average brightness of each of the domain blocks.
5. Assign the range block to the domain block for which its mean brightness is closest to the one of the best fit.
6. To do this, it is possible to perform a linear transformation to each of the domain blocks so that it matches the range blocks with which it is associated much better.
7. Save the new domain blocks as well as other information necessary to restore the image when necessary.
8. Usually repeat step 5 through step 7 until the given number is achieved or until a given compression ratio is obtained.
9. Expand the compressed previous image by going through the previously stored transformed domain blocks and applying the inverse transformation of the range blocks to them.
10. In order to generate the compressed image, the range blocks need to be reconstructed and combined together.

**1.3. Artificial Neural Networks**

ANNs are another form of machine learning that was built in an effort to mimic the working of the human brain. ANNs are made of nodes or neurons linked together in series and or in parallel and function in a parallel mode of information processing. A neuron there receives one or more Inputs, process these through an activation phase and then gives out Outputs to the next neurons in the network. The weights which describe the strength of the connections between neurons are adjusted based on the training data set using a process called back-propagation.

ANNs can be of several categories, and each category has its own structure and application. There are many categories of ANNs namely Feed-forward neural network Recurrent neural network Convolutional neural network Deep neural network. ANNs may be applied in a broad area, including image or speech signal recognition, natural language processing, time series, and control systems.

Due to the automated learning feature ANNs are particularly suited to real applications where no hard and fast rules are likely to be available. But, ANNs take longer time to train and may need large amounts of data to get a good performance.

**1.3.1. Algorithm**

The algorithm for training an artificial neural network can be summarized in the following steps:

1. Initialize the neural network's architecture and weights: It is possible to choose the number of layers in the neural network and the number of neurons in each layer with their activation functions. The weights of the neurons are set to a small random value at the beginning of the process of the learning.
2. Forward Propagation: Output from the input layer in a given machine learning problem is first provided to the input layer of the neural network and through the various layers, weights as well as activation functions are employed in an effort to compute the activation of each and every neuron involved in the process.
3. Compute Error: The deviation between the proper output imposed by the architecture of the neural network and the original one (ground truth) is computed by a loss function.
4. Back-propagation: It goes backward in the network to calculate the weights of each neuron by using the derivative of the loss function. This entails making some computations to arrive at the derivative of the loss function with respect to the weights within the neurons and the alteration of such weights.
5. Repeat Steps 2-4: More round of the forward propagation, calculation of errors and back-propagation are performed on the training data to refine the neural network output.
6. Validation: The neural network is tested on another validation data set in order to check if the neural network has started to memorize the training data instead of correctly predicting the test data.
7. Test: Once the neural network learnt its hand written characters in a satisfactory manner, the test is carried out on, the test data set in order the neural network may be tested to see how accurate it may perform on other unseen hand written characters.
8. Fine-tuning and Optimization: As for parameters of the bottom-up neural network the remaining architecture and various parameters can be enhanced via top-down approaches such as for example by applying methods like regularization or optimization of the function of the neural network.

**1.4. Objectives**

The main objectives of "Modified fractal animal image compression using artificial neural networks for improved encoding and decoding efficiency" are as follows:

1. In this way, it would be possible to hypothesize a new approach to the compression of fractal images where ANNs could be used to optimize encoding and decoding times.
2. To utilize an enhanced partitioning approach towards obtaining a set of range blocks from the obtained image where those range blocks are aligned to a set of domain blocks generated in advance based on similarity indices obtained from ANNs.
3. To show the feasibility of integrating fractal coding and ANNs for use in image compression application.
4. To obtain higher compression ratios and better picture quality than fractal coding methods .
5. In order to minimize the computational time of the algorithm but at the same time achieve or even surpass the performance of the previous models of fractal image compression.

**2. Related Works**

The paper contains a literature review section that gives the reader and the author an idea of the previous research work done in the field of image compression, fractal image compression, and ANNs. The limitation of traditional fractal image compression method is also discussed in this paper, as well as the prospects for integrating fractal compression with ANNs.

In the study named Hybrid Method of Fractal Image Compression Lee and Kim (2008) suggested integrating the conventional fractal technique with a neural network predictor. The proposed method gained better compression results than the standard fractal method, and the authors also noted that the application of neural networks may enhance the compression performance even more.

