Dynamic Selection of Suitable Wavelet for Effective Color Image Compression using Neural Networks and Modified RLC

By Mr. P. Sreenivasulu & Dr. K. Anitha Sheela
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Abstract- Image Compression has become extremely important today with the continuous development of internet, remote sensing and satellite communication techniques. In general, single Wavelet is not suitable for all types of images. This paper proposes a novel approach for dynamic selection of suitable wavelet and effective Image Compression. Dynamic selection of suitable wavelet for different types of images, like natural images, synthetic images, medical images and etc, is done using Counter Propagation Neural Network which consists of two layers: Unsupervised Kohonen (SOFM) and Supervised Gross berg layers. Selection of suitable wavelet is done by measuring some of the statistical parameters of image, like Image Activity Measure (IAM) and Spatial Frequency (SF), as they are strongly correlated with each other. After selecting suitable wavelet, effective image compression is done with MLFFNN with EBP training algorithm for LL2 component. Modified run length coding is applied on LH2 and HL2 components with hard threshold and discarding all other sub-bands which do not effect much the quality (both subjective and objective) (HH2, LH1, HL1 and HH1). Highest CR (191.53), PSNR (78.38 dB), and minimum MSE (0.00094) of still color images are obtained compared to SOFM, EZW and SPIHT.

Keywords: image compression, dynamic selection, wavelet, counter propagation neural network, MLFFNN, EBP.

GJCST-F Classification: F.1.1

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Dynamic Selection of Suitable Wavelet for Effective Color Image Compression using Neural Networks and Modified RLC

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Keywords: image compression, dynamic selection, wavelet, counter propagation neural network, MLFFNN, EBP.

I. Introduction

Uncompressed text, graphics, audio and video data require considerable storage capacity for today’s storage technology. Similarly for multimedia communications, data transfer of uncompressed images and video over digital network require very high bandwidth. For example, an uncompressed still image of size 640x480 pixels with 24 bits of color require about 7.37 M bits of storage and an uncompressed full-motion video (30 frames/sec) of 10 sec duration needs 2.21 G bits of storage and a bandwidth of 221 M bits/sec. Even if there is availability of enough storage capacity, it is impossible to transmit large number of images or play video (sequence of images) in real time due to insufficient data transfer rates as well as limited network bandwidths.

The encryption algorithms aim at achieving confidentiality, not inhibiting unauthorized content duplication. The requirements of these two applications are different. Systems for inhibiting unauthorized content duplication attempt to prevent unauthorized users and devices from getting multimedia data with feasible quality. Such a system could be considered successful if the attacker without the correct key could only get highly degraded contents. Most selective encryption algorithms in the literature are adequate for this purpose. Encryption for confidentiality, on the other hand, must prevent attackers without the correct key from obtaining any intelligible data. Such a system fails if the hacker, after a lot of work, could make out a few words in the encrypted speech or a vague partial image from the encrypted video.

To sum up, at the present state of art technology only solution is to compress Multimedia data before storage and transmission and decompress it at the receiver for play back [1]. Discrete Cosine Transform (DCT) is the Transform of choice in image compression standard such as JPEG. Furthermore DCT has advantages such as simplicity and can be implemented in hardware thereby improving its performance. However, DCT suffer from blocky artifacts around sharp edges at low bit rate.

In general, wavelets in recent years have gained widespread acceptance in signal processing and image compression in particular. Wavelet-based image coders are comprised of three major components: A Wavelet filter bank decomposes the image into wavelet coefficients which are then quantized in a quantizer, finally an entropy encoder encodes these quantized coefficients into an output bit stream (compress image). Although the interplay among these components is important and one has the freedom to choose each of these components from a pool of candidates, it is often the choice of wavelet filter that is crucial in determining the ultimate performance of the coder.

A wide variety of wavelet-based image compression schemes have been developed in recent years [2]. Most of these well known Images coding algorithms use novel quantization and encoding techniques to improve Coding Performance (PSNR). However, they use a fixed wavelet filter built into the...
algorithm for coding and decoding all types of color images whether it is a natural, synthetic, medical, scanned or compound image. But, in this work we propose dynamic selection of suitable wavelet for different types of images to achieve better PSNR and excellent false acceptance and rejection ratio with minimum computational complexity and better recognition rate.

Wavelets provide new class of powerful algorithm. They can be used for noise reduction, edge detection and compression. The usage of wavelets has superseded the use of DCTs for image compression in JPEG2000 image compression algorithm.

