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EZW Coding System with Artificial Neural Networks

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Abstract**—**Image compression plays a vital role in today's communication. The limitation in allocated bandwidth leads to slower communication. To exchange the rate of transmission in the limited bandwidth the Image data must be compressed before transmission. Basically there are two types of compressions, 1) LOSSY compression and 2) LOSSLESS compression. Lossy compression though gives more compression compared to lossless compression; the accuracy in retrievation is less in case of lossy compression as compared to lossless compression. JPEG, JPEG2000 image compression system follows huffman coding for image compression. JPEG 2000 coding system use wavelet transform, which decompose the image into different levels, where the coefficient in each sub band are uncorrelated from coefficient of other sub bands. Embedded Zero tree wavelet (EZW) coding exploits the multi-resolution properties of the wavelet transform to give a computationally simple algorithm with better performance compared to existing wavelet transforms. For further improvement of compression applications other coding methods were recently been suggested. An ANN base approach is one such method. Artificial Neural Network has been applied to many problems in image processing and has demonstrated their superiority over classical methods when dealing with noisy or incomplete data for image compression applications. The performance analysis of different images is proposed with an analysis of EZW coding system with Error Backpropagation algorithm. The implementation and analysis shows approximately 30% more accuracy in retrieved image compare to the existing EZW coding system.

Keywords**—**Accuracy, Compression, EZW, JPEG2000, Performance.

I. INTRODUCTION

DIGITAL imagery has an enormous impact on industrial, scientific and computer applications. It is no surprise that image coding has been a subject of great commercial interest in today's world. Uncompressed digital images require considerable storage capacity and transmission bandwidth. Efficient image compression solutions are becoming more critical with the recent growth of data intensive, multimedia-based web applications.

Various research works were carried out on both lossy and lossless image compression. The JPEG committee released a new image-coding standard, JPEG2000 that serves the enhancement to the existing JPEG system. The JPEG2000 implements a new way of compressing images based on the wavelet transform in contrast to the Discrete Cosine Transformation (DCT) used in JPEG standard.

The problem of image compression is more important in many applications, particularly for progressive transmission, image browsing, multimedia applications, and compatible transcoding [2] for multiple bit rates. A majority of today's internet bandwidth is estimated to be used for images and video transmission. Recent multimedia applications for handheld and portable devices place a limit on the available wireless bandwidth. The bandwidth is limited even with new connection standards. Wavelet based image compression techniques such as JPEG 2000 offers more compression than conventional methods in terms of compression ratio.

Very few works on generation of an accurate bit stream that claims higher PSNR performance at rates between 0.25 and 1 bit/pixel were made. Z. Xiong, K. Ramchandran and M. Orchad [3] uses a tree coding where the said value is zero if its energy is less than perceptually based threshold. An approach to the low bit rate image transform coding is presented by S.Mallat and F.Falzon [2]. The overview to lossy wavelet image compression for JPEG 2000 [9] and wavelet transformation with embedded zerotree coding were presented by Bryan E. Usevitch [8]. Colm Mulcahy presented the application of embedded coding on an isolated tile image for image compression in his paper [10] using haar wavelet. The paper gives an approach towards embedded coding using haar wavelet transform for real images.

'The embedded zerotree wavelet coding for image processing' presented by Shapiro in his paper [1] uses embedded coding for image compression. The embedded zerotree wavelet coding [1], [8] uses the wavelet coefficient [5], [6] for encoding. Wavelets use the multiresolution analysis [6] for decomposing the image into sub-band [4] as detail and approximate coefficients. In subband coding systems [4], the coefficients from a given image are extracted. The JPEG2000 coding system [7], [9] presents image compression using wavelet transform. These papers present the JPEG 2000 coding system architecture for still image compression.

