An Image Compression Approach using Wavelet Transform and Modified Self Organizing Map

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Abstract

Image compression helps in storing the transmitted data in proficient way by decreasing its redundancy. This technique helps in transferring more digital or multimedia data over internet as it increases the storage space. It is important to maintain the image quality even if it is compressed to certain extent. Depends upon this the image compression is classified into two categories: lossy and lossless image compression. There are many lossy digital image compression techniques exists. Among this Wavelet Transform based image compression is the most familiar one. The good picture quality can be retrieved if Wavelet-based image compression technique is used for compression and also provides better compression ratio. In the past few years Artificial Neural Network becomes popular in the field of image compression. This paper proposes a technique for image compression using modified Self-Organizing Map (SOM) based vector quantization. Self-Organizing Feature Map (SOFM) algorithm is a type of neural network model which consists of one input and one output layer. Each input node is connected with output node by adaptive weights. By modifying the weights between input nodes and output nodes, SOFM generate codebook for vector quantization. If the compression is performed using Vector Quantization (VQ), then it results in enhanced performance in compression than any other existing algorithms. Vector Quantization is based on the encoding of scalar quantities. The experimental result shows that the proposed technique obtained better PSNR value end also reduces Mean Square Error.

***Keywords*—**Data Compression, Image Compression, Neural Networks, Self-Organizing Feature Map, Vector Quantization, Wavelet Transform

1. Introduction

Image compression is a result of applying data compression to the digital image. The main objective of image compression is to decrease the redundancy of the image data which helps in increasing the capacity of storage and efficient transmission. Image compression aids in decreasing the size in bytes of a digital image without degrading the quality of the image to an undesirable level. There are two classifications in image compression: lossless and lossy compression. The reduction in file size allows more images to be stored in a given amount of disk or memory space. This supports in decreasing the time required for the image to send or download from internet. Consequently compression methods are being hastily developed to compress large data files such as images, where data compression in multimedia applications has recently become very important [1].

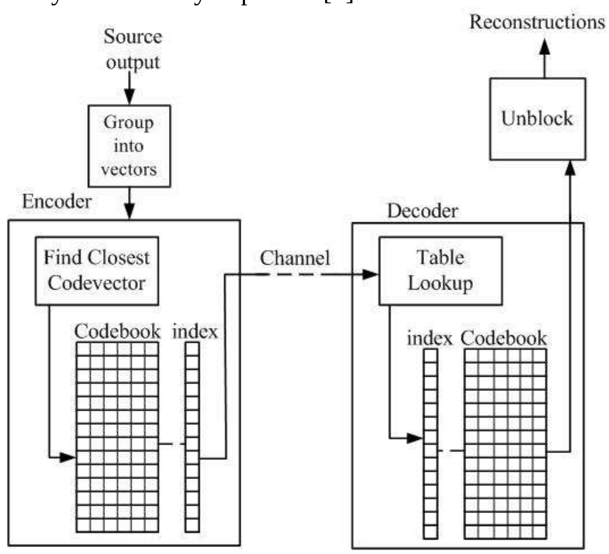


Figure 1.Vector Quantization

In general wavelets are a mathematical tool for hierarchically decomposing functions. The huge numbers of lossy compression techniques are proposed in the past. Among this Wavelet Transform based image compression is the most familiar one. Wavelet-based image compression provides better enhancements in picture quality even at higher compression ratios. It is an established transform used for a number of image compression standards in lossy compression methods. Divergentto the discrete cosine transforms, the wavelet transform is not Fourier-based and therefore wavelets do a superior job of handling discontinuities in data. Wavelet Transforms (WT) based image compression is a prevailing method that is favored by most of the researchers to get the compressed images at higher compression ratios with higher PSNR values [2].

