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A TECHNIQUE OF IMAGE COMPRESSION BASED ON DISCRETE WAVELET IMAGE DECOMPOSITION AND SELF ORGANIZING MAP

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Abstract. Image compression is the growing research area for the real world applications which is spreading day by day by the explosive growth of image transmission and storage. This paper presents the algorithm for gray scale image compression using self organizing map (SOM) and discrete wavelet transform (DWT). Self organizing map network is trained with input patterns in the form of vectors which gives code vector (weight matrix) and index values as the output. The discrete wavelet transform is applied on the code vectors and storing only the approximation coefficients (LL) and the index values obtained from the self organizing map. The result obtained shows the better compression ratio as well as better peak signal to noise ratio (PSNR) in comparison with the existing techniques.

Keywords: Image compression, Wavelet transform, Self organizing map, Gray scale image.

1 Introduction

Image compression [1], the science of removing the redundant data, is one of the most widely used and commercially successful technologies in the field of digital image processing. Web page images and high-resolution digital camera photos also are compressed routinely to save storage space and reduce transmission time. An image compression system is composed of two distinct functional components: an encoder and a decoder. In an artificial neural network, simple artificial nodes, called "neurons", are connected together to form a network which mimics a biological neural network. Self organizing map is a kind of artificial neural network (ANN) which consists of component called nodes (neurons) and is based upon unsupervised learning which gives a low dimensional and discretized representation of the input space of the training samples which is known as Map. The self-organizing map describes a mapping from a higher dimensional input space to a lower dimensional map space. A wavelet transform is the representation of a function by wavelets. The wavelets are translated and scaled copies (known as “daughter wavelets”) of finite-length or fast-decaying oscillating waveform (known as the “mother wavelet”).

The use of self organizing map and its application was given by Kohonen in 1990 [2]. Lu and Shin [3] have proposed a compression technique by first classifying edge block and background block using Kohonen self organizing feature maps to preserve edge integrity and improve the efficiency of the code book design. Amerijckx et al. [4] presented a compression scheme for digital still images by using the Kohonen’s neural network algorithm. A survey was conducted by Jiang [5] in 1999 on the effect and impact of various neural networks over image compression namely back propagation neural network based image compression, Hebbian learning based image compression, vector quantization based image compression, wavelet neural network based image compression, fractal neural network based image compression. Park and Woo [6] have proposed an edge preserving image compression algorithm based on unsupervised competitive neural network called Weighted Centroid Neural Network (WCNN), utilizes the characteristics of the image blocks from edge areas. The edge strength of image block data was utilized as a tool to allocate the proper code vector in the WCNN. The WCNN successfully allocated more code vectors to the edge block data from edge area while it allocated less code vectors to the image black data from shade or non-edge area when compared to conventional neural networks based on VQ algorithm. A method to reduce the convergence time in self organizing feature map (SOFM) based image compression was proposed by Anna Durai and Anna Saro [7]. In this, cumulative distribution function is first estimated and used for mapping image pixels which act as input for SOM. Sharma et al. [8] have proposed a six step SOM algorithm for image compression using Kohonen self organizing map which is a class of neural network. In this approach, as we increased the dimensions, the picture was reduced by number of bytes and started to closely resemble the actual picture through the feature extraction property of SOM thereby making very convenient for storage and transmission. Tsai et al. [9] have proposed the new hierarchical self organizing map (NHSOM) technique for efficient and effective code book design for image compression. New hierarchical self organizing map uses an estimation function to adjust numbers of maps dynamically and reflects the distribution of data efficiently. Moreover, NHSOM takes splitting LBG and reduce the training time. Sarlin [10] has focused the use of self organizing map neural network for monitoring millennium development goals.