For improving the ANN efficiency for image compression various works were suggested in past. In [11] the author expounds the principle of BP neural network with applications to image compression and the neural network models. Then an image compressing algorithm based on improved BP network is developed. Wavelet-based image compression [12] provides substantial improvements in picture quality at higher

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compression ratios. A neural auto associative technique [13] applied to image compression is presented where particular attention is devoted to the preprocessing stage. The author in [14] suggests that the classic image compression techniques such as JPEG and MPEG have serious limitations at high compression rate; the decompressed image gets really fuzzy or indistinguishable. To overcome this problem, artificial neural network techniques are used where he propose a bipolar sigmoidal backpropagation BBP algorithm to train a feed forward auto associative neural network. The idea of author in [15] is that a neural network could be trained to recognize an optimum ratio for DCT compression of an image upon presenting the image to the network. The neural network associates the image intensity with its compression ratios in search for an optimum ratio. A new co-evolutionary method [16] is proposed to further improve the compression efficiency. A heterogeneous set of networks co-evolve and compete to compress different parts of an image with different characteristics. In [17] a method is proposed for compression of medical images. The approach is called DLC2 (Diagnostically Lossless Compression-2). To get lossless effect, the author use lossy coding followed by error image coding. An NNVQ (Neural Network Vector Quantizer) is used for lossy compression and huffman coding is used to code the difference image losslessly. It is a spatial domain technique. No frequency domain transformations are required; this makes the proposed scheme simple and computationally economical. Feedforward networks using backpropagation algorithm [18] adopting the method of steepest descent for error minimization is popular and widely adopted and is directly applied to image compression. Image data compression using Vector Quantization (VQ) has received a lot of attention because of its simplicity and adaptability. VQ requires the input image to be processed as vectors or blocks of image pixels. The Finite-state vector quantization (FSVQ) is known to give better performance than the memory less vector quantization (VQ). The author in [19] presents a novel combining technique for image compression based on the Hierarchical Finite State Vector Quantization (HFSVQ). Edge preserving image compression technique [20] using one hidden layer feed forward neural network of which the neurons are determined adaptively. This proposes initialization of weights between the input and lone hidden layer by transforming pixel coordinates of the input pattern block into its equivalent one-dimensional representation. A modified Kohonen's algorithm, the time enhanced self-organizing map (TESOM) [21], discusses its advantages over traditional self-organizing maps. The time-enhanced map extends into the temporal domain the capabilities of the SOM because it matches input vectors both by similitude and sequentially. In [22] the author presents an image compression scheme that uses the wavelet transform and neural network. Firstly, image is decomposed at different scales by using the wavelet transform. Then, the different quantization and coding schemes for each sub-image are carried out in accordance with its statistical properties and distributed properties of the wavelet coefficients. Kohonen's neural network algorithm [23] presents a compression scheme for digital still images, not only for its vector quantization feature, but also for its topological property. This property allows an increase of about 80% for the compression rate. Compared to the JPEG standard, this compression scheme shows better performances (in terms of PSNR) for compression rates higher than 30.

II. Embedded Zero Tree Wavelet Coding

Embedded Zerotree Wavelet encoder is based on progressive encoding to compress an image into a bit stream with increasing accuracy. When more bits are added to the stream, the decoded image is contain more detail of the image a property similar to JPEG encoded images.

Coding an image using the EZW scheme, together with some optimizations results in a remarkably effective image compression with the property that the compressed data stream can have any bit rate desired. Any bit rate is only possible if there is information loss somewhere so that the compression is lossy. However, lossless compression is also possible with an EZW encoder, with less optimal results.

A. The Algorithm

The EZW output stream starts with information to synchronize the decoder. The minimum information required by the decoder for its functionality is the number of wavelet transforms levels used and the initial threshold, basically a constant levels (3) of wavelet transform were used for transformation. The first step in the EZW coding algorithm is to determine the initial threshold. The initial threshold t_0 is given as $t_0=2^{[\log_2(MAX(|\gamma(x,y)|))]}$.Where $MAX(|\gamma(x,y)|)$ means the maximum coefficient value in the image and $\gamma(x,y)$ denotes the coefficient. Then taking the obtained threshold as the initial value the scaled sub-band samples are been passed for dominant pass and subordinate pass. Under each pass the threshold is decreased by half the value. This comparison is carried out until the threshold reaches to the minimum threshold, the algorithm implemented as presented below.

```
threshold = initial_threshold;
do {
dominant_pass(image);
subordinate_pass(image);
threshold = threshold/2;
} while (threshold>minimum_threshold);
```