The usage of Artificial neural network (ANN) in image processing applications has been increased in recent years. Due to the advantages over the existing methods in terms of handling the noisy or partial data, the Artificial Neural Networks can be used in image compression technique. An Artificial Neural network is appropriate technique for image compression as it has the ability to reproduce the original data with the help of available fewer components. Different types of Artificial Neural Networks have been trained to perform Image Compression. Some of them are Feed-Forward Neural Networks, Self-Organizing Feature Maps and Learning Vector Quantizer Network

Artificial neural networks are well-resembled in function approximation, owing to their capability to fairly accurate complicated nonlinear functions. Several techniques have been projected previously for image compression using neural networks and wavelet transform. In the past wavelet transform and a neural network are suggested for image compression [4].Similarly, variety of image compression techniques were combined with neural network classifier for various applications [5] [6].Some recent papers show that the combination of neural network based approach and classical wavelet based approach leads to better compression ratio [7]. Combining the Wavelet Transform and Artificial Neural Networks utilizes the advantages of the two techniques thereby improving the compression ratio. They may also ensure the quality of the compressed image.

The modified Self-Organizing Feature Map (SOFM) based vector quantization for image compression is proposed in this paper. Self-Organizing Feature Map (SOFM) algorithm is a type of neural network model which consists of one input and one output layer. Each input node is connected with output node by adaptive weights. By modifying the weights between input nodes and output nodes SOFM will generate codebook for vector quantization. If the compression is performed using Vector Quantization (VQ), then it results in enhanced performance in compression than any other existing algorithms. Vector Quantization is based on the encoding of scalar quantities. The experimental shows that the proposed technique will provide better PSNR value and also reduces Mean Square Error.

The remainder of this paper is organized as follows. Section 2 of the paper discusses the earlier proposed techniques related to image compression using wavelet transform and neural networks. Section 3 explains the proposed approach for image compression. Section 4 illustrates the experimental results with relevant explanations and Section 5 concludes the paper with fewer discussions for future work.

2. Related Work

A lot of works were found in literature related to the wavelet based image compression technique using the neural network technique. This section of the paper discusses some of the earlier work proposed on image compression using neural networks and wavelet transform.

Debnath et al., proposed an image compression method combining discrete wavelet transform (DWT) and vector quantization (VQ). First, a three-level DWT is carried out on the original image resulting in ten separate subbands (ten codebooks are generated using the Self Organizing Feature Map algorithm, which are then used in Vector Quantization, of the wavelet transformed subband images, i.e. one codebook for one subband). These subbands are then vector quantized. VQ indices are Huffman coded to raise the compression ratio. A new iterative error correction scheme is presented to continuously check the image quality after sending the Huffman coded bit stream of the error codebook indices through the channel so as to improve the peak signal to noise ratio (PSNR) of the reconstructed image. Ten errors are also generated for the error correction method by means of the difference between the original and the reconstructed images in the wavelet domain. This technique shows better image quality in terms of PSNR at the same compression ratio as compared to other DWT and VQ based image compression techniques found in the literature.

A method of still image compression was put forth by Wilford Gillespie in [11]. The fundamental approach to image compression consists of a number of key steps. They are wavelet packet decomposition, quantization, organization of vectors, neural networks approximation or storage, and lossless encoding and reduction. As an initial stage of image compression, the image is put through several layers of wavelet packet decomposition. The results of the decomposition are then divide or processed in some way, depending on the method. Integer quantization is performed on all of the decomposed wavelet sections. The quantization value is the determining factor of quality. A quantization value of 1 is near lossless quality, although little to no compression is achieved. This is accomplished by taking each section and dividing it by a set value and rounding to the nearest integer. There are many ways to systematize a tree of decomposition sections. Three methods were tried with this compression scheme. The type of neural network used in their approach was a two-layer feed-forward network with a standard back propagation learning function. At last, the entire data stream is taken and is processed by a run length encoded (RLE) method and saved in a lossless state using the ZIP file format.

A Neuro-Wavelet based approach for image compression was put forth by Singh et al. in [12]. Images have large data quantity. For storage and transmission of images, high efficiency image compression methods are under wide attention. They proposed a neuro- wavelet based model for image compression which combines the advantage of wavelet transform and neural network. Images are decomposed using wavelet filters into a set of sub bands with different resolution corresponding to different frequency bands. Different quantization and coding schemes are used for different sub bands based on their statistical properties. The coefficients in low frequency band are compressed by differential pulse code modulation (DPCM) and the coefficients in higher frequency bands are compressed using neural network. Using their proposed scheme one can accomplish satisfactory reconstructed images with large compression ratios. Their experimental results revealed that their proposed technique of image compression out performed some of the conventional image compression approaches.