A technique for analyzing various algorithms for image compression based on wavelet approximation has been presented by Devore et al. [11] in 1992. The combination of wavelet decomposition, vector quantization using LBG and fuzzy algorithm for image compression have proposed by karayiannis et al. [12]. In this technique, the images are decomposed using wavelet filters into a set of sub-bands are vector quantized using LBG algorithm and various fuzzy algorithm for learning vector quantization (FALVQ). Berghorn et al. [13] presented a fast embedded wavelet coding algorithm based on adaptive coding of significant state symbols and distance differences of significant 2x2 blocks in scan modes across scales. LTW (lower tree wavelet) was presented by Oliver and Malumbres [14], which is another solution for resolution scalable wavelet image coding with low complexity, based on non-embedded coding. Improvement on clustering based on feature learning weight learning has been proposed by Wang et al. [15] and Yeung and Wang [16]. According to them, an appropriate assignment of feature-weight can improve the performance of fuzzy C-means clustering. Highly scalable set partitioning in hierarchical trees (HS-SPIHT) presented by Danyali and Mertins [17], enables the SPIHT algorithm to have spatial scalability. This method mainly presented expansion of scalability instead of reduction of computation. Jain and Jain [18] have performed a detailed study on image compression based on wavelet transform along with evaluation and comparison of seven wavelet families i.e., Haar, Daubechies, Symlets, Coiflects, Biothogonal, Reverse Biorthogonal and Discrete approximation of Meyer on variety of test images. Cho and Pearlman [19] have used progressive resolution coding for fast and efficient image decompression based on prediction of dynamic ranges of wavelet sub-bands. Venkateswaran and Rao [20] have used different methodology to achieve image compression. In their work, instead of applying DWT over whole image, sub-blocks of size 16x16 from an image are subjected to one level wavelet decomposition and the wavelet coefficients are clustered using k-means clustering. The important features should not remove during image compression but at the same time unwanted feature need not be considered for compression. So sensitivity measure has been proposed to remove the redundant feature of the network [21]. Considering the inputs of a feed-forward neural network as random variables, this paper provides a definition of partial derivative of a function with respect to a random variable in the probability measure space. Designing a vector quantization codebook using fuzzy probabilistic C-means clustering algorithm over wavelet packet tree coefficient has been implemented by Nagendran and Arockia Jansi Rani [22]. The idea is to achieve higher compression ratio based on clustering the wavelet coefficients of each wavelet packet tree (WPT) bands. The image is reconstructed using the inverse WPT followed by rearranging and the subsequent encoder.

Self organizing map and wavelet transform combined together have been used in many applications like image compression, code book generation, image segmentation etc. Image segmentation of astronomical images using SOM and wavelets have implemented by Nunez and Llacer [23]. Chatellier et al. [24] have developed compression module by applying DWT over the image first and then SOM vector quantization is applied to generate code books. This method was designed for transmission of fixed images for wireless communication. A technique where generic code book is implemented using SOFM, discrete cosine transform (DCT) and DWT have proposed by Pandian and Anitha [25] and similar work has been done by Dandawate and Londhe [26]. Rawat and Meher [27] has been implemented the image compression using set partitioning in hierarchical trees (SPIHT) and SOFM vector quantization. Dandawate et al [28] has also proposed an idea of designing code book for vector quantization based on SOFM and DWT. A survey on training approaches for neural network and extreme learning machines have done by Huang et al. [29]. Wang et al. [30] has been proposed a extreme learning mechanism with upper integral network for classification system.

This technique aims at reducing the size of the gray scale image file by combining the technique of self organizing map and wavelet transform. Experimentally, this method has been implemented on various test images and the better compression is achieved in the result and retaining the visual quality of the various test images.

1.1 Self Organizing Map

The aim of self organizing map is to transform an incoming signal pattern of arbitrary dimension into a one or two dimensional discrete map. Higher dimensional maps are also possible but not so common. Like most artificial neural networks, self organizing maps operate in two modes. These modes are: training and mapping. Training is used to build the map using input examples and mapping automatically classifies a new input vector. A SOM consist of components called nodes or neurons. Associated with each neuron is a weight vector of the same dimension as the input data vectors and a position in the map space. The procedure for placing a vector from data space onto the map is to find the node with the closest (smallest distance metric) weight vector to the data space vector. Fig.1 shows 16x16 neurons in the Kohonen layer of the SOM network with 16 inputs.

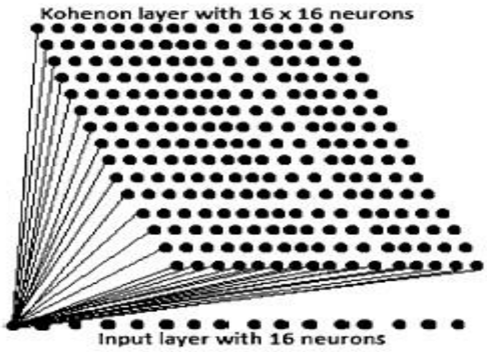

Fig. 1. SOM neural network with 16 inputs.