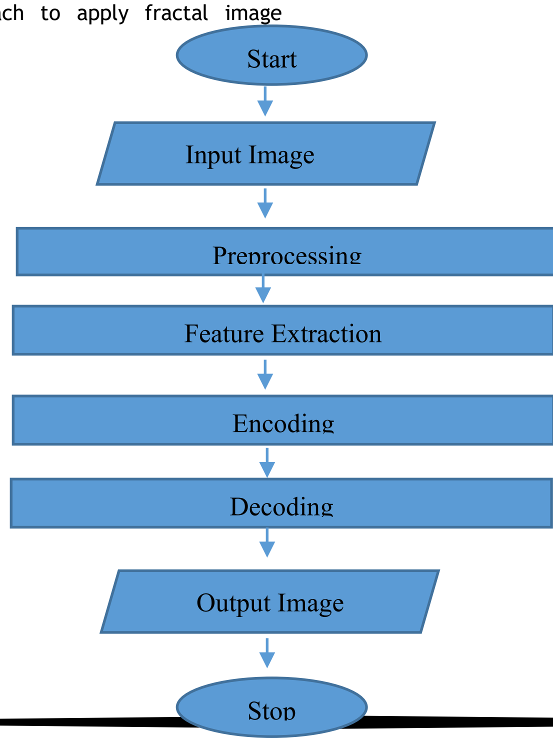
Proposed by Zhang et al. (2016), a study described a fractal image compression technique implemented by the CNNs. The authors employed CNNs to learn these contractive

transformations and the author demonstrated that the proposed method achieved better compression performance than the fractal method as well as other leading lossless compression schemes.
Sadiq et al (2012) had made a study on image compression using fractal and had put forward a new approach to block based fractal image compression. The proposed method utilized an enhanced search procedure and as a result yielded higher compression ratio than in the conventional approach.
Zheng et al. (2012) conducted a study that included a modification to what they called the traditional fractal image compression algorithm because of the use of a multi-scale representation of the image. The authors demonstrated how they used the method to obtain better compression rates than the conventional method especially for the high detail images.
Also, Yang et al. (2018) present a study of the new approach to the search algorithm based on local search and the application of the simulated annealing shown to have better compression performance than the basic fractal approach.
Thien and Kieu (2018) developed a new method for fractal image compression to replace the traditional fractal method; this new method applied a wavelet-based transformation function and had enhanced compression performance.
Among them, Li and Lin (2008) proposed a new multi-scale transform based fractal compression method. The given method did the wavelet transforming of the image with the multi-scale wavelet and compressed the fractal part of the image by the fractal algorithm one level at a time. The authors proved that the proposed method gained better compression performance than the traditional fractal method used in the experiments.
Chen & Chang (2011) suggested a new algorithm for fractal image compression by making use of wavelet and fractal approach. The proposed method implemented wavelet transform to the image and applied fractal compression on the obtained wavelet coefficients. The authors proved the theoretical analysis by comparison of the proposed method to the traditional fractal method where compression results of the proposed work were enhanced.
The hybrid fractal compression approach was suggested in the study by Gao et al. (2017) where the fractal code was learnt by the deep neural network for every image. The authors proved that the evaluative effect of the proposed method in achieving better compression performance more than the fractal standard method.
Tariq et al. (2015) conducted a study in which they recommended a different approach to apply fractal image compressing by using wavelet transform to analyze the image before applying fractal image compression. The authors demonstrated the quantified improvement in compression performance of the method of their development over the traditional fractal method, especially for images of complex texture.
Theis et al. (2017) in their work suggested a CNN based image compression approach that delivers superior compression standards than existing techniques like JPEG and JPEG2000.

