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A Survey on Image Compression Techniques Using Artificial Neural Networks

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ABSTRACT:This Survey paper covers neural network built on image compression method. Image compression performs an important part in communication application, to reduce the redundancy of pixels from the image, broadcast cast and the transmission cost of image data in such a way that it allows the same image restoration at the receiver end. Image compression built on back propagation neural network with levenberg-marquardt algorithm and this is achieved by dividing the number of pixels of a image and select one neural network for each block according to its complexity value. Back propagation algorithm is used to reduce the convergence time and improve the performance of high compression ratio of image. Also, neural network's parallel architecture and flexibility made it to more useful in image compression. In this survey paper, we deliberate diverse methodologies and will know how neural networks are assimilated in image compression.

KEYWORDS:Artificial neural network, Image compression, L-M algorithm, Back propagation neural network, principal component analysis (PCA), Counter propagation algorithm.

I. INTRODUCTION

Image Processing is very prevalent for image Compression and day to day development of image compression. Today, a developing technology necessitates effective compression of a static picture or image to decrease redundancy and storing capacity. Number of different image-compression techniques have been designed in the last few years. In specific, cosine-transform-based techniques (JPEG) have been developed to gain excellent results in many digital-image-compression applications. In recent times, neural networks are used that are based on the parallel architecture and biological neuron in the human brains.

An artificial neural network is a technique that is deliberate to model the way in which human brain performs a specific task, the network is generally implemented by using electronic components or is counterfeit in software on a digital computer. 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 this survey different approaches of image compression have been developed, one of these algorithms have been developed on the basics of a neural network, develops the two multilayer neural network that icepacks the image in 2 stage. Also, one more approach developed in is using principal component technique (PCA) and back propagation algorithm for training the neurons. As a continuation of algorithm developments, a new method has been developed in for compressing colour images using counter propagation neural network.

In this survey paper, section II defines modular structured neural networks and how its disadvantages are overcome. And section III clarifies image compression using back propagation neural network. Then section IV clarifies colour

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images compression using counter propagation neural network. Lastly, in section V we will discuss the results of different approaches.

II. RELATED WORK

A. IMAGE COMPRESSION

The main application of Image compression is the data compression on digital images. The objective of image compression is to decrease redundancy & duplication of pixels of the image in the appropriate way of storing media or in the transmission of data (e-mail). The main types of image compression is Lossy Compression & Lossless Image Compression

Lossy: Lossy compression is a data compression technique which drops some of the data from original data which is result in reduce the image size. Most common files type are JPG and BMP. Lossless: Lossless compression is a data compression system in this there are no loss of compressed data that it's permits for a smaller file size, but also decompressed back to the original size. Most common file varieties are like TIFF, PSD, PNG, GIF, and RAW. Image compression emphases on the problem of decreasing the amount of data required to signify a digital image. Compression is obtained by the elimination of one or more of the three data redundancies: When less than Coding redundancy is optimum code words are used. Inter pixel redundancy results from associations between the pixels of an image. Psycho visual redundancy is because of the data that is ignored by the human visual system.

Image compression methods is used to decrease the number of bits requisite by representing an image and taking Image advantage of these redundancies. An inverse process called decompression or decoding is applied to the compressed data to get original image. Image compression process is composed of two different blocks: an encoder and a decoder. Image $F(x, y)$ is nursed into the encoder, which is created a set of symbols form the input data and uses them to represent the image.