1.2 Wavelet Transform

The wavelet transform [31] is almost same as the Fourier transform (or much more to the windowed Fourier transform) but having a completely different merit function. The main difference between them is the Fourier transform decomposes the signal into sines and cosines means the functions are localized in the Fourier space whereas the wavelet transform uses functions that are localized in both the real and Fourier space. The discrete wavelet transform (DWT) returns a data vector of the same as the length of input data. Generally, even in this vector many data are almost zero. This implies that it decomposes into a set of wavelets (functions) that are orthogonal to its translations and scaling. Hence we decompose such a signal to a same or lower number of the wavelet coefficient spectrum as is the number of signal data points. Such kind of wavelet spectrum is good for signal processing and compression. DWT

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when applied over the weight matrix, it decomposes and produces four components namely, LL, LH, HL and HH coefficients and it can be applied to many levels. Single level Haar DWT used in our work. Single level DWT is shown in Fig.2.

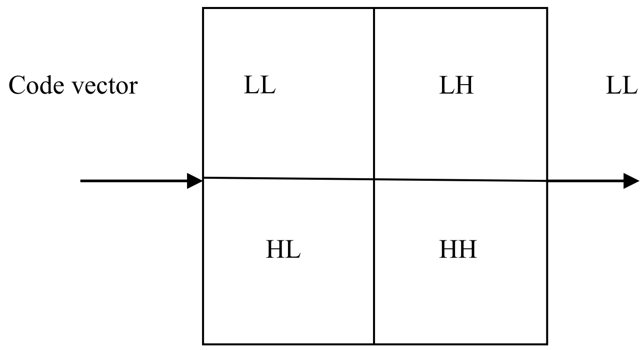

Fig. 2. Single level DWT

2 Compression and Decompression using SOM and DWT

For compression, a gray scale image of 256x256 pixels is first split into the 4,096 blocks, each block of size 4x4. Every 4x4 block is converted into 16 element vector i.e., 4,096 vectors corresponding to 4,096 blocks. Input the 4,096 vectors to SOM network and train the network. As a result, 16x256 weight matrix (code vector) and 4,096 indexes are obtained. Single level Haar DWT is then applied over each 4x4 sub block which will result in four components i.e., approximation coefficient (LL), horizontal coefficient (LH), vertical coefficient (HL) and diagonal coefficient (HH). For each code vector only approximation coefficient part will be stored and rest will not be considered since the detailed coefficients contains less important information and will not improve the quality of image. 4,096 index values are applied to the arithmetic encoder and the approximation coefficient part is then quantized and encode. Arithmetic encoded values of 4,096 indexes and quantized and encoded value of approximation coefficient are stored as a binary file. Fig. 3 shows the block diagram of compression scheme.

For decompression, first read the compressed binary file and extract the value of index part and LL part. Arithmetic decoding is applied over the indexes and LL component of the code vector is dequantized and decode. Here horizontal coefficient (LH), vertical coefficient (HL), and diagonal coefficient (HH) are assigned zero because they have not been stored during compression. Now, inverse DWT is applied over all the wavelet coefficients. Map the 256 reconstructed code vectors with 4,096 index values which gives 4,096 output vectors each with 16 elements. Then convert each output vector into 4x4 sub block which forms the final decompressed image. Fig.4 shows the block diagram of decompression scheme.

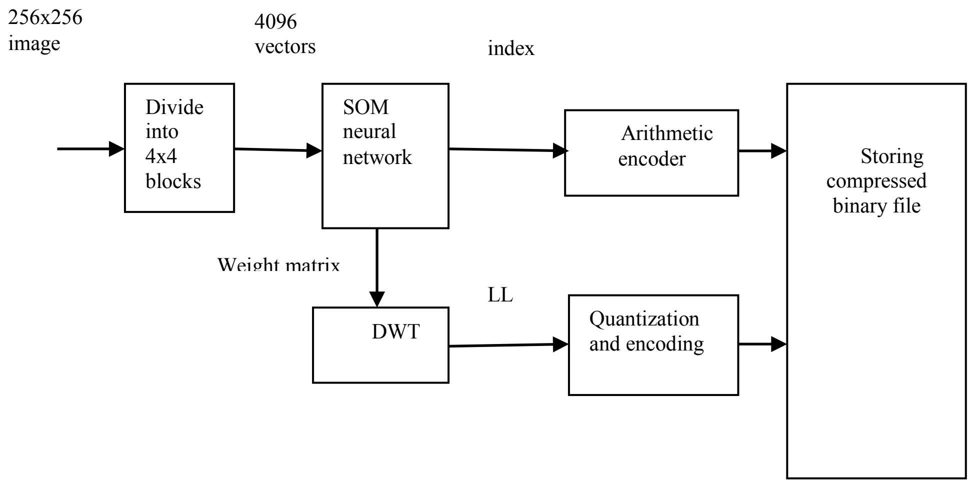

Fig. 3. Block diagram of compression scheme.

