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Image Compression Using Back Propagation Neural Network

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Abstract: ***Image compression technique is used to reduce the number of bits required in representing image, which helps to reduce the storage space and transmission cost. In the present research work back propagation neural network training algorithm has been used. Back propagation neural network algorithm helps to increase the performance of the system and to decrease the convergence time for the training of the neural network. The proposed scheme has been demonstrated through several experiments including cameraman and very promising results in compression as well as in reconstructed image over convectional neural network based technique.***

Keywords: Neural Networks, Image Compression, Image Decompression, MATLAB

1. Introduction

Image compression is a process of efficiently coding digital image, to reduce the number of bits required in representing image. Its purpose is to reduce the storage space and transmission cost while maintaining good quality. A number of neural network based image compression scheme have been proposed for this purpose, Abbas Rizwi introduced an image compression algorithm with a new bit rate control capability [1]. Ronald.A. Devore proposed a new theory for analyzing image compression methods that are based on compression of wavelet decompositions [2]. David Jeff Jackson et.al. Examined several topics concerning image compression including generic data compression algorithms, file format schemes and fractal image compression. An overview of the popular LZW compression algorithm and its subsequent variations is also given[3]. P. Moravie et.al emphasized that in the digitized satellite image domain, the needs for high dimension images increase considerably [4]. J Jiang proposed an extensive survey on the development of neural network technology for image compression [5]. Michael T.Kurdziel proposed that HF communication channel was notorious for its degraded channel including low signal to noise ratio, Doppler and multi path spreading and high level of interference. Image transmission over HF radio system could particularly challenging the size of some digital image[6].Aaron T. Deever et.al laid the emphasis on Reversible integer wavelet transforms are increasingly popular in lossless image compression, as evidenced by their use in the recently developed JPEG2000 image coding standard[7,11].

Mei Tian et.al discusses the possibility of Singular Value Decomposition in Image Compression applications [8]. Kin

Wah Ching Eugene et.al proposed an improvement scheme, so named the Two Pass Improved Encoding Scheme (TIES), for the application to image compression through the extension of the existing concept of Fractal Image Compression (FIC), which capitalizes on the self similarity within a given image to be compressed [9].Jian Li et.al introduced a quadtree partitioning fractal image compression method used for the partial discharge (PD) image remote recognition system.

In most of the methods, an image is divided into number of non overlapping pixel blocks, and fed as patterns for network training. Image compression is achieved by encoding the pixel blocks into the trained weight set, which is transmitted to the receiving side for reconstruction of the image In comparison with the vector quantization, this method has certain advantage because here no utilization of code books are required and encoding/decoding time are much less. But in such cases very limited amount of compression is achieved since it exploited only the correlation between pixel within each of the training patterns. Higher compression ratio was achieved in by developing hierarchical NN that cost heavily due to the physical structure of the NN. To make image compression practical, it is mandatory to reduce the huge size of most image data that eventually reduces physical structure of the NN. In order to reduce the size considerable several image processing steps namely edge detection, thresholding, thinning are applied on the image and discussed briefly. The main concern of the second phase of the work is to adaptively determine the structure of the NN that encodes the image using back propagation training method.

A new technique has been adopted in the paper while initializing the weight between input and hidden layer neurons instead of randomizing the initial weight, here spatial coordinates of the pixel of the image block are converted from two to one dimensional value and normalized with in [0,1].This approach demonstrate fast rate of convergence of the training algorithm and has been tested for a number of images. In this paper Exploration of a supervised learning algorithm for artificial neural networks i.e. the Error Back propagation learning algorithm for a layered feed forward network has been implemented for image compression and the analysis of the simulation results of Back Propagation algorithm are done.

2. Implementation of Back Propagation Algorithm

The back propagation algorithm consists of the following steps

Each Input is then multiplied by a weight that would either inhibit the input or excite the input. The weighted sum of then inputs in then calculated first, it computes the total weighted input Xj, using the formula

$$Xi = \sum_i Yi\ Wij$$

Where Yi is the activity level of the jth unit in the previous layer and Wij is the weight of the connection between the ith and the jth unit. Then the weighed Xj is passed through a sigmoid function that would scale the output in between 0 and 1. Next, the unit calculates the activity yj using some function of the total weighted input. Typically we use the sigmoid function

$$Y_j = \frac{1}{1+e^{-x_j}}$$

Once the output is calculated, it is compared with the required output and the total Error E is computed. Once the activities of all output units have been determined, the network computes the error E, which is defined by the expression

$$E = \frac{1}{2}\sum_j \left(Y_j - d_j\right)^2$$

where Yj is the activity level of the ith unit in the top layer and dj is the desired output of the ith unit. Now the error is propagated backwards.

