A Survey On Image Compression Techniques Using Neural Networks

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Abstract— **Image compression plays an important role in communication application, to remove the redundancy from the image data in such a way that it allows the same image reconstruction at the receiver end. Also, the neural network have proved to be useful in image compression because of their parallel architecture and flexibility. In this paper, we study how neural networks are incorporated in image compression and also discuss different approaches.**

Keywords: Image compression, neural network, feed forward back propagation algorithm, principal component analysis (PCA), counter propagation algorithm.

I. Introduction

Today, a growing technology requires efficient compression of a still picture or image to reduce redundancy and storage capacity. Numerous lossy image-compression techniques have been developed in the past years. In particular, cosine-transform-based techniques (JPEG) have been found to obtain excellent results in many digital-image-compression applications. Recently, neural networks are used that are based on the parallel architecture and inspired from human brains.

A neural network [8] is a machine that is designed to model the way in which brain performs a particular task or function of interest, the network is usually implemented by using electronic components or is simulated in software on a digital computer. The use of the neural network offers useful properties and capabilities. An artificial neuron can be linear or non-linear and a neural network, made up of an interconnection of non-linear neurons, is itself non-linear. It performs input-output mapping and acquires knowledge through learning and stores knowledge within inter neuron connection strengths known as synaptic weights. Then the neural network has a built-in capability to adapt their synaptic weights to changes in the surrounding environment. The massively parallel nature of a neural network makes neural network makes it potentially fast for the computation of certain tasks.

In the literature different approaches of image compression have been developed, one of these algorithms [1] have been developed on the basics of a neural network, [2] develops the two multilayer neural network that compresses the image in 2 stage. Also, another approach developed in [3] is using principal component technique (PCA) and back propagation algorithm for training the neurons. As a continuation of algorithm developments, a new approach has been developed in [4] for compressing colour images using counter propagation neural network.

In this paper, section II describes modular structured neural networks and how its drawbacks are overcome. And section III explains image compression using back propagation neural network. Then section IV explains colour images compression using counter propagation neural network. Finally, in section V we will discuss the results of different approaches.

II. LOSSY IMAGE COMPRESSION USING MODULAR STRUCTURED NEURAL NETWORK

Modular structured neural network [1] consists of multiple neural networks with different block sizes for region segmentation. Usually, to compress edge or texture region, the neural network with smaller block size are applied and to compress flat regions, neural network with larger block size are applied. This method overcomes the difficulty of compressing image using single neural network, where in single neural network it is difficult to compress the region(where $E_{BIAS,P}$ is small and $E_{VARIANCE,P}$ is large and on the other hand, $E_{BIAS,P}$ is large and $E_{VARIANCE,P}$ is small) with adequate precision.

In lossy modular structured neural network method, region segmentation is executed as follows: firstly, it assumes that the objective image consists of flat region and it is compressed by neural network with larger block size, next, the block with maximum learning error is removed from the objective image. Further, repeating this search, procedure for each block and performing region segmentation on the basis of the learning ability of neural networks. But this method gives reasonable results for region segmentation.

To overcome this, in [2], the image compression system consists of two multilayer neural networks (MNN) that compress the image in 2 stages. First image is compressed using a MNN with a linear or sigmoid activation function and error is compressed using another MNN. In both the networks N units are considered in the input and output layers, and h1 (respt h2) units in the hidden layer. During training phase of the system, network1 is trained to compress and decompress the image. Then the error is obtained by comparing the original image and output of network1. Then this error is given as input to the network2 which is trained to produce an output i.e. same as input, that compresses the error. And, during operation phase of this system the image to be compressed is subdivided into a number of non-overlapping blocks of $N=p\times p$ pixels each. Then each block is compressed using compressor system and decompressed using decompressor system, when decomposed, at the output the blocks are combined to get original image.

