Image Compression with Back Propagation Combined with Histogram Equalization

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Abstract

This paper focuses on key research going in Neural Networks arena now days. It brings out its utility in area of Image compression .Image compression is not a novice concept. It has been in research for many years but continuously invites the improved techniques, for carrying out the compression effectively and efficiently. Role of Artificial Intelligence is being probe in area of compression and various neural network architectures are explored for Image compression. Basic Back propagation neural network is one among them. It employs simple three layer concept of: Input, Hidden and Output layer to perform compression but the loophole appears in it, in the form of Convergence time. Back propagation took longer time to compress because of its long process of weight adjustment. To circumvent this problem, Image preprocessing technique: Histogram Equalization is employed, which improves the No. of Epochs and thus the time required for compression.

Keywords : Histogram Equalization, Image Compression, Back Propagation, Image Processing.

1. Introduction

Image compression[3,9,11] is a pertinent technology in the development of various multimedia computer services and telecommunication applications such as teleconferencing; digital broadcast codec and video technology, etc Traditional technology for achieving Image compression is divided into Lossless and Lossy. Lossless involves Huffman coding, Arithmetic coding, Run length coding, Markov source. Problem with this technique is that they are basically 1D algorithm and achieves low compression ratio of 3:1. Lossy techniques involves Pulse code modulation, Transform coding, Vector Quantization, Sub band coding and Block truncation coding. The higher compression ratios have been achieved using "lossy" techniques that remove visual information that is not perceived by the human eye. Higher compression ratios can only be achieved at the expense of higher distortion that degrades the quality of the image. This is due to the general architecture of existing compressors, which are designed to be general enough to accommodate a variety of input characteristics. Traditional compressors are unable to take advantage of specific characteristics of the inputs to achieve better compression ratios while maintaining the same or lower levels of distortion. Neural network approaches such as using Neural networks and Genetic algorithm, in compression is attracting a lot of attention now a

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days. Neural network exploits the learning function of human brains to achieve efficiency. Neural network are typically organized in layers. Layers are made up of a number of interconnected 'nodes', which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is represented by output layer Various approaches of Neural network like Back propagation network, Hierarchical Back propagation, Adaptive Back propagation, Hebbian learning based image compression, Vector quantization neural network [1,8,10,12-15] are in developing stage and exploring their capabilities specially in area of Image compression. Artificial Neural Networks have been applied to image compression problems, due to their superiority over traditional methods when dealing with noisy or incomplete data. Artificial Neural networks seem to be well suited to image compression, as they have the ability to combine with various Image preprocessing techniques available which enhances the image components. This compressed information preserves the full information obtained from the external environment.. Many different training algorithms and architectures have been used. Different types of Artificial Neural Networks have been trained to perform Image Compression. Feed-Forward Neural Networks, Self-Organizing Feature Maps, Learning Vector Quantizer Network, have been applied to Image Compression. These networks contain at least one hidden layer, with fewer units than the input and output layers. The Neural Network is then trained to recreate the input data. Its bottleneck architecture forces the network to project the original data onto a lower dimensional manifold from which the original data should be predicted. The Back Propagation Neural Network Algorithm performs a gradient-descent to minimize an appropriate error function. The weight update equations minimize this error. But the problem lies with its convergence time .It took long time to converge. . There are various parameters of Back propagation algorithm which can be contemplated to be improved, to enhance its performance. This paper proposes the improvement in Number of Epochs taken by Back propagation algorithm when combined with Histogram equalization preprocessing technique. It is divided into four sections. Section II discuss Back propagation algorithm, Section III focuses on Histogram Equalization and Section IV wrap up the paper by discussing Experimental results.

2. Back Propagation Algorithm

Back propagation algorithm [7, 12] trains a given feed-forward multilayer neural network for a given set of input patterns with known classifications. When each entry of the sample set is presented to the network, the network examines its output response to the sample input pattern. The output response is then compared to the known and desired output and the error value is calculated. Based on the error, the connection weights are adjusted. The set of these sample patterns are repeatedly presented to the network until the error value is minimized. The back propagation multilayer network with M layers. N_j represents the number of neurons in jth layer. Here, the network is presented the pth pattern of training sample set with N_0-dimensional input $X_{p1}, X_{p2}.........X_{pNo}$ and N_M dimensional known output response $T_{p1}, T_{p2}...T_{pNM}$. The actual response to the input pattern by the network is represented as $O_{p1}, O_{p2}.........O_{pNM}$. Let Y_{ji} be the output from the ith neuron in layer j for pth pattern; W_{jik} be the connection weight from kth neuron in layer j-1 to ith neuron in layerj; and ∂_{ji} be the error value associated with the ith neuron in layer j.

