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Various Novel Wavelet – Based Image Compression Algorithms Using a Neural Network as a Predictor

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ABSTRACT

An important issue in image compression is the volume of pixels which will be compressed. This paper presents a novel technique in image compression with different algorithms by using the transform of wavelet accompanied by neural network as a predictor. The details subbands in different low levels of image wavelet decomposition are used as training data for neural network. In addition, It predicts high level details subbands using low level details subbands. This Paper consists of four novel algorithms for image compression as well as comparing them with each other and well- known jpeg and jpeg2000 methods.
KEYWORDS: lossy image compression; wavelet transform; neural networks; prediction; PSNR.

I. INTRODUCTION

We are in the middle of an exciting period of time in the field of image processing. One aspect of image processing that makes it such an interesting topic of study is the amazing image compression. Indeed, when we send an image, encounter with a large volume of data. So, we should compress image and then send it. There are two kinds of image compression: Lossy and Lossless. In this paper we focus on the lossy one. The goal of lossy compression is to achieve the best possible fidelity given an available communication or storage bit-rate capacity, or to minimize the number bits representing the image signal subject to some allowable loss of information, thereby speeding up transmission and minimizing storage requirements [1,2].

An important part of compression is transformation. This stage applies a reversible (one-to-one) transformation to the input image data. The purpose of this stage is to convert the input image data into a form that can be compressed more efficiently. For this purpose, the selected transformation can aid in reducing the data correlation (interdependency, redundancy), alter the data statistical distribution, and pack a large amount of information into few data samples or subband regions. Typical transformations include differential and predictive mapping, unitary transforms such as the discrete cosine transform (DCT), subband decompositions such as wavelet transforms, and color space conversions such as conversion from the highly correlated RGB representation to the less correlated luminance-chrominance representation[2].

There are two standards in image compression: jpeg and jpeg2000. In jpeg, compression should be based on the DCT and in the jpeg2000 should be based on the Discrete Wavelet Transform (DWT) techniques. Both of the two methods (JPEG and JPEG-2000) define lossy and lossless compression algorithms. Transform coding has been extensively developed for coding of images, where the DCT is commonly used because of its computational simplicity and its good performance. But the DCT is giving way to the wavelet transform because of the latter's superior energy compaction capability when applied to natural images. The significant difference between the proposed method and jpeg is the type of transform and the noticeable difference between proposed method and jpeg2000 is that we apply neural network as a predictor in the process of compression.

The scientific contributions of this paper are: 1) Using neural network as a predictor in receiver.2) Having better performance in comparing with jpeg.

In the following, some of studies on image compression methods are introduced.

In [1], there is a much more popular image compression framework that forms the basis of current commercial image compression standards like JPEG. The transform coding paradigm can be construed as a practical special case

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of vector quantization (VQ) that can attain the promised gains of processing source symbols in vectors through the use of efficiently implemented high-dimensional source transforms.

In [3], a new class of algorithms has been developed that achieve significantly improved performance over the EZW coder. Set partitioning in hierarchical trees (SPIHT), has established zero-tree techniques as the current state-of-the-art of wavelet image coding since the SPIHT algorithm proves to be very successful for both lossy and lossless compression. A wavelet image representation can be thought of as a tree structured spatial set of coefficients. A wavelet coefficient tree is defined as the set of coefficients from different bands that represent the same spatial region in the image. The lowest frequency band of the decomposition is represented by the root nodes (top) of the tree, the highest frequency bands by the leaf nodes (bottom) of the tree, and each parent node represents a lower frequency component than its children. Except for a root node, which has only three children nodes, each parent node has four children nodes, the 2 x 2 region of the same spatial location in the immediately higher frequency band. Both the EZW and SPIHT algorithms [3,4] are based on the idea of using multipass zero-tree coding to transmit the largest wavelet coefficients (in magnitude) at first.

In[5], a compression technique is proposed by using two neural networks. One of the neural networks is used for the original image compression and the other one is applied for compression of the residual image. However, it is effective to compress each region, which is divided in to the edge and flat regions. Simulation results show that the proposed algorithm yields to a higher compression ratio as well as high PSNR compared with the conventional compression method using a single neural network.