Barbalho et al., [13] presented a novel approach involving vector quantization (VQ) that relies on the design of a finite set of codes which will substitute the original signal during transmission with a minimal of distortion, taking advantage of the spatial redundancy of image to compress them. Algorithms for instance LBG and SOM work in an unsupervised way toward finding a good codebook for a given training data. However, the number of code vectors (N) required for VQ.

increases with the vector dimension, and full-search algorithms such as LBG and SOM can lead to large training and coding times. An alternative for reducing the computational difficulty is the use of a tree-structured vector quantization algorithm. This approach presents an application of a hierarchical SOM for image compression which reduces the search complexity from O(N) to O(log N), enabling a faster training and image coding. Results when compared with conventional SOM, LBG and HSOM, shows the better image compression result.

Amar et al. in [14] proposed a wavelet networks approach for image compression. Wavelet networks are a combination of radial basis function (RBF) networks and wavelet decomposition, where radial basis functions were replaced by wavelets. The wavelet network is a combination of wavelets and neural networks. The network can be considered composed of three layers: a layer with N_i inputs, a hidden layer with N_w wavelets and an output linear neuron receiving the weighted outputs of wavelets. Both input and output layers are fully connected to the hidden layer. Moreover they used a feed forward propagation algorithm from input neurons to output neurons. The main similarity between the proposed wavelet network and the neural network is that both networks calculate a linear combination of nonlinear functions to adjust parameters. These nonlinear functions depend on adjustable parameters (dilations and translations). During training stage the weights, dilations and translations parameters, are iteratively adjusted to minimize the network error. They used a quadratic cost function to evaluate this error. In order to test the robustness of their approach, they have implemented and compared the results with some other approaches based on neural networks (MLP).

Kwang-Baek et al., [15] puts forth a novel vector quantization approach for image compression using wavelet transform and enhanced SOM algorithm for medical image compression. The enhanced self-organizing algorithm is presented to improve the defects of SOM algorithm, which, at first, reflects the error between the winner node and the input vector to the weight adaptation by using the frequency of the winner node. Secondly, it adjusts the weight in proportion to the weight change at hand and the previous weight change as well. To decrease the blocking effect and Improve the resolution, by using wavelet transform the vectors are constructed and applied the enhanced SOM algorithm to them.

Khashman et al. in [16] proposed a technique for compressing the digital image using neural networks and Haar Wavelet transform. The aim of the work presented within the paper was to develop an optimum image compression system using Haar wavelet transform and a neural network. With Wavelet transform based compression, the quality of compressed images is typically high, and the option of a perfect compression ratio is complicated to formulate as it varies depending on the content of the image. They proposed that neural networks can be trained to ascertain the non-linear relationship between the image intensity and its compression ratios in search for an optimum ratio. Moreover their paper suggested that a neural network could be trained to be familiar with an optimum ratio for Haar wavelet compression of an image upon presenting the image to the network. The method utilized Haar compression with nine compression ratios and a supervised neural network that learns to correlate the grey image intensity (pixel values) with a single optimum compression ratio. Two neural networks receiving different input image sizes are developed in their work and a comparison between their performances in finding optimum Haar-based compression was presented.

3. Proposed approach

The proposed methodology deals with the combination of wavelet and vector quantization for image compression. The image compression technique proposed here is applicable to those areas of digital images where high precision reconstructed image is required like criminal investigations, medical imaging, etc., The image of certain quality is need to be transmitted by user in order to retrieve the original image without any loss in quality. This method is tested on gray scale images, but it can be easily extended to color images by processing the three color matrices separately.

A. Self-Organizing Map

Each data from data set recognizes themselves by competing for representation. The weight vectors initialization is the starting process of SOM mapping. Then the sample vector is randomly selected and the map of weight vectors is searched to find which weight best represents that sample. Each weight vector has neighboring weights that are close to it. The weight that is chosen is rewarded by being able to become more like that randomly selected sample vector. The neighbors of that weight are also rewarded by being able to become more like the chosen sample vector. From this step the number of neighbors and how much each weight can learn decreases over time. This whole process is repeated a large number of times, usually more than 1000 times.