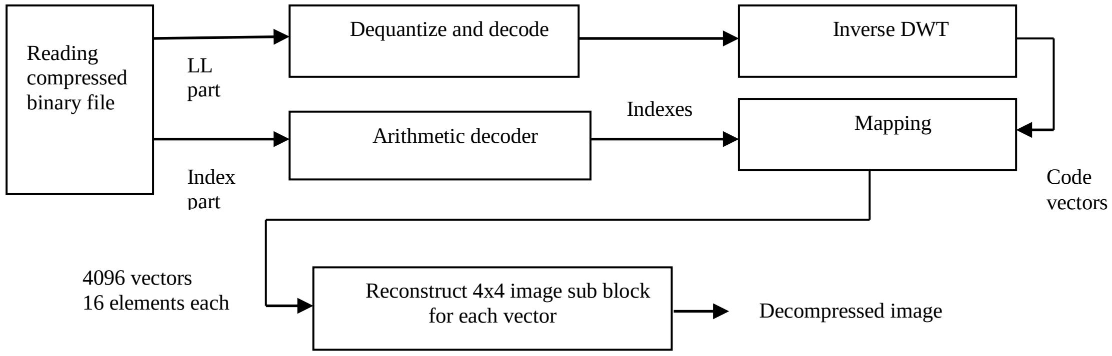

Fig. 4. Block diagram of decompression scheme.

2.1 Compression and Decompression algorithm

Following are the steps for compression of the 256x256 image:
1. Input image of size 256x256 is divided into blocks of size 4x4. Convert each block as vector (4,096 vectors).
2. 4,096 vectors are trained using SOM neural network which results in 16x256 weight matrix and 4,096 index values.
3. 4,096 index values are applied to the arithmetic encoder.
4. DWT is applied over 4x4 sub blocks of the weight matrix and only approximation coefficient component are quantized and encode.
5. store the encoded index values and encoded approximation coefficient component of the code vector which forms compressed binary file.

Following are the steps for decompression of compressed binary file:
1. Read the approximation coefficient part of the code vector and index part from the compressed binary file.
2. Dequantize and decode the approximation coefficient component of the code vector as well as decode the 4,096 index values.
3. Inverse discrete wavelet transform is applied over dequantized and decoded approximation coefficient component by considering HL, LH and HH component as zero.
4. The reconstructed code vectors are mapped with decoded 4,096 indexes which results in 4,096 output vectors each with 16 elements.
5. The output vector of 16 elements is then converted into 4x4 block to get the final decompressed image.

3 Experimental result and result analysis

The algorithm of hybridizing self organizing map and discrete wavelet transform is tested over various test images like Lena, Mandrill, Pepper and Cameraman and the PNSR, RMSE and CR are calculated are shown in Table 1. The image measures like root mean square error, peak signal to noise ratio and compression ratio can be calculated as follows:

Root mean square error, RMSE= $\sqrt{\frac{(\sum_{i=1}^{N}(yi-xi)^2)}{N}}$

where yi is the intensity of the ith pixel of the original image, xi is the intensity of the ith pixel of the decompressed image and N is the number of pixels in the image.

Peak signal to noise ratio, PSNR= $20log_{10}\frac{255}{RMSE}$

Compression ratio, CR= $\frac{number\ of\ bits\ in\ the\ original\ image}{number\ of\ bits\ in\ the\ compressed\ image}$

The visual illustrations of the applied algorithm over various images are shown in Fig. 5. The comparison of this technique over the existing techniques based on PSNR over Lena image is shown in Table 2 and Table 3 shows the comparison of PSNR and compression ratio over existing technique. Fig.6 shows the comparison with existing techniques on the basis of PNSR and CR through graphical representation.

Table 1. Result of the given algorithm tested over various images.

Image	RMSE	PSNR	Compressed size bytes	Original size bytes	CR	BPP
Lena.jpg	4.93	34.2738	4628	56506	12.20	0.565
Mandrill.jpg	7.34	30.8168	4889	32690	6.686	0.597
Pepper.jpg	4.82	34.4698	4701	14728	3.133	0.574
Cameraman.jpg	5.57	33.2136	4428	23650	5.341	0.582

Table 2. Comparison with existing techniques based on PSNR over Lena image.