Fig. 1 EZW algorithm

The EZW encoder is based on two important observations: 1) Natural images in general have a low pass spectrum. When an image is wavelet transformed the energy in the subbands decreases as the scale decreases (low scale means high resolution), so the wavelet coefficients is, on average, be smaller in the higher subbands than in the lower subbands. This shows that progressive encoding is a very natural choice for compressing wavelet-transformed images, since the higher subbands only add detail parameter. 2) Large wavelet coefficients are more important than small wavelet coefficients.

These two observations are used for encoding the wavelet coefficients in decreasing order, in several passes. For every pass a threshold is chosen against which all the wavelet coefficients are measured. If a wavelet coefficient is larger than the threshold it is encoded and removed from the image, if it is smaller it is left for the next pass. When all the wavelet coefficients have been visited the threshold is lowered and the image is scanned again to add more detail to the already encoded image. This process is repeated until all the wavelet coefficients have been encoded completely.

B. Dominant Pass

The image is scanned and a symbol is returned for every coefficient. If the coefficient is larger than the threshold a **P** (positive) is coded. If the coefficient is smaller than negative of threshold an **N** (negative) is coded. If the coefficient is the root of a zerotree then a **T** (zerotree) is coded and finally, if the coefficient is smaller than the threshold but it is not the root of a zerotree, then a **Z** (isolated zero) is coded. This happens when the coefficient larger than the threshold in the subtree. All the coefficients that are in positive value, larger than the current threshold are extracted and placed without their sign on the subordinate list and their positions in the image are filled with zeros. This prevents them from being coded again. The dominant pass can thus be implemented as;

```
initialize_fifo();
while (fifo_not_empty) {
get_coded_coefficient_from_fifo();
if coefficient was coded as P, N or Z then {
code_next_scan_coefficient();
put_coded_coefficient_in_fifo();
if coefficient was coded as P or N then {
add abs(coefficient) to subordinate list;
set coefficient position to zero;
}
}
}
```

Fig. 2 Dominant Pass

C. Subordinate Pass

The dominant pass is always followed by a subordinate pass where the coded data get coded in 1 or 0 to be transmitted, the process for subordinate pass is as illustrated;

```
subordinate_threshold = current_threshold/2;
for all elements on subordinate list do {
if coefficient>subordinate_threshold then {
output a one;
coefficient = coefficient-subordinate_threshold;
}
else output a zero;
}
```

Fig. 3 Subordinate Pass

A wavelet transform transforms a signal from the time domain to the joint time-scale domain. i.e. the wavelet coefficients are two-dimensional. To compress the transformed signal not only the coefficient values, but also their position in time has to be coded. When the signal is an image then the position in time is better expressed as the position in space. After wavelet transforming an image it can be represented using trees because of the subsampling that is performed in the transform. A coefficient in a lower subband can be thought of as having four descendants in the next higher subband as shown in the below Fig.4. The four descendants each also have four descendants in the next higher subband, which gives a quad-tree, with every root having four leafs. A zerotree is defined as a quad-tree of which all nodes are equal to or smaller than the root and the root is smaller than the threshold against which the wavelet coefficients are currently being measured. The tree is coded with a single symbol and reconstructed by the decoder as a quad-tree filled with zeroes. The EZW encoder codes the zerotree based on the observation that wavelet coefficients decrease with scale. In a zerotree all the coefficients in a quad tree are smaller than the threshold if the root is smaller than this threshold. Under this case the whole tree can be coded with a single zerotree (T) symbol.