In sum, learning occurs in several steps and over much iteration:

1. Each node's weights are initialized.
2. A vector is chosen at random from the set of training data.
3. Every node is examined to calculate which one's weights are most like the input vector. The winning node is commonly known as the Best Matching Unit (BMU).
4. Then the neighborhood of the BMU is calculated. The amount of neighbors decreases over time.
5. The winning weight is rewarded with becoming more like the sample vector. The neighbors also become more like the sample vector. The closer a node is to the BMU, the more its weights get altered and the farther away the neighbor is from the BMU, the less it learns.
6. Repeat step 2 for N iterations.

B. Modified Self Organizing Feature Map

The basic operation of the Kohonen’s network is to classify the input patterns with a set of m× n weight matrix where m is the number of nodes in input layer and n is the grid size. Existing learning system considers the previously learned patterns while adopting the weight matrix for the current input pattern that is avoided by the proposed subsystem. The modification in existing learning system is highlighted below –

1. *Adoption of Weights*: Existing learning systems deals with the previously stored patterns which are already been learnt. It increases the learning time exhaustively. Learning time for each pattern is a factor of the number of previously learned patterns. But the modified system only tries to operate on the recently given pattern sample. It avoids the previously learned patterns for the swiftness of learning process.

2. *Regular learning system* using KSOM offers the modification of weights for all the connections among the two layers. It indicates the static size of neighbors. Due to the rapid change of neighborhood size, number of weight adoption easily decreased with the time. The modified MKSOM system proposes a function for changing the neighborhood size along with the change of the distance of winner node

$\nu(t+1) = \nu(t) - 0(t)(d(t) - d(t-1))$.

A 3-level 2-D DWT is firstly applied to the test image in the proposed method (i.e. the image to be compressed) and then VQ is used to different subbands for compression. Ten subbands are created after the application of 3-level 2-D DWT using SOFM, and thus all these codebooks are used for this all subbands individually. 3-level 2-D DWT is applied to images because the low frequency subband, which contains the maximum energy content of the original image, becomes of smaller size so that in case of vector quantization this subband is treated with a codebook size of 7-bits only. These vector indices are subjected to Huffman coding [6] for improving the compression ratio of the transmitted data. Whole compression process of this work is divided into three steps, i) Codebook generation, ii) Encoding of the original image and iii) Decoding of the image. All of these steps will now be discussed. The proposed method uses a total of twenty codebooks, ten codebooks for original image reconstruction and other ten are used to reconstruct the error images.

Algorithm

Step 1:

Initial image= Input image;
Input image→10 sub-images using 3-Level DWT;
For (each of 10 image)
Vector quantization using separate codebook foreach subband;
Codebook indices are now Huffman coded and then transmitted to the decoder;
End;
If (PSNR < Threshold T_h)
Move to step 2;
Else
Stop;
End;

Step 2:
At the encoder end
Initial image (I.I) = obtained subbands;
For (each image)
Subbands are reconstructed→ this is the reconstructed image (R.I);
End;
goto step 3;
Step 3:
Image Error (I.E) = Difference between I.I and R.I;
These I.E's (Ten error subbands)→ Vector Quantized using the error codebooks (Ten different error codebooks used);
Error Codebook →Huffman coding →transmitted to the decoder;
Again at the encoder end
Using these error codebooks I.E's are reconstructed = R.I.E;
R.Inew=R.I + R.I.E; \\ Recalculate the new Reconstructed image
If (PSNR<Th)
If No. of Iteration < 3
Goto step 3;
Else
Stop;
End;
Stop;
End;

C. Codebook Generation

In the codebook generation step (i.e. the training stage) four different standard images (namely Lena, Couple, Frog, and Baboon) are used to generate ten original codebooks and also ten error codebooks are generated in this step.3-level 2-D DWT is applied to each of these original training images in all ten codebook generation step. These generate ten wavelet sub bands for each of the original images. Similar sub bands of each image are then combined to form a single frame and this frame is then considered as a new image. Therefore there are ten separate images available at this stage. Using these ten separate images, ten separate codebooks are generated using SOFM. Then in the error codebook generation step, using these generated ten codebooks ten sub band images are vector quantized and then these sub bands are reconstructed. These ten reconstructed images are then compared with the original ten images in the wavelet domain; the error of this comparison was taken to generate the error codebooks. In this case SOFM or Modified SOFM is used.