In[8], a new method of compression on medical image has been studied that decompose and reconstruct the medical image by wavelet packet. Before the construction the image, use neural network instead of other coding method to code the coefficients in the wavelet packet domain. This paper use Kohonen's neural network algorithm, not only for its vector quantization feature, but also for its topological property. On the other hand, our proposed method use back propagation feed forward multi-layer neural network for prediction. Compared to the JPEG standard, both compression scheme show better performances (in terms of PSNR) for compression rates.

In this paper, a new lossy images compression method based on wavelet transform is presented. The proposed method is combined with neural Network as predictor. The remainder of the paper is organized as follows. In section II, we discuss the principles of the proposed method such as wavelet transform, neural networks. In section III, the proposed method is introduced. In section IV, the simulation results are presented. This is followed by conclusions in section V.

II. BASIC PRINCIPLES AND FUNDAMENTALS

A. Wavelet Transform

In recent years, many studies have been made on wavelets. Image compression is one of the most visible applications of wavelets. Our proposed method is based on discrete wavelet transform (DWT). WT performs multiresolution image analysis. The result of multiresolution analysis is simultaneous image representation on different resolution (and quality) levels. The resolution is determined by a threshold below which all fluctuations or details are ignored. The difference between two neighboring resolutions represents details. Therefore, an image can be represented by a low-resolution image (approximation or average part) and the details on each higher resolution level. The resulting four transform components consist of all possible combinations of high- and low-pass filtering in the two directions. By using these filters in one stage, an image can be decomposed into four bands. There are three types of detail images for each resolution: horizontal (HL), vertical (LH), diagonal (HH) and approximation band named LL. The operations can be repeated on the low–low band (approximation) using the second stage of identical filter bank. Thus, a typical 2-D DWT, used in image compression, will generate the hierarchical pyramidal structure shown in Figure 1 [6]. Each pixel is equivalent to four pixels at a higher level which have large correlation between each other (see Figure 1). We use this feature to predict the higher level of a lower level. In Figure1, four-level Wavelet decomposition and the correlation between pixels in different levels of correlation are shown.

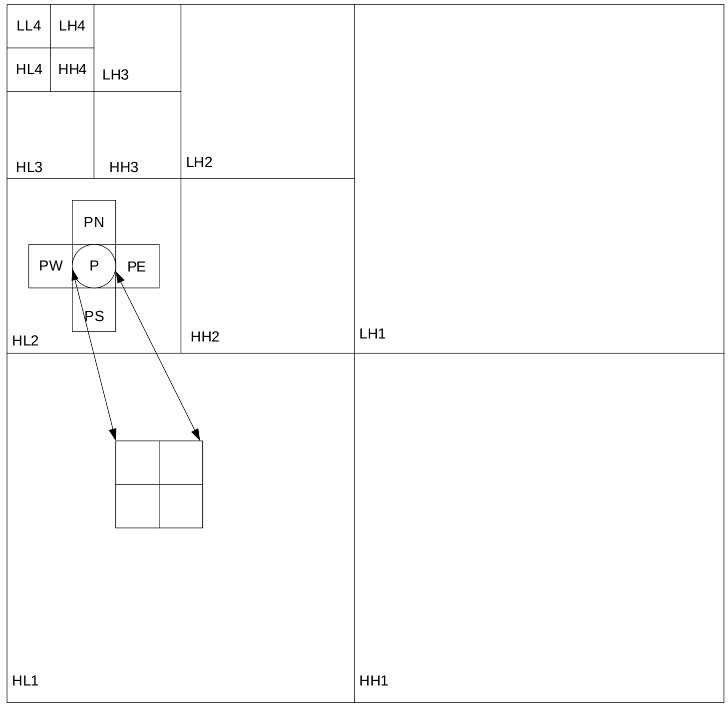

Figure 1. Four-level Wavelet decomposition and the correlation between pixels in different levels of correlation.

B. Artificial Neural Networks

The existing conventional image compression technology can be developed right into various learning algorithms to build up neural networks for image compression. This will be a significant development in the sense that various existing image compression algorithms can actually be implemented by one neural network architecture empowered with different learning algorithms. Hence, the powerful parallel computing and learning capability with neural networks can be fully exploited to build up a universal test bed where various compression algorithms can be evaluated and assessed.