This paper is organized as follows: Importance and procedural steps of wavelet transforms is explained in section II, calculation of statistical parameters like IAM, SF and their importance is explained in section III, Training of counter propagation neural network is presented in section IV, Multilayer feed forward neural network with error back propagation training algorithm is explained in section V, proposed method for dynamic selection of suitable wavelet and effective compression with MLFFNN with EBP and modified RLC is explained in section VI, Simulation results are presented in section VII, Conclusion and future scope is given in section VIII.

II. WAVELET TRANSFORM OF AN IMAGE

Wavelet transform is used to decompose an input signal into a series of successive lower resolution reference signals and their associated detail coefficients, which contains the information needed to reconstruct the reference signal at the next higher resolution level.

In discrete wavelet transform, an image signal can be analyzed by passing it through analysis filter bank followed by decimation operation. This analysis filter bank which consists of both low pass and high pass filters at each decomposition stage is commonly used in image compression. When signal passes through these filters, it is split into two bands. The low pass filter, which corresponds to averaging operation, extracts the coarse information of the signal. The high pass filter, which corresponds to differencing operation, extracts the detail information of the signal. The output of the filtering operation is then decimated by two.

A two dimensional transform can be accomplished by performing two separate one dimensional transform(Fig.1) First, the image is filtered along the X-dimension using low pass and high pass analysis filter and decimated by two. Low pass filtered coefficients are stored on the left part of the matrix and high pass filtered on the right. Because of decimation, the total size of transformed image is same as the original image. It is then followed by filtering the sub image along the Y-dimension and decimated by two. Finally the image is split into four bands LL1, HL1, LH1 and HH1 through first level decomposition and second stage of filtering. Again the LL1 band is split into four bands viz LL2, HL2, LH2 and HH2 through second level decomposition.

![Decomposition of the two dimensional DWT](image)

III. STATISTICAL FEATURES OF AN IMAGE

In literature, many image features have been evaluated: they are range, mean, median, different (mean-median), standard deviation, variance, coefficient variance, skewness, kurtosis, brightness energy [6], gray/colour energy, zero order entropy, first-order entropy and second-order entropy. Other spatial characteristics explored include image gradient [6-9], spatial frequency (SF) [10] and spectral flatness measure (SFM) [3]. The result shows that almost all the characteristics have no good correlation with the codec performance. However, the image gradient (IAM) and spatial frequency (SF) have strong correlation with the performance of the wavelet-based compression [6-9, 11]. Image gradient measure is a measure of image boundary power and direction. An edge is defined by a change in gray level in gray scale or colour level in colour image. Image gradient is used to provide an indication of activity for an image in terms of edges.

Saha and Vemuri [7] defined image gradient as:
IV. **Counter Propagation Neural Network**

The counter propagation network is two-layered consisting of two feed forward layers. It performs vector to vector mapping similar to Hetero Associative memory networks. Compared to Bidirectional Associative Memory (BAM), there is no feedback and delay activation during the recall operation mode. The advantage of the Counter propagation network is that it can be trained to perform associative mappings much faster than a typical two-layer network. The counter propagation network is useful in pattern mapping and associations, data compression, and classification.

The network is essentially a partial self-organizing look-up table that maps $\mathbb{R}^n$ into $\mathbb{R}^q$ and is taught in response to a set of training examples. The objective of the counter propagation network is to map input data vectors $X_i$ into bipolar binary responses $Z_i$, for $i=1, 2, ..., p$. We assume that data vectors can be arranged into $p$ clusters, and the training data are noisy versions of vectors $X_i$. The essential part of the counter propagation network structure is shown in Fig.2. However, counter propagation combines two different; novel learning strategies and neither of them is gradient descent technique. The network’s recall operation is also different from previously seen architecture.

The first layer of the network is the Kohonen layer, which is trained in the unsupervised winner-take-all mode. Each of the Kohonen layer neurons represents an input cluster or pattern class, so if the layer works in a local representation, this particular neurons input and response are larger. Similar input vectors belong to the same cluster activate the same $m$'th neuron of the layer. Note that first-layer neurons are assumed to have continuous activation function during learning. However, during recall they respond with the binary unipolar values $0$ and $1$, specifically when recalling with input representing a cluster, for example, $m$ and the output vector $y$ of the kohonen layer becomes

$$y_1 y_2 \ldots y_m \ldots y_p = [0 \ 0 \ 1 \ \ldots \ 0]$$  \hspace{1cm} (3)

Such response can be generated as a result of lateral inhibitions within the layer which is to be activated during recall in a physical system. The second layer is called the Grossberg layer due to its outstar learning mode. This layer, with weights $V_{ij}$ functions in a familiar manner

$$Z = r[Vy]$$  \hspace{1cm} (4)