D. Encoding and Decoding

In this step, 3-level 2-D DWT is applied to the test image (i.e. the image to be compressed). Then each of these available ten subbands is vector quantized using the original codebooks, so that separate codebook is used for different sub bands. The codebook indices of this VQ process are transmitted to the decoder after Huffman coding. At the encoder end image is reconstructed using the transmitted image indices and peak signal to noise ratio (PSNR) of this transmitted image is calculated to test the image quality. If the calculated PSNR is higher or equal to the desired PSNR then the process ends, otherwise the iterative error correction method is executed. In this iterative error correction method, error between the original image and the reconstructed image (I.E), is calculated in the wavelet domain. Vector quantization using the available error codebooks is then applied to these subband errors between the original and reconstructed image (R.I.). Error codebook indices are also transmitted to the decoder after Huffman coding. The transmitted error image is reconstructed from the transmitted error codebook indices (at the encoder or transmission end). Then the reconstructed image errors (R.I.E) are added (algebraically) to the previously reconstructed image, and thus R.I. is modified. This iterative error correction process continues until the PSNR of the modified reconstructed image is larger than or equal to the desired PSNR or the maximum number of iteration (considering the case of infinite loop, the iteration process stopped by force at the third iteration) is reached. In the decoding phase the decoder first receives the Huffman coded bit-stream of the VQ indices corresponding to the original wavelet coefficients from the channel. It then reconstructs the codebook indices of the different wavelet sub bands. In the initial stage the receiver receives the reconstructed image and successively in the later steps the receiver receives image errors (actually it receives Huffman coded image errors, and reconstructs the image error coefficients from these Huffman coded indices). The receiver adds (algebraically) the received errors of each sub band. In the final step the image is reconstructed using 3-level inverse 2-D DWT.

4. Experimental Results

In order to evaluate the performance of the proposed approach of image compression using modified SOM algorithm based vector quantization two standard images are considered. The work is implemented using MATLAB. Lena and Cameraman are the two standard images used to explore the performance of the proposed approach of image compression. The experiments are carried out with the number of clusters of 4, 8, 16, 32 and 64. The evaluation of the proposed approach in image compression was performed using the following measures,

$$bpp = \frac{\text{Encoded number of bits}}{\text{Number of Pixels}}$$

$$PSNR = 10\log_{10}\left[\frac{255^2}{MSE}\right](dB)$$

$$MSE = \frac{1}{3MXN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\sum_{k=1}^{3}\left\{X_k(j,i) - \overline{X}_k(j,i)\right\}^2$$

These three factors will decide about the image noise ratio, retrieval quality and ratio of compression for the digital image. The PSNR is most familiarly used as a measure of quality of reconstruction of lossy image compression. The MSE (Mean Square Error) is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error.

The experimental results that evaluate the performance of the proposed approach by comparing it with the self-organizing map are tabulated. Table 1 shows the experimental results applied for Lena image and table 2 shows the experimental results of proposed approach applied for Cameraman image.

From table1 and table 2, it can be observed that the bits per pixel (bpp) are more for the proposed modified SOM when compared to the standard SOM. That is bpp for Lena image using modified SOM is 1.84, 2.54, 4.62, 5.12 and 6.76 for cluster size 4, 8, 16, 32 and 64 respectively, whereas in standard SOM less bpp is obtained. With this analysis it can be said that the bits obtained after reconstruction of compressed image will be similar to the original image which undergoes compression.