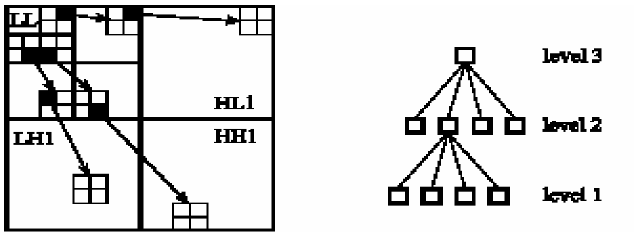


Fig. 4 The inter relationship of multiple levels in wavelet scaled image

EZW encoding uses a predefined scan order to encode the position of the wavelet coefficients. Through the use of zerotree many positions are encoded implicitly. Several scan orders are possible, as long as the lower subbands are completely scanned before going on to the higher subbands. The relations between wavelet coefficients in different subbands, and there scan path is show in Fig. 4 and Fig. 5.

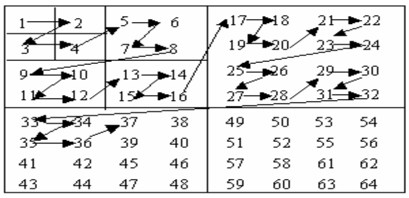


Fig. 5 Scan order for embedded coding

III. BACKPROPAGATION LEARNING ALGORITHM

Step 1: Normalize the inputs and outputs with respect to their maximum values. It is proved that the neural networks work better if input and outputs lie between 0-1. For each training pair, assume there are 'l' inputs given by $\underset{l \times 1}{\{I\}_I}$ and 'n' outputs $\underset{n \times 1}{\{O\}_O}$ in a normalized form.

Step 2: Assume the number of neurons in the hidden layer to lie between l < m <2l

Step 3: [V] Represents the weights of synapses connecting input neurons and hidden neurons and [W] represents weights of synapses connecting hidden neurons and output neurons. Initialize the neurons to small random values usually from -1 to 1. For general problems, λ can be assumed as 1 and the threshold values can be taken as zero.

$$[\mathrm{V}]^0 = \text{[random weights]}$$

$$[W]^0 = \text{[random weights]}$$

$$[\Delta \mathrm{V}]^0 = [\Delta W]^0 = [0]$$

Step 4: For the training data, present one set of inputs and outputs. Present the pattern to the input layer {I}I as function, the output of the input layer may be evaluated as

$$\underset{1\times 1}{\{\mathrm{O}\}_\mathrm{I}} = \underset{1\times 1}{\{\mathrm{I}\}_\mathrm{I}} \qquad (1)$$

Step 5: Compute the inputs to the hidden layer by multiplying corresponding weights of synapses as

$$\underset{m\times 1}{\{\mathrm{I}\}_\mathrm{H}} = \underset{m\times 1}{[\mathrm{V}]^\mathrm{T}} \underset{1\times 1}{\{\mathrm{O}\}_\mathrm{I}} \qquad (2)$$

Step 6: Let the hidden layer units evaluate the output using the sigmoidal function as

$$\{\mathrm{O}\}_\mathrm{H} = \left\{ \begin{matrix} . \\ . \\ \dfrac{1}{\left(1+e^{-I_{Hi}}\right)} \\ . \\ . \\ m\times 1 \end{matrix} \right\}$$

Step 7: Compute the inputs to the output layer by multiplying corresponding weights of synapses as

$$\underset{n\times 1}{\{\mathrm{I}\}_\mathrm{O}} = \underset{n\times m}{[\mathrm{W}]^\mathrm{T}} \underset{m\times 1}{\{\mathrm{O}\}_\mathrm{H}} \qquad (3)$$

Step 8: Let the output layer units evaluate the output using sigmoidal function as

$$\{\mathrm{O}\}_\mathrm{O} = \left\{ \begin{matrix} . \\ . \\ \dfrac{1}{\left(1+e^{-I_{Oj}}\right)} \end{matrix} \right\}$$

The above is the network output.