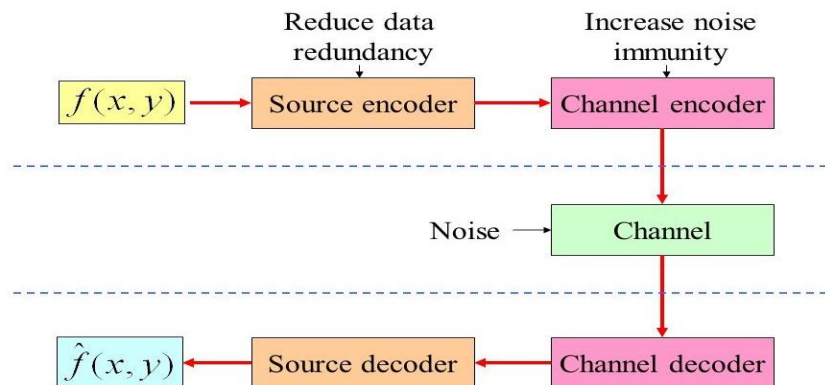


Fig : Image Compression Model

Let x & y denote the number of information carrying unit in original form as shown in the figure. The Source encoder is responsible for decreasing the data coding, inter pixel of image and psycho visual redundancies of input image. In first stage, the channel mapper encoder which work on the transforms the input image into a format calculated to reduce inters pixel redundancies.

In the second stage, quantized block is to reduce the accuracy of channel mapper's output in according to defined criteria. In the last stage, a symbol decoder is responsible for creating a code for quantize output and maps the output in according to the code. These operation is also perform in reverse order to get reverse output from the compressed image data. In quantization process is irreversible; an inverse process is not included.

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B. IMAGE COMPRESSION BY USING BACK PROPAGATION NEURAL NETWORK

In feed forward back propagation neural network is used with principal component analysis (PCA) technique for image compression. Principal Component Analysis method offers a simple solution in several applications like linear modeling, image restoring and pattern recognition etc. This PCA technique extracts features from the image in the form of matrix, then computes covariance matrix. Then, obtains Eigen values by solving the characteristics equation and in the same way obtains the Eigen vectors for each Eigen values. Later this matrix is transformed by seeing the Eigen vectors as their columns. Then the new features are generated from this transformation matrix that is linearly independent. Hence 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.

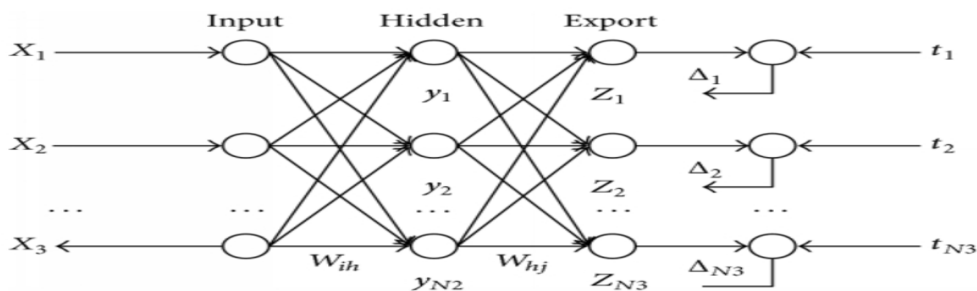


Fig 1. Architecture of feed forward neural network Here, the input layer encrypts up to 64 input and transmit output to hidden layer. The output layer accepts the 16 hidden output of hidden layer and produces the 64 output. For training the network an original image is converted into non-overlapping blocks of $n \times n$ pixels. Each block represent $N = n \times n$ 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:

Hence image compression is accomplished by:

1. Isolating image into small 8×8 pixel in matrix form.
2. Then 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.

C. IMAGE COMPRESSION 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.

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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, 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. These 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.

D. LOSSY IMAGE COMPRESSION USING MODULAR STRUCTURED NEURAL NETWORK

Modular structured neural network 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 h_1 (resp h_2) 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.

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III. EXPERIMENTAL RESULTS

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] where 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 $h_1 + h_2 = 16$ i.e. compression rate CR=16. For investigating the performance, different pairing (h_1, h_2) are used and for 5 different image. Also SNR is calculated as

And (h_1, h_2) = (4, 12) pair has highest SNR=6.3.

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When this result is compared to the performance of 64×64 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, 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. While further compression in 'Squall' and 'Mandrill' image may cause a significant fall in quality. Thus quicker training is accomplished using counter propagation neural network to successfully compress and decomposed image data.

IV. CONCLUSION

In the image compression technique convergence time play important role for quality of image and the back propagation is very popular for image compression technique. The back propagation neural network and levenberg-marquardt algorithms estimating a connection count up that image compression and convergence time can be improved. This survey paper covers different image compression techniques using back propagation neural network with levenberg-marquardt algorithm and calculate the peak signal to noise ratio and compression ratio for image compression.



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