Then if PSNR is considered, the proposed modified SOM produces PSNR value as 22.15,23.14, 24.23, 26.78 and 28.32 for cluster size 4, 8, 16, 32 and 64 respectively, whereas in standard SOM the PSNR value is minimum when compared with proposed one. This clearly indicates that the noise produced in reconstructed image after compression will be minimum than the noise obtained in the previous methods

Table.1 Experimental Results for Lena Image

Number of Clusters	bpp		PSNR (dB)		MSE	
	Modified SOM	Standard SOM	Modified SOM	Standard SOM	Modified SOM	Standard SOM
4	1.84	1.70	22.15	19.24	503.89	342.45
8	2.54	2.17	23.14	21.33	368.65	187.24
16	4.62	3.82	24.23	22.42	210.42	97.24
32	5.12	5.66	26.78	24.22	111.81	62.21
64	6.76	4.26	28.32	27.10	46.42	36.97

Table.2 Experimental Results for Cameraman Image

Number of Clusters	bpp		PSNR (dB)		MSE	
	Modified SOM	Standard SOM	Modified SOM	Standard SOM	Modified SOM	Standard SOM
4	2.32	1.79	23.65	20.67	453.34	402.52
8	3.34	3.25	24.77	22.65	199.68	190.54
16	4.54	4.32	25.72	25.76	117.84	109.63
32	5.11	5.03	27.91	26.04	68.94	84.32
64	7.47	5.78	30.88	27.57	48.52	73.98

Then the Mean Square Error is considered for analysis. From table 1 and 2 , it can be observed that Mean Square Error (MSE) for Lena image using modified SOM is higher than the standard SOM (ie,. 503.89, 368.65, 210.42,111.81 and 46.42 for cluster size 4, 8, 16, 32 and 64 respectively for modified SOM, whereas 342.45, 187.24, 97.24, 62.21 and 36.97 in case of standard SOM). As the cumulative squared error between the compressed and the original image is minimum in the proposed approach, it reduces the possibility of increasing the noise ratio for the decompressed image

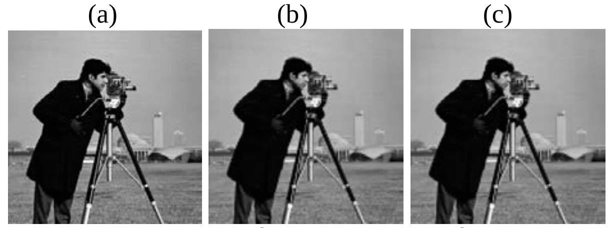
Figure 1 Lena Image

(a) (b) (c)

(a) Sample (b) Resultant image by existing approach (c) Resultant image by proposed approach

Figure 2 Cameraman Image

(a) (b) (c)



Cameraman Image — Resultant image by existing approach — Resultant image By proposed approach

The Lena and Cameraman Image given for compression and the decompressed image by the existing and the modified approaches are presented above. Figure 1(a) and 2(a) shows the sample input image of Lena and Cameraman respectively and the retrieved image when the existing and proposed approaches used for compression are given in Fig (b) and (c) respectively. The experimental results of the proposed approach of image compression using modified self-organizing feature map algorithm based vector quantization codebook generation revealed the fact that the compression ratio of the proposed approach is high when comparing with other conventional image compression techniques. The decompressed image obtained when the proposed approach used resembles the original image. Thus the proposed approach performs better than the other image compression techniques.

5. Conclusion

Self-organizing map is a popular learning based method and has been widely applied for image compression. This proposed paper introduced a modified self-organizing map algorithm for image compression. This modification overcomes the limitation of the standard SOM algorithm. The Vector Quantization (VQ) codebook is generated by a modified SOM algorithm. This proposed paper modifies the standard SOM algorithm that integrates both the local and the non-local information into the standard SOM algorithm using a novel dissimilarity index in place of the usual distance metric. To evaluate the performance of SOM based vector quantization for image compression some standard image set are considered. The experimental results revealed the fact that the compression ratio of the proposed approach is high when comparing with other conventional image compression techniques. The major limitation of the proposed approach is that it is computationally expensive, and this may limit its applicability to large 3D volume data. Implementation of some suppression technique during the process of iteration helps to overcome this limitation. The future work relies on implementing a suppression technique that can reduce the number of iterations and increase convergence speed of our proposed algorithm effectively.

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