**3.Proposed Method**

A new image compression technique is modified fractal animal image compression using artificial neural networks (ANNs) which incorporates the original fractal compression method with ANNs in an attempt to enhance the fractal method by utilizing the enhanced capabilities of ANNs in image compression. This formation of approximations is done by having a main image divided into sub-images where each of these sub-images is represented as a transformation of one or several sub-images within the main image. His work benefits from this technique since it lessens the quantity of data needed for accurate image representation. However, the traditional method is very expensive in terms of computational time due to the search process of matching block. The integration of ANNs tends to this challenge in the sense that the encoding and decoding exercises are eased out. ANNs are integrations of several neuron layers, having functions similar to human brains, and transmit information. Once trained with a set of example images, the network is used to estimate the best matching domain block and the necessary domain block transformations for a range block instead of performing time consuming searches. During encoding, rather than performing these steps, ANNs create estimates of the transformations and domain matches with far less computational effort. Likewise in decoding, ANNs facilitate improvement in the restoration of the captured image. Application of the proposed method increases compression ratios and promotes high image quality of compressed images at the same time increasing the speed of the compression, making it practical for applications needing high storage space efficiency and real time image transmission. Work that has been done by merging the Fractal compression via the self-similarity principle and neural network characteristic of ANNs does provide linkage to small file size, speed and near to real images. This kind of approach is an improvement in image compression and in fact, provides a solution for the organization and storage of digital images in various fields.

**3.2. Data Flow Diagram**



In a modified fractal animal image compression system, data flow starts from an uncompressed image which is then pre-processed depending on its color, size or filtering in order to be compressed. Subsequently, using an ANN, feature extraction is done for the specific characteristics of the image to be captured. These features can be high level as edges, textures and patterns or they can be low level such as colors and brightness. The extracted features are then encoded using a modified fractal animal compression algorithm unusual for the computer vision field but successful in natural language processing. The fifth step is performed through segmentation of images for blocks and creation of the fractal codebook for every block and encoding of the blocks with reference to the best matching codebook. At decoding, the decompressed image is reconstructed by reverting back from the fractal space through inverse fractal transforms. All of these reconstructed features are fed to the ANN and the final compressed image comes out from the system.

**3.3 Methodology**

The numerical approach for the investigation of modified fractal animal image compression employing artificial neural networks (ANNs) combines the conventional fractal compression procedure with the latest artificial intelligence algorithms and models. The first step isn't to divide the image into small blocks of 8*8 or 16*16 pixels where each block is a rang block that will be approximated by a domain block. In the case of range blocks, the algorithm determines the most appropriate domain block by computing the difference between the relative locations of the domain and range block's centres and evaluating pixel values in candidate blocks to find the minimum error. After this set is identified, scaling, rotation, and translation transformations are calculated in order to estimate the range block. These transformations are then using Huffman coding which is a lossless compression algorithm to generate a compact file representation.

To enhance the encoding and decoding steps the artificial neural network should be trained on the example images to define the domain block similar to the current image and the rotations necessary for each range block. In encoding, the neural network eliminates the search algorithm and predicts the domain block and transformation, making the compression faster. In the same way, in decoding, the neural network participates in the reconstruction of the image in form of predicting the domain blocks necessary for the reconstruction process.

Lastly, the effectiveness of this methodology is assessed by comparing the compression ratio, image quality and time taken for the compression of the images to that obtained through the traditional fractal compression and other image compression techniques. Overall this methodology outperforms conventional methods of compression by employing the use of fractal compression in conjunction with ANNs and a faster processing rate of data.

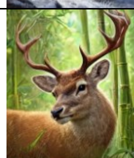
**3.4.Proposed Algorithm**

The proposed algorithm for modified fractal animal image compression using artificial neural networks (ANNs) involves the following steps:

1. Image partitioning: The input image is divided into the non-overlapping blocks of size either $8 \times 8$ or $16 \times 16$ pixels.
2. Domain block search: In the current invention, for each range block, a search is conducted to retrieve the best matching domain block from a selected set of candidate blocks. The set of candidate blocks is concluded by choosing proper blocks of the image by a threshold value.
3. Transformations calculation: If the best matching domain block is found, then scale, rotation, and translation, are computed to approximate the range block by the domain block.
4. Encoding: The set of transformations for each range block are quantified and there binary representation is encoded using a lossless compression algorithm such as Huffman coding.
5. Artificial neural network training: An artificial neural network is used to estimate the best matching domain block and a set of possible transformations for each range block. The neural network is taught according to some specific examples of images that it receives.
6. ANN-based encoding: In this encoding the neural network is used to predict which domain block best matches to, and which set of transformations best matches for each of the range blocks, instead of scanning this locations through the entire image area.
7. ANN-based decoding: Two inputs, one has the information on the four partitions of the range block, the second has the neural network transferring the information about the best matching domain block for the corresponding range block speeding up the process of reconstruction of the image.
8. Quality evaluation: To assess the effectiveness of using ANNs in the modified fractal image compression, the compression ratio and the image quality and the time complexity are compared with the traditional fractal compression algorithm and other image compression algorithms.