Step 9: Calculate the error and the difference between the network output and the desired output as for the i[th] training set as

$$\mathrm{E}^\mathrm{P} = \frac{\sqrt{\Sigma\left(T_j - O_{Oj}\right)^2}}{n} \qquad (4)$$

Step 10: Find $\{\mathrm{d}\}$ as

$$\{\mathrm{d}\} = \left\{ \begin{matrix} . \\ . \\ (T_k - O_{Ok})O_{Ok}(1-O_{Ok}) \\ . \\ . \\ n\times 1 \end{matrix} \right\}$$

Step 11: Find $[\mathrm{Y}]$ matrix as

$$\underset{m\times n}{[\mathrm{Y}]} = \underset{m\times 1}{\{\mathrm{O}\}_\mathrm{H}} \underset{1\times n}{\langle \mathrm{d} \rangle} \qquad (5)$$

Step 12: Find

$$\underset{m\times n}{[\Delta W]^{t+1}} = \alpha \underset{m\times n}{[\Delta W]^{t}} + \eta \underset{m\times n}{[\mathrm{Y}]} \qquad (6)$$

Step 13: Find $\underset{m\times 1}{\{e\}} = \underset{m\times n}{[W]} \underset{n\times 1}{\{d\}}$ (7)

$$\{d^*\} = \left\{ \begin{matrix} . \\ . \\ \underset{m\times 1}{e_i} \underset{m\times 1}{(O_{Hi})(1-O_{Hi})} \\ . \\ . \end{matrix} \right\}$$

Find $[\mathrm{X}]$ matrix as

$$\underset{1\times m}{[\mathrm{X}]} = \underset{1\times 1}{\{\mathrm{O}\}_\mathrm{I}} \underset{1\times m}{\langle \mathrm{d}^* \rangle} = \underset{1\times 1}{\{\mathrm{I}\}_\mathrm{I}} \underset{1\times m}{\langle \mathrm{d}^* \rangle} \qquad (8)$$

Step 14 : Find $\underset{1\times m}{[\Delta V]^{t+1}} = \alpha \underset{1\times m}{[\Delta V]^{t}} + \eta \underset{1\times m}{[X]}$ (9)

Step 15 : Find $[V]^{t+1} = [V]^{t} + [\Delta V]^{t+1}$ (10)

$$[W]^{t+1} = [W]^{t} + [\Delta W]^{t+1} \quad (11)$$

Step 16 : Find error rate as

$$errorrate = \frac{\sum E_P}{nset}$$

Step 17: Repeat steps 4-16 until the convergence in the error rate is less than the tolerance value.

IV. APPROACH

The design unit implements the Embedded Zerotree Wavelet coding system with Artificial Neural Networks for data compression. The coding system reads the multiresolution component of the image obtain from the transformation module and pass the data to the decoder unit to retrieve the image back. Fig.6 below shows the implemented embedded zero tree wavelet coding system with backpropagation learning algorithm for image processing.

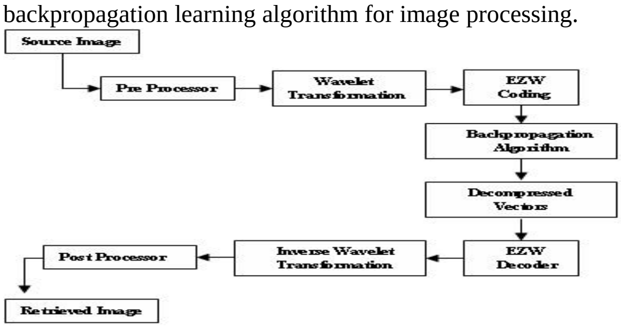


Fig. 6 Block diagram for the proposed EZW coding system with Backpropagation learning algorithm

Before the processing of image data the image are preprocessed to improve the rate of operation for the coding system. Under preprocessing tiling of the original image is carried out. The term “tiling” refers to the partition of the original (source) image into rectangular nonoverlapping blocks (tiles), which are compressed independently, as though they were entirely distinct images. All operations, including component mixing, wavelet transform, quantization and entropy coding are performed independently on the image tiles. Tiling reduces memory requirements, and since they are also reconstructed independently, they can be used for decoding specific parts of the image instead of the whole image. All tiles have exactly the same dimensions, except may be those at the boundary of the image. Arbitrary tile sizes are allowed, up to and including the entire image (i.e., the whole image is regarded as one tile). This unit transforms the input image from time domain to frequency domain and decomposes the original image into its fundamental components.