In our method, we have used a back propagation feed forward multi-layer neural network for prediction. So, it is used to estimate each subband from its corresponding lower subband.

Designed network in the proposed method is a two-layer neural network with 10 neurons in hidden layer and 1 neuron in output layer and 5 inputs. As there are not so much elements in the input's vector, the Levenberg-Marquardt optimization algorithm was exploited to present the fastest and best response. For the input layer and the hidden layer, S-shape tangent hyperbolic is used as the transform function; and the linear function is chosen for the output layer. This network is shown in Figure 2. Thus, we used five coefficients named Parent (P), Parent North (PN), Parent East (PE), Parent West (PW) and Parent South (PS) in lower levels to predict four coefficients in their corresponding higher levels.

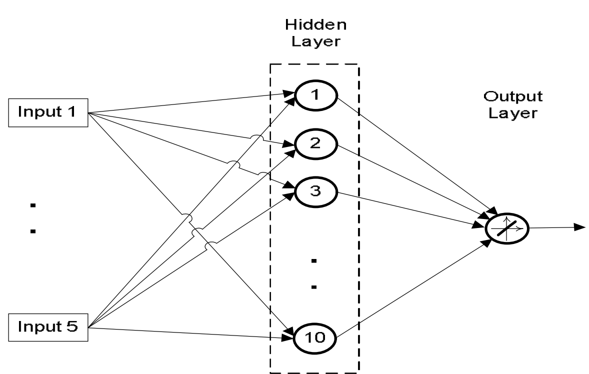

Figure 2.Neural network in proposed method with 5 inputs, 10 neurons in hidden layer and 1 neuron in output layer.

III. THE COMPRESSION METHOD

As we said, we designed four algorithms in order to compressed image.

a) First of all, perform wavelet transform on image.

b) After decomposition in 3 levels, by using the procedure explained in section II, we build the inputs of neural networks and train them. It should be noted that, we use only three neural networks for horizontal, vertical and diagonal subbands of each level. We exploit subbands of level 2 as the inputs and subbands of level 1 as the targets of the neural networks, in order to train them. Now, we can use these trained networks to predict each subband by its corresponding lower level subband

c) Then, we reconstruct each higher level from its corresponding lower level using the proposed neural network. So, for every level of the reconstruction, we have 3 errors which correspond to horizontal (LH), vertical (HL) and diagonal (LL) subbands, and thus, we have 9 errors totally.

d) Now, we would be able to choose one of the following methods. First algorithm sends approximation subbands and the errors of details subbands which both are quantized (Aq+Eq). The second algorithm includes approximation subbands and the errors of detail subbands which are quantized (A+Eq). In the third one we have approximation subbands with the quantized errors of detail subbands and quantized weights of the neural network (A+Eq+Wq). In the last algorithm, we send quantized approximation subbands, quantized errors of details subbands and quantized weights of the neural network (Aq+Eq+Wq). Figure 3 shows block diagram of this method. By eliminating quantization block, we could choose other methods.

e) At the receiver, we decompose LL3 by applying a discrete wavelet transform and again, by using the trained neural networks, we reconstruct higher levels from lower levels. This procedure can continues, to obtain the subbands of horizontal, vertical and diagonal of level one.

f) Finally, the image is reconstructed as the decompressed image by applying an inverse wavelet transform on reconstructed subbands.