III. IMAGE COMPRESSION USING BACK PROPAGATION NEURAL NETWORK

In [3] feed forward back propagation neural network with principal component analysis (PCA) technique is used for image compression. PCA technique gives the simple solution in many applications like linear modeling, image restoring and pattern recognition etc. This PCA method extracts features from the image in the form of matrix, then computes covariance matrix. Later, obtains Eigen values by solving the scharacteristics equation and similarly obtains the Eigen vectors for each Eigen values. Then this matrix is transformed by considering the Eigen vectors as their columns. Then, new features are obtained from this transformation matrix that is linearly independent. Thus for compression the dimension of the new feature vector is reduced by setting to zero components with low values. Here feed forward back propagation neural network is used to change the dimension of feature vector matrix.

The architecture of feed forward neural network is shown in figure 1.

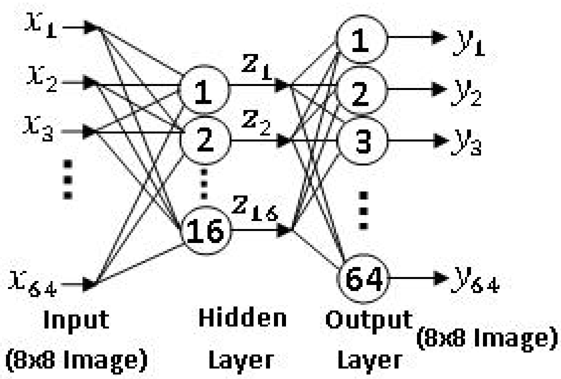

Fig 1. Architecture of feed forward neural network

Here, the input layer encodes 64 input and transmit output to hidden layer. The output layer receives the 16 hidden output of hidden layer and generates the 64 output. For training the network an original image is converted into non-overlapping blocks of n×n pixels. Each block represent N= n×n dimensional space. The goal of an image compression is to obtain the replica of original input image. Each output unit receives a target pattern corresponding to an input pattern.

Error information is calculated as:

$$\delta_k = (t_k - y_k) f(y_{ink})$$

And weights are updated using this equation:

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$$
$$w_{ok}(new) = w_{ok}(old) + \Delta$$

Then weight correction term is $\Delta v_{ij} = \propto$

And bias correction term is: $\Delta v_{oj} =$

Therefore new biases:

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij}$$
$$V_{oj}(new) = V_{oj}(old) + \Delta V_{oj}$$

Thus image compression is achieved by:

1. Dividing image into small 8×8 pixel in matrix form.
2. Converting pixel to real values (0 to 255) in the range-1 to +1.
3. Applying feed forward back propagation training algorithm.
4. Once the training is completed, 8×8 pixels are selected in sequence.
5. Digital bits converted to real values.
6. Matrix ranges from -1 to +1 reconverted from real to pixel mapping.
7. Recall phase to demonstrate the decomposed image.

IV. USING COUNTER PROPAGATION ALGORITHM

In 2-layer neural network, image compression is carried out using back propagation training algorithm and it exploits only the correlation between pixel patches within each of the training patches, therefore only limited compression is done. To overcome this multi-layer hierarchical network is used which uses nested training algorithm to make training faster. But this is also limited by back propagation technique that works only with the gray scale images and the compression ratio achieved using this technique is 8:1. And to overcome this all, new method is proposed by clustering the vectors based on compression requirement and uses counter propagation network method.

In an uncompressed bitmap-file [4], the colour information of image is mainly stored pixel by pixel and defined by 3 colour quantities i.e. red, green, blue quantity. And by varying these 3 quantities various pixels are formed. To achieve compression effectively, we need to reduce total number of colours of an image. To do this, [4] groups these pixels together that may be exactly same or close to each other with respect to their colour information. For compression and decompression, firstly clusters are formed of all the pixels into predetermined number of groups. Then produces a representative colour for each these formed groups. Finally, during compression each pixels are stored with cluster number and during decompression cluster number are restored and representative colour of that cluster is stored.

For clustering purpose, counter propagation neural networks are used because of its simplicity in calculations and strong power of generalization, since back propagation algorithm utilizes more training time because of the complexity in its equation. This network has 3 layers: input layer, kohonen layer and grossberg layer. The number of neurons in input layer and grossberg layer is 3 and that of kohonen layer will vary based on the total number of clusters we allow and has connecting weights for each of the neuron of previous layer. There weights are responsible for clustering the pixels into groups and are trained using real life image in unsupervised mode. After training, weights are adjusted to a point on which they can distinguish the similar pixels from the dissimilar pixels. Finally, last layer produces the colour information of pixels, and this representative colour for a particular cluster will be average of all the colours within the cluster.