With diagonal elements of the operator $r$ being a $\text{sgn}()$ function operates component wise on entries of the vector $Vy$. Let us denote the column vectors of the weight matrix $V$ as $V_1, V_2, \ldots, V_m, \ldots, V_p$, now each weight vector $v_m$ for $i=1, 2, \ldots, q$, contains entries that are fanning out from the $m$'th neuron of the kohonen layer. Substituting (3) & (4) then

$$Z = r[V_m]$$  \hspace{1cm} (5)

Where $V_m = [v_{1m} \ v_{2m} \ldots \ v_{qm}]^t$

It is observed that the operation of this layer with bipolar binary neurons is simply to output $z_i = 1$ if $v_{im} > 0$, and $z_i = -1$ if $v_{im} < 0$, for $i=1, 2, \ldots, q$, by assigning any positive and negative values for weights $v_{im}$ highlighted in fig.2. A desired vector-to-vector mapping $x \rightarrow y \rightarrow z$ can be implemented by this architecture. This is done under the assumption that the Kohonen layer responds as expressed in (3). The target vector $z$ for each cluster must be available for learning, so that the
The training rule of Kohonen layer involves adjustment of weight vectors in proportion to the probability of occurrence and distribution of winning events. Using the outstar learning rule of eqn (4), incrementally and not binarily as in eqn (6), it permits us to treat a stationary additive noise in output z in a manner similar to the way we considered distributed clusters during the training of the kohonen layer with “noisy” inputs. The outstar learning rule makes use of the fact that the learning of vector pairs, denoted by the set of mappings \( \{(x_1, z_1), ..., (x_p, z_p)\} \) will be done gradually and thus involve eventual statistical balancing within the weight matrix \( V \). The supervised learning rule for this layer in such a case becomes incremental and takes the form of the out star learning rule.

\[
\Delta V_m = \beta (z - V_m)
\]

(7)

Where \( \beta \) is set to approximately 0.1 at the beginning of learning and reduces gradually during the training process. Index \( m \) denotes the number of the winning neurons in the Kohonen layer. Vectors \( Z_i, i=1, 2 ... p \), used for training are stationary random process vectors with statistical properties that make the training possible.

Note that the supervised outstar rule learning eqn (7) starts after completion of the unsupervised training of the first layer. Also as indicated, the weight of the Grossberg layer is adjusted if and only if it fans out from a winning neuron of the kohonen layer. As training progresses, the weights of the second layer tend to converge to the average value of the desired outputs. Let us also note that the unsupervised training of the first layer produces active outputs at indeterminate positions. The second layer introduces ordering in the mapping so that the network becomes a desirable look-up memory table. During the normal recall mode, the grossberg layer output weight values \( z=V_m \), connects each output node to the first layer winning neuron. No processing, except for addition and \( \text{sgn} \) (net) computation, is performed by the output layer neurons if outputs are binary bipolar vectors.

The network discussed and shown in figure 2(a) is simply feed forward and does not refer the counter flow of signals for which the original network was named. The full version of the counter propagation network makes use of bidirectional signal flow. The entire network consists of doubled network from figure 2(a). It can be simultaneously both trained and operated in the recall mode in arrangement as shown in Figure 2(a). This makes possible to use it as an auto associator according to the formula

\[
\begin{bmatrix}
  z' \\
  x'
\end{bmatrix} = \begin{bmatrix}
  \Gamma_1(x) \\
  \Gamma_1(z)
\end{bmatrix}
\]

(8)

Input signals generated by vector \( x \) input, and by vector \( z \), desired output, propagate through bidirectional network in opposite directions. Vectors \( x' \) and \( z' \) are respective outputs that are intended to be approximations, or auto associations, of \( x \) and \( z \), respectively.

Let us summarize the main features of this architecture in its simple feed forward version. The counter propagation network functions in the recall mode as the nearest match look-up table. The input vector \( x \) finds the weight vector \( w_m \) which is its closest match among \( p \) vectors available in the first layer, then the weights that are entries of vector \( V_m \), which are fanning out from winning mth kohonen’s neuron, after \( \text{sgn} \) (.) computation, become binary outputs. Due to the specific training of the counter propagation network, it outputs the statistical averages of vector \( z \) associated with input \( x \), practically, the network performs as well as a look-up table can do to approximate vector matching. Counter propagation can also be used as a continuous function approximator. Assume that the training pairs are \( (x_i, z_i) \) and \( z_i = g(x_i) \), where \( g \) is a continuous function on the set of input vectors \( \{x\} \). The mean square error of approximation can be made as small as desired by choosing sufficiently large number \( p \) of kohonen layer neurons. However, for continuous function approximation, the network is not as efficient as error back-propagation trained networks, since counter propagation networks can be used for rapid prototyping of mapping and to speed up system development, they typically require orders of magnitude fewer training cycles than usually needed in error back-propagation training.