2.1 Back Propagation Algorithm

The following is the steps of the back propagation learning algorithm:

1. Initialize connection weights into small random values.
2. Present the pth sample input vector of pattern $X_p = X_{p1}, Xp2..........X_{pNo}$ and the corresponding output target $T_p = T_{p1}, Tp2...........T_{pNM}$ the network.
3. Pass the input values to the first layer, layer 1. For every input node i in layer 0, perform : $Y_{0i} = X_{pi}$
4. For every neuron i in every layer j = 1,2,3........M, from input to output layer, find the output from the neuron:

$$Yji = f\left(\sum_{K=1}^{N_{J-1}} Y_{(j-1)K} W_{jik}\right)$$

Where

$$F(x) = \frac{1}{1+\exp(-x)}$$

5. Obtain output values. For every output node i in layer M, perform:

$$O_{pi} = Y_{Mi}$$

6. Calculate error value ∂_{ji} for every neuron i in every layer in backward order j=M, M-1.......2, 1, from output to input layer, followed by weight adjustments. For the output layer, the error value is:

$$\partial_{Mi} = Y_M i\,(1 - Y_{Mi})(T_{pi} - Y_{Mi})$$

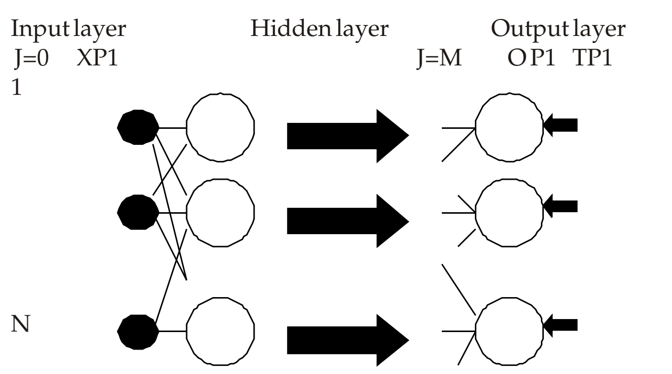
7. For hidden layers

$$\partial_{ji} = Yji(1-Yji)\left(\sum_{K=1}^{N_{J+1}} \partial_{(j+1)K} W_{(j+1)Ki}\right)$$

8. The weight adjustment can be done for every connection from neuron K in layer (i-1) to every neuron i in every layer i: $W_{jik} = W_{jik} + \beta\, \partial jiYji$

   Where β represents weight adjustment factor normalized between 0 and 1. The actions in steps 2 through 6 will be repeated for every training sample pattern p, and repeated for these sets until the root mean square (RMS) of output errors is minimized. The Root Mean Square (RMS) of the errors in the output layer is defined as:

$$E_p = \frac{1}{2}\sum_{j=1}^{N_M}\left(T_{pj} - O_{pj}\right)$$



XPN_0 OPN_M TPN_M

Fig 1.Back propagation neural network

2.2 How Image is compressed by Back propagation

Image to be compressed is applied at the input layer of network. It is then split into non-overlapping sub-images, for example 256 x 256 bit image will be split into 4 x 4 or 8 x 8 or 16 x 16 pixels. Pixel value of the sub-image needs to be normalized to avoid dealing with large pixel values. The three-layered back propagation-learning network will train each sub-image. The number of neurons in the hidden layer will be designed for the desired compression ratio ,say, if number of neurones at input layer is 64 and desired compression ratio is 4:1 ,then number of hidden layer neurones are taken as 16. The number of neurons in the output layer will be the same as that in the input layer. The input layer and output layer are fully connected to the hidden layer. The Weights of synapses connecting input neurons and hidden neurons and weight of synapses connecting hidden neurons and weight of synapses connecting hidden neurons and output neurons are initialized to small random values from say –1 to +1.. The input to the hidden layer is computed by multiplying the corresponding weights of synapses. The hidden layer units evaluate the output using the sigmoidal function. The input to the output layer is computed by multiplying the corresponding weights of synapses. The output layer neuron evaluates the output using sigmoidal function. The Mean Square error of the difference between the network output a d the desired output is calculated. This error is back propagated and the weight synapses of output and input neurons are adjusted. With the updated weights error is calculated again [12,16,17]. Iterations are carried out till the error is less than the tolerance. Minimum error value is assumed at the start of compression which decides the quality of decompressed image produced at output layer. The compression performance is assessed in terms of Compression ratio and execution time which is assessed in terms of number of Epochs taken by Back propagation.

3. Histogram Equalization Preprocessing Technique

Histogram equalization [3, 9] is a method in image processing of contrast adjustment using the image's histogram It usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. It leads to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. Consider a discrete grayscale image {x} and let ni be the number of occurrences of gray level *i*. The probability of an occurrence of a pixel of level i in the image is

$$p_x(i) = p(x=i) = \frac{ni}{n}, \quad 0 <= i < L$$

L being the total number of gray levels in the image, n being the total number of pixels in the image, and p_x being in fact the image's histogram, normalized to [0,1].Cumulative Distribution function corresponding to p_x is defined as

$$Cdfx(i) = \sum_{j=0}^{i} p_x(j)$$

which is also the image's accumulated normalized histogram. To create a transformation of the form y = T(x) to produce a new image {y}, its CDF will be linearized across the value range, i.e.

$$Cdfy(i) = iK$$

for some constant K and Transformation thus produced is defined as

$$y = T(x) = Cdf_x(x)$$

The general histogram equalization formula is :

$$H(y) = \text{round}\left(\frac{Cdf_x(x) - Cdf_{min}}{(M*N) - Cdf_{min}} * (L-1)\right)$$

Where Cdf_{min} is the minimum value of the cumulative distribution function, M × N gives the image's number of pixels and L is the number of grey levels used. Through Histogram Equalization, intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast without affecting the global contrast

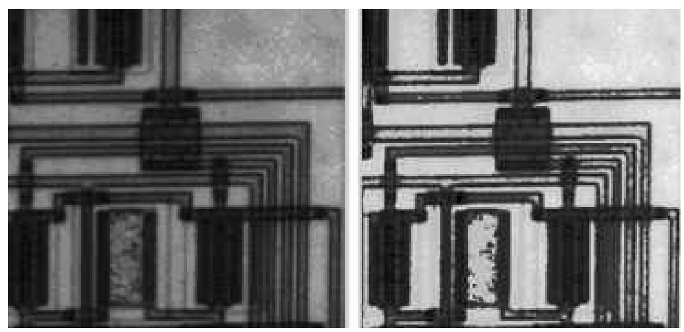


Fig 2. (a)Original image *(b) Equalized image*

Fig 3. (a) Original image *(b) Degraded image*

A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal Equalization plays vital role in improving compression with Back propagation [2, 4, 5, 6] .An image may contain a number of distinct gray levels with narrow difference with their neighborhood pixels. If the gray levels of the pixels in an image and their neighbors are mapped in such a way that the difference in the gray levels of the neighbor with the pixel is minimum, then compression ratio as well as the convergence of the network can be improved. Thus difference between neighboring pixels can be reduced by means of Equalization process.

4. Experimental Results

The performance of the Back-Propagation Neural Network for image compression with the concept of mapping the image by Image preprocessing technique Histogram Equalization has been tested for various types of images. The number of neurones in hidden layer is fixed to 32 and those in input layer and output layer are 16. Compression ratio thus achieved is 2:1. Various parameters of Back propagation network are fixed like minimum error value is taken as .01 and threshold is taken as 1. The Speed of Convergence of the Back propagation Neural Network were compared for both the conditions; image without mapping by Histogram Equalization and for the same image mapped by Histogram Equalization. Compression is observed in both cases and results are tabulated in Tables I and II. It has been illustrated that number of epochs taken by Back propagation network are different .Images without preprocessing requires more steps to converge as compared to images mapped by Histogram Equalization. Original image is feed into a network to start the training process during which weight connection are adjusted to satisfy the criteria fixed by network. When training phase completes, testing starts. Original image is applied at input layer, weight adjustment process starts which will take time to fulfill the fixed parameters to achieve compression. When training completes original image is again applied and compressed image is produced at hidden layer which get stored and Decompressed image produced at output layer is also stored. Finally results are displayed. Compressed image is not in viewable form and decompressed is the same as that of original image.