1. Compute how fast the error changes as the activity of an output unit is changed. This error derivative (EA) is the difference between the actual and the desired activity.

$$EA_j = \frac{\delta E}{\delta Y_j} = Y_j - d_j$$

2. Compute how fast the error changes as the total input received by an output unit is changed. This quantity (EI) is the answer from step 1 multiplied by the rate at which the output of a unit changes as its total input is changed.

$$EI_j = \frac{\delta E}{\delta x_j} = \frac{\delta E}{\delta Y_j} \times \frac{\delta Y_j}{\delta x_j} = EA_j Y_j (1 - y_j)$$

3. Compute how fast the error changes as a weight on the connection into an output unit is changed. This quantity (EW) is the answer from step 2 multiplied by the activity level of the unit from which the connection emanates.

$$EW_{ij} = \frac{\delta E}{\delta W_{ij}} = \frac{\delta E}{\delta x_j} \times \frac{\delta x_j}{\delta W_{ij}} = EI_j Y_i$$

4. Compute how fast the error changes as the activity of a unit in the previous layer is changed. This crucial step allows back propagation to be applied to multi layer networks. When the activity of a unit in the previous layer changes, it affects the activities of all the output units to which it is connected. So to compute the overall effect on the error, we add together all these separate effects on output units. But each effect is simple to calculate. It is the answer in step 2 multiplied by the weight on the connection to that output unit. By using steps 2 and 4, we can convert the EA's of one layer of units into EA's for the previous layer. This procedure can be repeated to get the EA's for as many previous layers as desired. Once we know the EA of a unit, we can use steps 2 and 3 to compute the EW's on its incoming connections.

$$EA_i = \frac{\delta E}{\delta Y_i} = \sum_j \frac{\delta E}{\delta x_j} \times \frac{\delta x_j}{\delta Y_i} = \sum_j EI_j W_{ij}$$

3. Proposed Training Algorithm Used In the Back Propagation Algorithm

The main steps are as follows:

1. Initialize the weights to small random values.
2. Select a training vector pair (input and the corresponding output) from the training set and present the input vector to the inputs of the network.
3. Calculate the actual outputs this is the forward phase.
4. According to the difference between actual and desired outputs (error). Adjust the weights Wo and Wh to reduce the difference this is the backward phase.
5. Repeat from step 2 for all training vectors.
6. Repeat from step 2 until the error is acceptably small.

Back Propagation learning algorithm. In the forward phase the hidden layer weight matrix h W is multiplied by the input vector X=(X1, X2, X3…….X n) to calculate the α.

4. Result and Discussion

The quality of compressed image can be measured by many parameters, which compare to the different compression technique. The most commonly used parameters are Root Mean Square error (RMSE), peak signal to noise ratio error (PSNR), compression ratio(CR).The PSNR value used to measure the difference between a decoded image and its original image as follows. In general, the larger the PSNR value, the better will be the decoded image quality.

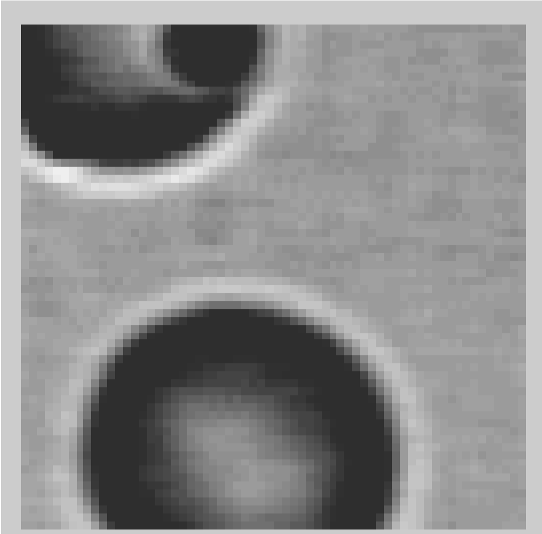
$$\text{RMSE} = \left[\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left[\hat{f}(i,j) - f(i,j)\right]^2\right]^{1/2}$$

$$\text{PSNR} = 10\log_{10}\left[\frac{M \times N}{RMSE^2}\right]$$

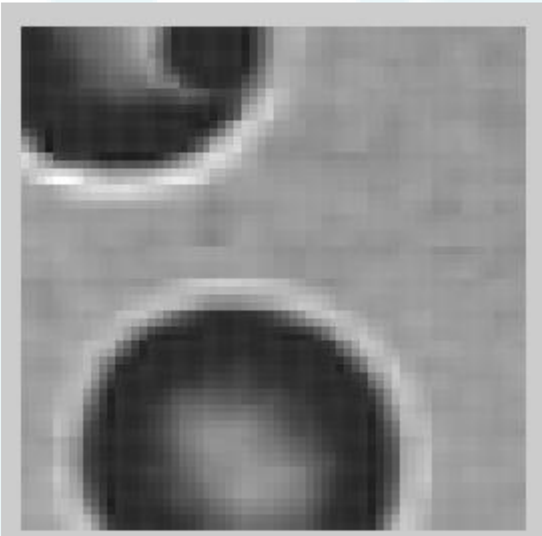
Where M*N is the size of the image f(i, j) and f (i, j) are the matrix element of the decompressed and the original image at (i,j) pixel. In order to evaluate the performance of image compression system, compression ratio matrix is often employed. In our results, compression ratio (CR) is computed as the ratio of non zero entries in the original image to the non zero entries in the decompressed image.