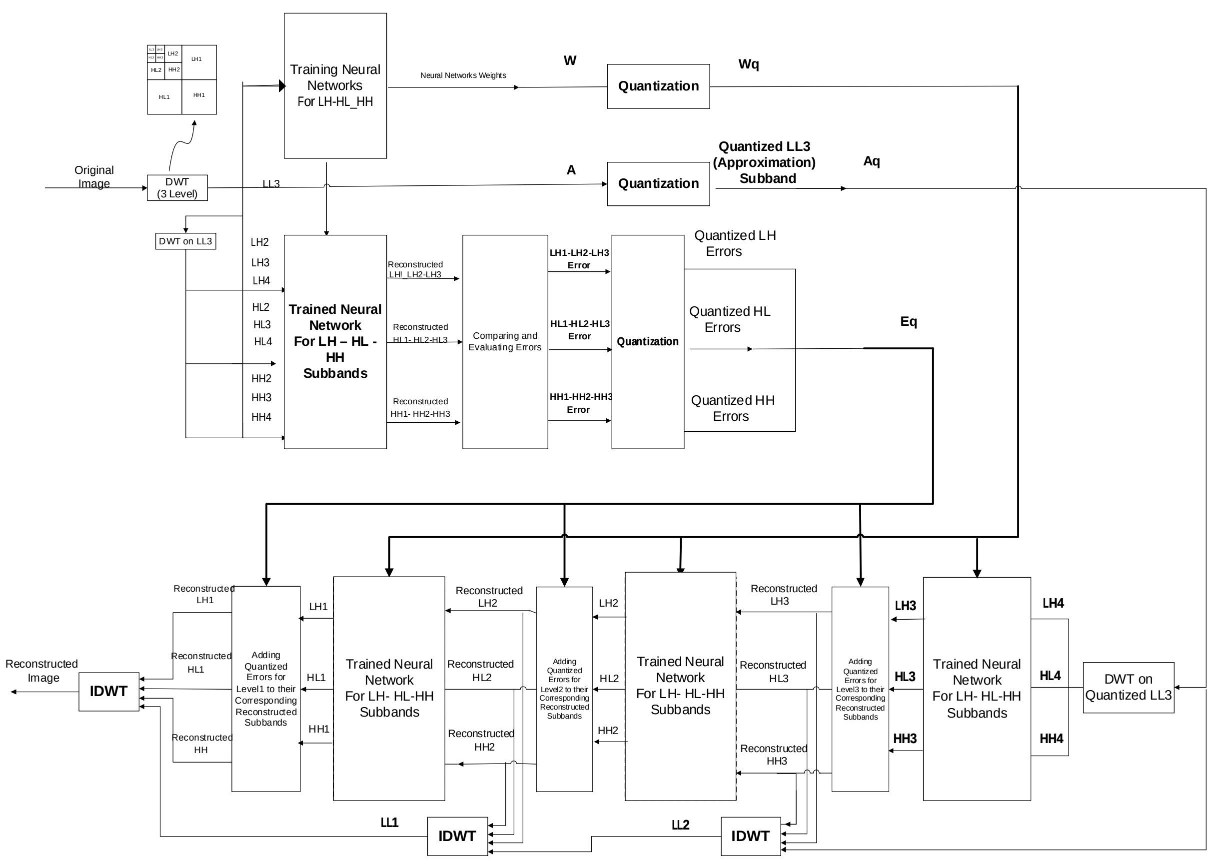

Figure 3. Block diagram of proposed image compression scheme

IV. EXPERIMENTAL RESULTS

In this study we used two images, Lena and a sample form satellite image as test images. Peak signal to noise ratio (PSNR) of images is a criterion used as quality comparison which is defined as:

$$PSNR = 10\log\left(\frac{MAX^2}{MSE}\right) \quad (1)$$

where,

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} \left\| I(i,j) - I_q\ (i,j)\ \right\|^2 \quad (2)$$

and Max is the maximum possible pixel value of the original image. In (2), I is the m*n original image and Iq is the reconstructed image.

In this paper we focus on the four different algorithms in image compression and compare them with each other. The result of our experiment has been showed in figure 4. According to the figure 4, we claim that the first method has better performance than the others. It means that, if we send quantized approximation subband and the quantized errors of details subbands, have higher PSNR in same compression ratio so we achieved a compressed image with better quality. It is clear, because we send less data through the channel. So we use the first method in rest of our paper.