The counter propagation can use a modified competitive training condition for kohonen layer. Thus it has been assumed that the winning neuron, for which weights are adjusted and one fulfilling condition of yielding the maximum scalar product of the weights and the training pattern vector. Another alternative for training is to choose the winning neuron of the kohonen layer such that the minimum distance criterion is used directly according to the formula

\[
\|x - w_m\| = \min_{i=1,2...p} \|x - w_i\|
\]

(9)

The remaining aspects of weight adaptation and of the training, recall mode. The only difference is that the weights do not have to be renormalized after each step in this training procedure.
V. Multi Layer Feed Forward Neural Network

Consider a feed forward neural network with a single hidden layer denoted by N-h-N, where N is the number of units in the input and output layers, and h is the number of units in the hidden layer. The input layer units are fully connected to the hidden layer units which are in turn fully connected to the output units. The output \( y_j \) of the jth unit is given by

\[
Y_j = f \sum_{i=1}^{N} W_{ji} i + b_j
\]  

(10)

\[
O_k = f \sum_{j=1}^{h} W_{kj} Y_j + b_k
\]  

(11)

Where, in equation (10), \( W_{ji} \) is the synaptic weight connecting the ith input node to the jth hidden layer, \( b_i \) is the bias of the ith unit, \( N \) is the number of input nodes, \( f \) is the activation function, \( Y_j \) is the output of the hidden layer. Analogously, eqn (11) describes the subsequent layer where \( O_k \) is the kth output in the second layer. The networks are trained using the variation of the Back propagation learning algorithm that minimizes the error between network’s output and the desired output. This error is given as follows.

\[
E = \sum_{k=1}^{N} (o_k - d_k)
\]  

(12)

Where \( o \) and \( d \) are the present output and desired outputs of the kth unit of the output layer. For image compression, the number of units in the hidden layer \( h \) should be smaller than that in the input and output layers (i.e. \( h < N \)). The compressed image is the output of hidden units and is of dimension \( h \).

a) Image compression using MLNN

The system for image compression uses two multilayer neural networks. Both networks have \( N \) units in the input and output layers, \( h_1 \) (and \( h_2 \)) units in the hidden layers.

i. Training phase

Fig 3 depicts the system during the training phase, Network-1 is trained to compress and decompress the image (i.e., it is trained to minimize the error between input image and the network output). Then the error is supplied to the second network (Network-2) which is trained to produce the output that is same as its input.

This means that Network-1 is trained to compress and decompress the image and Network-2 is trained to compress and decompress the residual error of Network-1.

Let \( X_1 \) be the input image of Network-1 and \( Y_1 \) is its output. The residual error to be minimized by Network-2 is \( E_{r1} = |Y_1 - X_1| \). The input of Network-2 is given by \( X_2 = X_1 - Y_1 \) and the residual error is given by \( E_{r2} = |Y_2 - (X_1 - Y_1)| \). Both networks are trained to perform an identity mapping using error back propagation training algorithm. The compressed coded image is given by

\[
C-\text{image}= [C_1, C_2]
\]

Where, vectors \( C_1 \) and \( C_2 \) are the outputs for the hidden layer of Network-1 and Network-2. The compression ratio is defined by

\[
CR = \frac{N}{h_1 + h_2}
\]  

(13)

Where \( N \) is the dimension of the image, \( h_1 \) and \( h_2 \) are the number of hidden units in Network-1 and Network-2, respectively. The dimension of the compressed image \( C \) is \( h_1 + h_2 \).

As in Fig (3), the Coder-1 (respectively Coder-2) compresses the input of Network-1(respectively Network-2), and Decoder-1(respectively Decoder-2) decompresses the output of the hidden layer of Network-1(respectively Network-2).

Moreover, the input of Network-2 is the residual error between the reconstructed image and original image. During the simulation, it is found that the error is maximal on the edges of the image and this error has to be compressed in a different way when compared to original images.