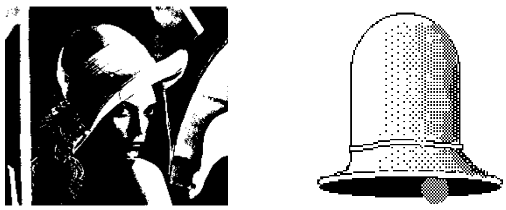
The wavelet transform uses filter banks for the decomposition of preprocessed original image into 3 details and 1 approximate coefficient. The filtering is carried out by convolving the input image with the filter coefficients passed. The Embedded Zerotree Wavelet(EZW) encoder encodes the decomposed image by recognizing the priority of decomposed image pixel. The encoder module calculates a initial threshold for coding given by $T_0 = 2\text{^}(\log_2 x_{max})$. The encoding process is performed using 2 passes namely dominant pass and subordinate pass. The dominant pass scan the coefficient using the threshold and assigned each coefficient with a symbol. Basically there are 4 isolated symbols for coding, they are positive significant(PS), negative significant(NS), isolated zero(IZ) and zerotree root(ZR). These passes are repeated for n cycles reducing the current threshold by 2 until the required data bit rate is reached.

After the image is broken down into symbols, it is necessary to alter them into a form ready for use with the ANN. A file is prepared where each symbol is written as two identical vectors to form a training pair. In other words, the first vector would be the input vector and the second vector would be the desired output. As many of the images tested were extremely large, there were many similar training pairs. To eliminate this redundant information, a program is used to search the training file for similar training pairs and delete them. This not only reduces the number of redundant training pairs, but reduces training time of the ANN. The Backpropagation Learning algorithm is then applied as shown in section 3 for image compression. Finally, the output produced by the ANN in the form of decompressed vectors or windows, is reconstructed and then given as input to EZW decoder.

The decoding unit reconstructs the values by identifying the symbols as positive, negative, zerotree and isolated zerotree. Inverse transformation is the process of retrieving back the image data from the obtained image values. The image data transformed and decomposed under encoding side is rearranged from higher level decomposition to lower level with the highest decomposed level been arranged at the top. Finally, the reconstruction of the obtained decomposed component into their proper graphical representation, and are then compared with the original image.

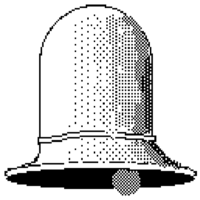
V. RESULTS

A. *Figures and Tables*



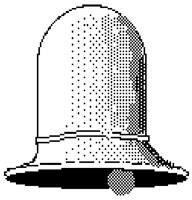
(a) (b)

Fig. 7 Original Image

(a) (b)

Fig.8 Using EZW

(a) (b)

Fig.9 Using EZW with ANN

TABLE I
ERROR RATE COMPARISON TABLE

Error rate comparison	Sample1(256x256 LENA.TIF)	Sample2(128x144 BELL. TIF)
EZW	2.6	1.02
EZW with ANN	2.34	0.61

VI. CONCLUSION

It is observed that embedded zerotree wavelet coding with artificial neural networks is able to achieve good performance with relatively less computational effort. EZW with backpropagation learning algorithm does not require complicated bit allocation procedures like subband coding does, and it does not require prior knowledge of the image source like JPEG does (to optimize quantization tables). EZW also has the desirable property, resulting from its successive approximation quantization.

The desirable result of an embedded bit stream is that it is very easy to generate coded outputs with the exact desired size for generating the training pairs. Discarding of the coded output stream does not produce visual artifacts. Since the truncation only eliminates the least significant refinement bits of coefficients rather than eliminating entire coefficients as is done in subband coding.

Embedded zerotree wavelet coding with artificial neural networks shows approximately 30% more accuracy in retrieving image compare to the existing EZW coding system.

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