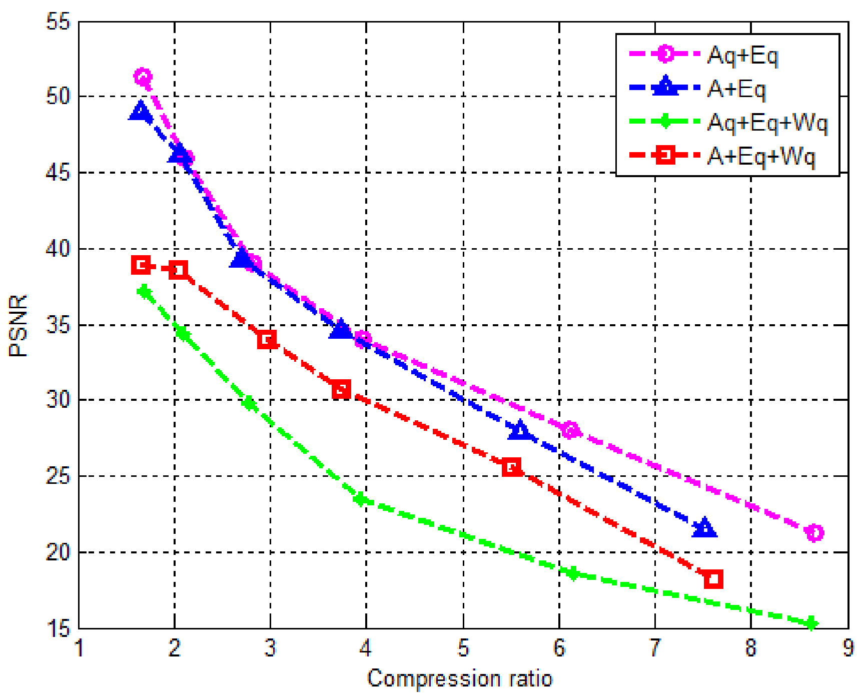

Figure 4.Comparison between different algorithms in compression of Lena image

In order to compare the performance of the proposed compression scheme with JPEG, we computed PSNR and CR of reconstructed image for various quantization levels. The results for PSNR and compression ratio (CR) for different quantization levels are presented in Table I.

By varying the quantization levels, we can obtain different compression ratios and consequently different PSNRs. However, it is difficult to adjust the quantization levels to have exactly the same compression ratios for our method as well as for JPEG. So we tried to compare two methods for close compression ratios Figure 5 shows the result of proposed compression method for Lena image in PSNR=53.28 and CR=2.09. Figure 6 shows the result of proposed compression method for the test satellite image for two quantization levels in PSNR=51.26 and CR=1.68 and in PSNR = 45.92, CR = 2.11.

In the wavelet transform, different filters can be used. The results reveal that the filter “coif1” performs better than the other filters in our proposed compression scheme. Comparison of CR vs. PSNR between different filters such as “db1”,“db10” and “coif1” for the test satellite image is shown in Figure 7.

Figure 5.Results of proposed compression method for Lena image. PSNR=53.28, CR=2.09 and Filter: Coif1

PSNR = 51.26 CR = 1.68 Q1 PSNR = 45.92 CR = 2.11 Q2

Figure 6. Results of proposed compression method in different quantization for satellite image by using Coif1 filter

TABLE I: PSNR and Compression ratio for different quantization levels for Lena and satellite images. Note that Q1> Q2> Q3> Q4> Q5> Q6.

Quantization	**Lena**		**Satellite Image**	
	PSNR	*Compression Ratio*	*PSNR*	***Compression Ratio***
Q1	53.28	2.09	47.24	2.83
Q2	47.69	2.33	43.81	3.75
Q3	42.85	3.75	40.31	5.13
Q4	36.38	5.39	35.47	7.32
Q5	31.52	8.63	31.07	10.91
Q6	23.18	12.58	25.43	14.73