During compression process, when 2-D image is considered and the weight vectors fall only in the first quadrant and are trained and not for the other quadrants. So this needs a retraining of the weight vectors and to avoid this we may exploit the symmetrical property of a sphere. And the quadrant number of each pixel will be stored using run length encoding and during decompression reverse algorithm of run-length encoding is applied to retrieve this quadrant number. Same thing applies for cluster number.

V. RESULTS AND DISCUSSION

In paper [1] where modular structured neural network is used, performance are evaluated by considering 4 different images, where

$$PSNR = 10 \log_{10} \frac{255^2}{E}$$

When single neural network is considered that consists of 4×4 output units, gives compression rate of 12.54% and when considering lossy compression method that consists of 3 types of block size i.e. 1×1, 2×2 4×4, and it gives the best PSNR for all learning and testing images with same compression rate of 12.5%. thus from simulation result, we can figure out that this method gives better compression performance compared with other conventional methods using single neural network. Also this method gives reasonable results for region segmentation.

In [2] were multilayer neural network is used, image is subdivided into 16×16 pixel sub image blocks, then the compression system is trained to compress the image blocks with h1+h2=16 i.e. compression rate CR=16. For investigating the performance, different paring (h1, h2) are used and for 5 different image. Also SNR is calculated as

$$SNR = \frac{\|original\_image\|}{\|original_{image} - reconstructed\_image\|}$$

And (h1, h2) = (4, 12) pair has highest SNR=6.3.

When this result is compared to the performance of 64-4-64 network, the SNR=7.4. this shows that 16×16 image block gives better results.

And in [3], author considers " lenna" and another "lucky" image. Performs image compression with 8,16 & 32 numbers of neurons in the hidden layer and 64 input neurons and 64 output neurons. He carries out PCA test using feed forward back propagation neural network (FFBPNN) for lucky image at 300 Epoch and we can figure out that for all number of hidden neurons the error remains constant and also it is difficult to find the covariance of a vector matrix with 64 input neuron and 64 output neuron in PCA technique. To overcome this several experiments were carried out for FFBPNN for constant values of alpha=0.4 and mf=0.6 for different number of Epoch. Here we can figure out that as the number of Epoch increases the training time increases with variation in error.

To overcome this all, in [4] 3 standard images are considered i.e. 'squall', 'lenna', 'mandrill', each allows different number of colours of the original size and after compression with various compression ratios for all the images, certainly we find that the quality fall with increasing compression ratios. This quality measure is PSNR and is calculated for 3-colour quantities separately and final value of PSNR is calculated by taking average of these three PSNR. Here we can figure out that 'mandrill' image varies from 21.34 dB with compression ratio of 2.55:1 to 17.85dB with CR of 5.08:1. This small change of 2.47 in CR causes a quality fall of 3.49dB in PSNR, which is quite acceptable. Similarly, the image 'Lenna' shows highest values in PSNR for every CR with respect to all other images. This indicates that the 'Lenna' image may be compressed further. Whereas further compression in 'Squall' and 'Mandrill' image may cause a significant fall in quality. Thus faster training is achieved using counter propagation neural network to successfully compress and decompress image data.

VI. CONCLUSION

In this paper we have discussed many approaches for image compression using neural networks. By region segmentation procedure, each neural network has been assigned to each region such as edge or flat regions. And by using a multilayer perceptron rather than the two-layer perceptron, higher quality for the same compression ratios has been achieved. PCA technique with feed forward neural network allows to concentrate on the original information. The accuracy of obtained results depends upon the threshold value at which the iteration process of learning is stopped. A counter propagation neural network based image compression technique has been used to successfully compress and decompress image data. Thus when all the network parameters and network sizes are properly specified, the network has the ability to both learn and generalize over a wide class of images. Based on these considerations, the neural network architecture should be considered as a viable alternative to other more traditional techniques.

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