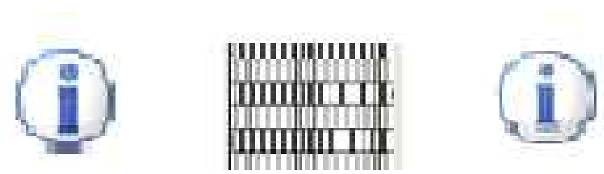


Fig 4. Standard I alphabet

(a) Original image (b) Compressed image (c) Decompressed image

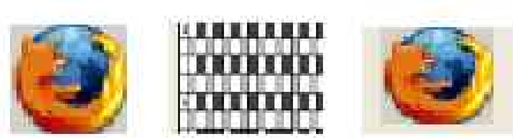


Fig 5 Globe image

(a) Original image (b) Compressed image (c) Decompressed image

To achieve the improvement in Back propagation network, image feed at input layer is now preprocessed by Histogram Equalization. There is no noticeable visual change in terms of appearance of image after preprocessing as images taken are small and clear. But, now pixel values are uniformly distributed and effect

Thus, in Fig 6(b) difference between neighboring pixels gets reduced and they are more uniformly distributed. This helps in reducing number of steps taken by Back propagation algorithm after image is being preprocessed.

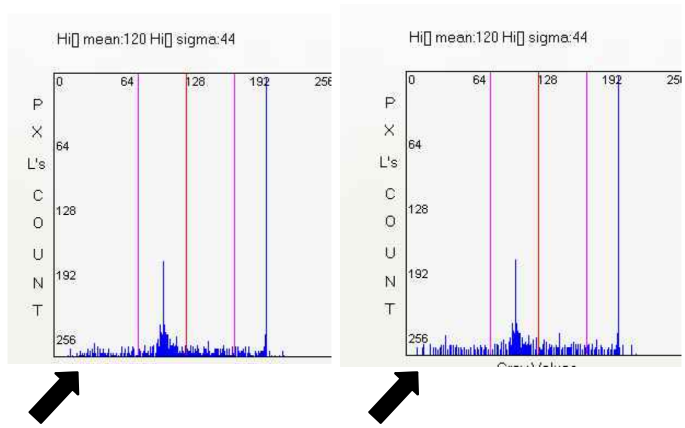


Fig 6 a) Histogram of image(5) before Equalization b) Histogram of image (5) after Equalization

5. Conclusion

The Back Propagation Neural Network has the simplest architecture of the various Artificial Neural Networks that have been developed for Image Compression. Low complexity gives this method an edge over other Neural network architectures.. But the drawbacks are very slow convergence due to long process of weight adjustment. Many research works have been carried out to improve the speed of convergence. All these methods are computationally complex in nature, which could be applied only to limited patterns. The proposed approach of improving the Back propagation which involves preprocessing the image before feeding it into network by Histogram Equalization. There will not be any loss in data in the preprocessing and hence the finer details in the image are preserved in the reconstructed image. But sometimes preprocessing increases the background noise of image which leads to problem. Size of image taken for compression is small since only one layer of hidden neurone is involved.

Table I
Experimental Results of Proposed Approach

S.No	Image	Compression ratio	No. of Epochs
1	Standard I alphabet	1.67:1	150
2	Tin of Corn	1.79:1	173
3	Globe	2.15:1	166
4	House	2.34:1	193
5	Bird	2.06:1	212

Table II
Experimental Results of Without Mapping

S.No	Image	Compression ratio	No. of Epochs
1	Standard I alphabet	1.67:1	175
2	Tin of Corn	1.79:1	192
3	Globe	2.15:1	185
4	House	2.34:1	216
5	Bird	2.06:1	227

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