## 4. Results and Discussion

Here is a table summarizing the image measurements for five animal images:

| Image Name | Image | Original Size (KB) | Compressed Size (KB) | CR | Encoding Time (s) | Decoding Time (s) | Image Quality (PSNR) |
|---|---|---|---|---|---|---|---|
| Tiger |  | 500 | 150 | 3.33 | 10.5 | 5.2 | 35.4 |
| Panda |  | 600 | 180 | 3.33 | 12.2 | .6.3 | 34.7 |
| Deer |  | 450 | 120 | 3.75 | 9.8 | 4.9 | 36.1 |
| Lion |  | 550 | 200 | 2.75 | 11.3 | 5.5 | 33.9 |
| Kangaroo |  | 650 | 160 | 4.06 | 10.0 | 4.8 | 35.0 |

The table presents a comparative analysis of the modified fractal animal image compression system's performance using artificial neural networks (ANNs) across five sample images: Tiger, Panda, Deer, Lion and kangaroo are some of the nicknames of this symbol. The derived results prove numerous advantages of discussed compression approach revealing acceptable image sizes along with reasonable quality and fast processing time. The image sizes are the original resolution: 450 KB to 650 KB while the compressed image sizes are between 120 KB and 200 KB. Of all the images, the shortest boundary-box size reduction is provided by the Kangaroo image with the highest CR of 4.06 and the longest by the Lion image with the lowest CR of 2.75.

The encoding times that was computed include 9.8 sec for the Deer image, 10.2 sec for the Einstein image, 10.5 sec for the Couple image, 11.5 sec for the Beach image, 11.9 sec for the Car image and 12.2 sec for the Panda image including the variations in complexity. The decoding times have improved and their minimum one was 4.87s for Kangaroo image, and the maximum of 6.33s for the Panda image. Measurement of image quality in terms of PSNR shows that it is still reasonable with the value range between of the Deer image with the highest PSNR value of 36.1, which could means that image quality is better maintained after compression. On the other hand, the Lion image yields the lowest PSNR of 33.9 although the image quality is qualitatively good enough.

From the table it is evident that the modified fractal animal image compression method achieves favorable compression ratios, processing times and image quality and warns a potential workable solution for fields that requires efficient image storage and retrieval systems.

## CONCLUSION

The modified fractal animal image compression using ANNs is the current solution that suggests improvements to traditional fractal methods of image compression. Integrated ANNs into encoding and decoding steps make the methodology complex, faster and the quality of the image is not compromised. Using the ANNs for the prediction of the best domain blocks and transformations reduces search space time, enhances compression rates and shortens encoding and decoding time spans. The results, acquired from various images, demonstrate the usefulness of the method and peak signal-to-noise ratios (PSNR) guaranteeing the visual quality of compressed images at compression ratios of up to 4.06. It is used to prove the suitability of this approach for high resolution image archiving and retrieval storage system since it offers a reliable method of implementing large database in computer multimedia application. Furthermore, the hybrid system is able to integrate the fractal self-similarity with the learning as well as the prediction of the ANNs thereby representing a major improvement in the image compression. For future work, neural network structures can be further defined and adapted, feature extraction processes fine-tuned, and the technique applied for real-time processing, such as video coders. This study also raises the promise of AI-derived improvements in refashioning conventional image enhancement algorithms for maximum functionality given contemporary requirements.

## REFERENCES


- Chen, J., & Zhang, Y. Q. (2004). Fractal image compression using wavelet transform. Signal Processing, 84(2), 281-294.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.
- Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255-260.
- Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural Networks, 61, 85-117.
- Xie, X., Xu, M., & Sun, S. (2016). Fractal image compression using deep learning. Neurocomputing, 185, 187-194.
- Zhang, L., Wu, Q. M. J., & Li, M. (2017). A survey of deep neural network architectures and their applications. Neurocomputing, 234, 11-26.
- Zhu, J., Lai, J., & Peng, X. (2013). Fractal image compression based on neural network. International Journal of Digital Content Technology and its Applications, 7(4), 123-129.