CR = original image /compressed image size
CR%= (1 (1/CR))*100 (6.3)

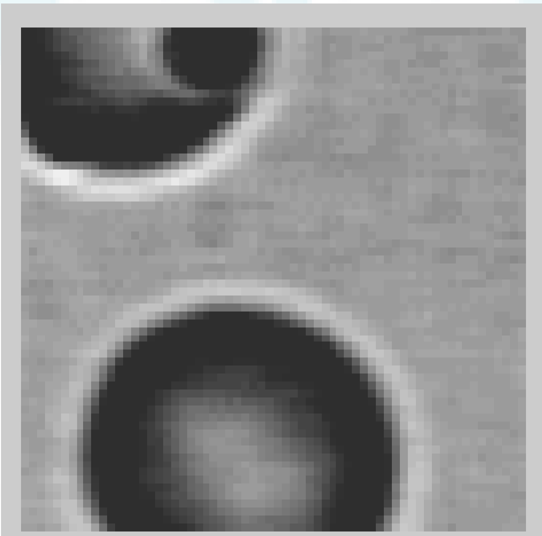
Image compression using Neural Network is conducted on many images.



Original Image



Compressed Image



Decompressed Image

The graph represents the output of the training of the network and 1000 epochs have been taken to get trained the network using the training function. In this case the performance goal of the network has been 644.412.

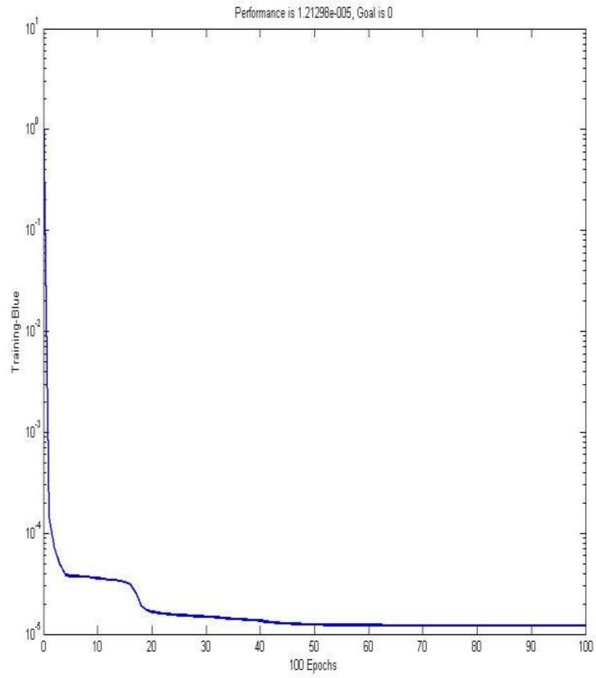


Figure 1

Table 1: Different value of CR, RMSE, PSNR, B/P taken at different epochs

EPOCH	CR	RMSE	PSNR	B/P
1100	0.99	27.11	19.318	0.5881
1202	0.9864	26.86	19.682	0.5952
1300	0.98	26.723	19.985	0.61
1340	0.9755	26.4427	20.153	0.62
1620	0.9689	26.1217	20.359	0.6351
1900	0.9612	25.9891	20.589	0.6493
2200	0.9556	25.8371	20.722	0.6534

The above values of CR, RMSE, PSNR shows that image is compressed with very low loss of image quality. As the values of epochs is increasing from 1100 epochs to 2200 epochs compression ratio have been decreased from.99 to.9556 and Peak signal to noise ratio has been increased from 19.318 to 20.722. This is because of network is getting more time to adjust their weight and more optimized weight are obtained to train the network.

5. Conclusion

The implementation of back propagation neural network algorithm on image compression system with good performance has been demonstrated. The back propagation neural network has been trained and tested for the analysis of different images. It has been observed that the convergence time for the training of back propagation neural network is very faster. Different attributes of compression such as compression ratio, peak signal to noise ratio, bits per pixel are calculated. It has been observed that there is significance change in compression ratio from.99 to.9556 in case of Cameraman image. It has also been observed that there is significance improvement in peak signal to noise ratio from 19.3181 to 20.722 in case Cameraman. The adaptive characteristics of the proposed approach provide modularity in structuring the architecture of the network, which not only speed up the processing but also less susceptible to failure and easy for rectification. Instead of generating multiple training patterns and imparting off-line training, here due to the considerable reduction of image size only single training pattern is used to train the NN and online training could be invoked with practical implication of the system. The technique of initialization of weights exhibits fast rate of convergence and using the trained weight sets, good quality of regenerated images are available at the receiving end.

6. Future Scope

The field of image processing has been growing at a very fast pace. The day to day emerging technology requires more and more revolution and evolution in the image processing field. As showed in this work, back propagation neural networks can be successfully to implement the image processing. The same experiments should also be conducted with other types of neural network to see the different types can improve the performance of the system as we got the experiments results with the back propagation neural network.

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Author Profile

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