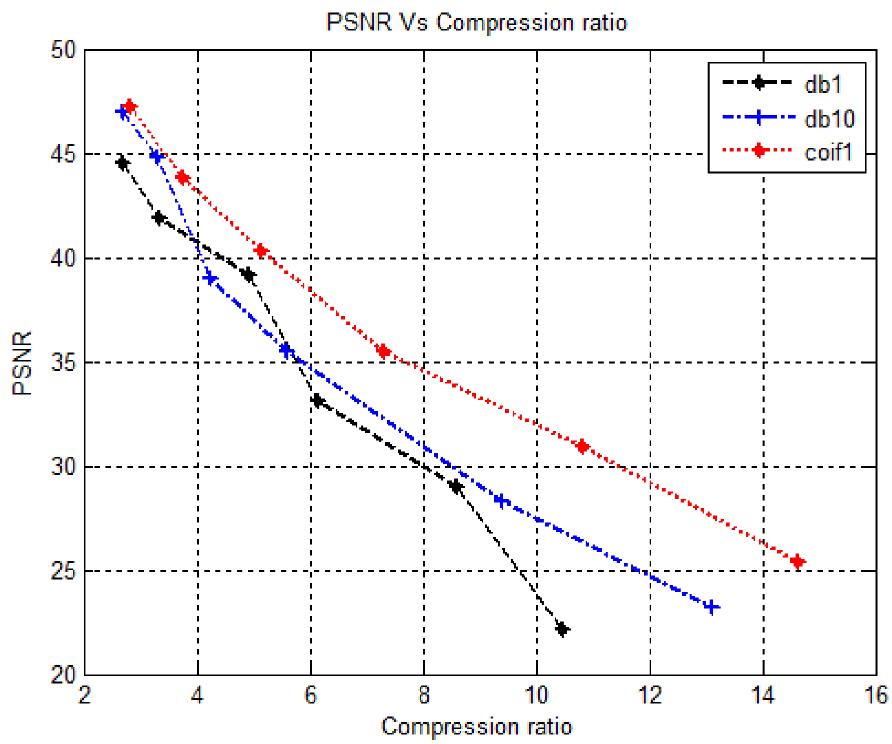

Figure 7. Comparison results of the proposed compression method for satellite image for filters "db1", "db10", "coif1".

For comparison between our proposed method and previous methods, the results of JPEG2000 standard [7] and our method for Lena image are illustrated in Figure8. It can be concluded that our proposed method is comparable to JPEG2000 especially in high CRs.

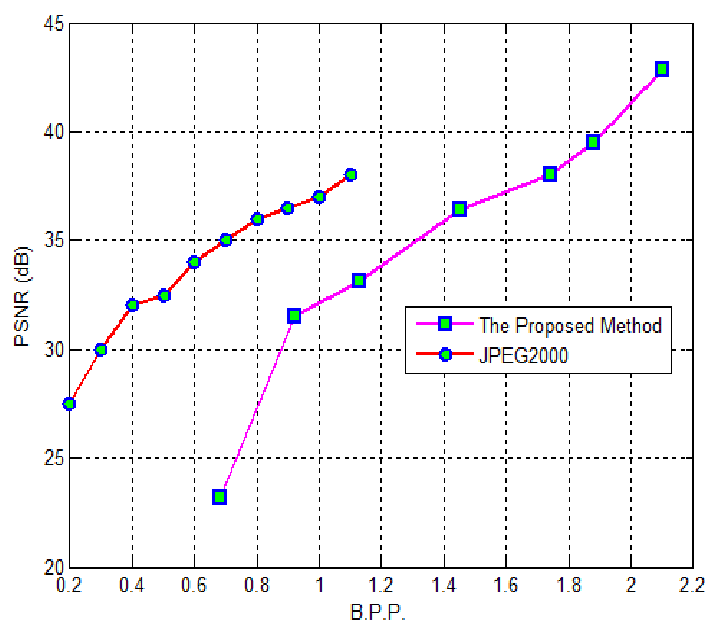

Figure 8.The numerical comparison between the results of our proposed method and JPEG2000 for Lena image.

V. CONCLUSION

In this paper, we proposed various algorithms for image compression based on wavelet transform by using neural network as a predictor for predicting and reconstructing the higher subbands of Wavelet decomposition of an image. We focus on four different methods for image compression. Simulation results show that the first algorithm has better performance in terms of PSNR and compression ratio. In other words, if we send quantized approximation subbands and the quantized errors of details subbands through the channel, we achieve higher compression ratio in the same PSNRs. On the other hand, we propose compression schemes in transform domain to compare the performance of the proposed methods and JPEG. The results reveal that our method has better performance against JPEG in achieving higher compression ratios and are comparable to JPEG2000 especially in high compression ratios.

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