Method	PSNR
LBG (Lu and Shin)	29.400
VQ (Lu and Shin)	30.030
Pure SOM (Amerijickx)	24.740
Weighted CNN (Park and Woo)	31.040
New hierarchical SOM (Tsai)	34.016
SOM and DWT	34.2738

Table 3. Comparison over existing techniques based on PSNR and compression ratio.

WORK	PSNR	CR
Sanchez [32]	18.3135	16.00
Sudhakar I [33]	27.8100	13.03
Sudhakar II	31.2800	6.57
Joshi [34]	27.1000	7.49
Sonja Grgic [35]	32.5200	10.00
SOM and DWT	34.0696	12.20

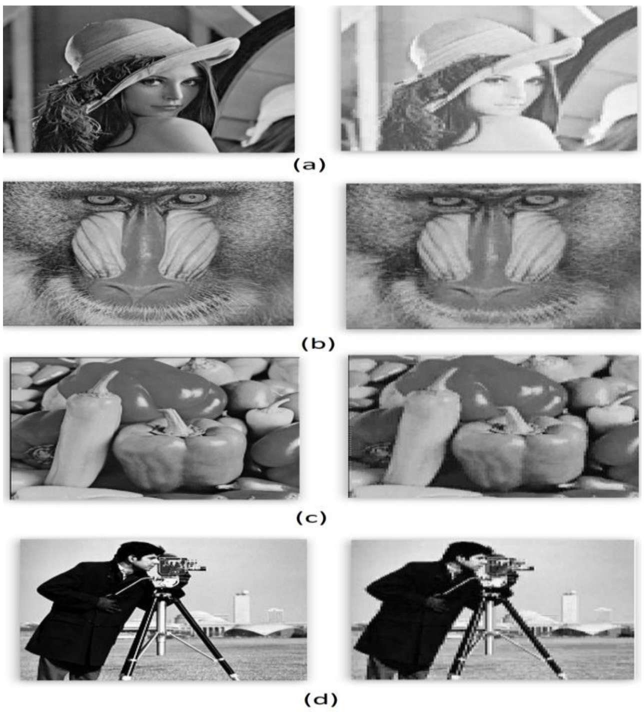

Fig. 5. Visual illustration of original image and compressed image for (a) Lena image, (b) Mandrill image, (c) Pepper image and (d) cameraman image.

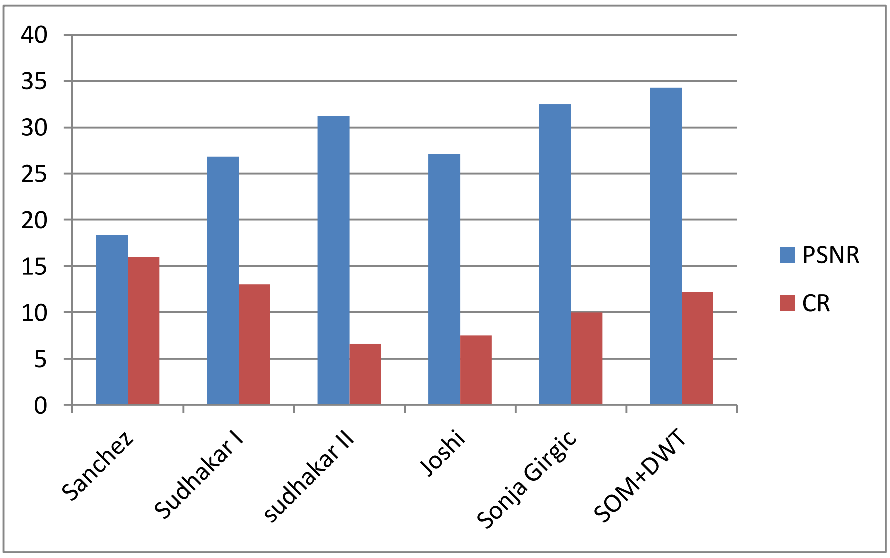

Fig. 6. Graph of comparison with existing technique on the basis of PSNR and CR.

4 Conclusion

The technique for compression of gray scale image using a combination of self organizing map and discrete wavelet transform are implemented successfully. This algorithm was tested over four different images (Lena, Mandrill, Pepper and Cameraman) of different dimensions and considerable reduction of file size is achieved in the result. Since both SOM and DWT are lossy compression techniques, the decompressed image is virtually acceptable and the reconstruction of the file is much faster than the existing techniques.

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