![Figure 3](image)

Figure 3: Neural image compression system during the training phase

ii. Operation Phase

a. Image compressor system

After completion of training, Decoder-1 of Network-1 is duplicated and can be used in both image compressor and decompressor systems. Fig (4) shows the image compressor system, which consists of Network-1 and Coder-2 of Network-2. When an image is...
presented to this system, it is compressed by Coder-1 and recovered by Decoder-1; then the difference between the original and the recovered image by Decoder-1 is compressed by Coder-2. The resulted compressed image, C-image is obtained at the output of Coder-1 and Coder-2 blocks. This compressed image can be stored or transmitted.

b. **Image decompression system**

The image decompressor system of Fig.5 consists of Decoder-1 and Decoder-2, which can be used to decompress/decode the output image of the compressor system of Fig.4, compressed image of Coder-1 is decompressed using the duplicate of Decoder-1 in Network-1 and compressed error C2 is decompressed using Decoder-2.

![Figure 4](image4.png)

**Figure 4:** The image compressor system. The input image is compressed into C1 and C2.

![Figure 5](image5.png)

**Figure 5:** The image decompressor/decoder system. The recovered image is obtained by decoding C= [C1, C2].

### VI. **Proposed Method**

Proposed method shown in fig.6 involves following steps. Given color image is separated into three individual RGB components and then calculating IAM, SF values for each component. These three components are applied as inputs to the counter propagation network (CPN) for training in order to get the best wavelet selection dynamically. Parameters used for dynamic selection are PSNR, Compression ratio and MSE as a measure of wavelet based codec performance. Different wavelets are used to transform the images, for these images corresponding PSNR, compression ratios and MSE are determined. Wavelet filters used in this Experiment are biorthogonal6.8, 5.5, daubechies10, 9, COIF4, SYM8. The best wavelet gives highest PSNR, Compression ratios and minimum MSE. Hence, the actual output of selected wavelet is taken as the output of the network for compression. The wavelets are coded in number 1, 2... 6 for six neurons in output layer.

![Figure 6](image6.png)

**Figure 6:** Proposed system

<table>
<thead>
<tr>
<th>Wavelet code</th>
<th>6 digit code</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100000</td>
</tr>
<tr>
<td>2</td>
<td>010000</td>
</tr>
<tr>
<td>3</td>
<td>001000</td>
</tr>
<tr>
<td>4</td>
<td>000100</td>
</tr>
<tr>
<td>5</td>
<td>000010</td>
</tr>
<tr>
<td>6</td>
<td>000001</td>
</tr>
</tbody>
</table>

**Table 1:** 6-Bit Wavelet Code

![Figure 7](image7.png)

**Figure 7:** Proposed compression system

a) **Algorithm for proposed method**
1. Reading a color image from the data base.
2. Separating color image into individual components of RGB.
3. Calculating IAM and SF values for these individual RGB components.
4. IAM and SF values are given as inputs to train counter propagation neural network for dynamic selection.
Individual RGB are decomposed into two levels using selected wavelet.

Discarding sub bands LH1, HL1, and HH1 of first level and HH2 of second level. Dividing LL2-sub band into non overlapping sub blocks of size P x P.

Applying hard threshold to LH2 & HL2-sub bands to discard insignificant coefficients. Encode the threshold coefficients using modified run length coding.

Sub blocks of LL1-sub band is given as input to neural network for training.

Weight matrix between hidden and output layers, hidden layer output and Modified run length encoded sequence are meant for storage or transmission.

b) Algorithm for modified run length coding

i. **Encoding**

1. Read the input vector a (i) and convert it into a single row.
2. Separate the non zero values of input vector a(i), and these non zero values are placed in b(i).
3. Replace the positions of non zero values with 1’s in a(i).
4. Apply run length encoding to a (i).
5. Second part of encoded a (i) and b (i) has to be transmitted.

ii. **Decoding**

1. Read the encoded a (i) and b (i).
2. Generate sequence (010101/101010) of size a(i) and concatenate with a(i)
3. Decode vector a(i)
4. Replace the positions of 1’s in vector a (i) with non zero elements from b (i) and reorder the vector a (i).

Procedural steps for modified run length coding

<table>
<thead>
<tr>
<th>Encoding</th>
<th>% separating non zero values in vector a %</th>
</tr>
</thead>
<tbody>
<tr>
<td>b=[ ]; % null matrix %</td>
<td></td>
</tr>
<tr>
<td>for i=1:length(a) % length of a %</td>
<td></td>
</tr>
<tr>
<td>if abs(a(i))&gt;0 % identifying non zero values of a %</td>
<td></td>
</tr>
<tr>
<td>b=[b a(i)]; % storing non zeros values in b %</td>
<td></td>
</tr>
<tr>
<td>for i=1: length(a) % length of a %</td>
<td></td>
</tr>
<tr>
<td>if abs(a(i))&gt;0 % identifying non zero values of a %</td>
<td></td>
</tr>
<tr>
<td>a(i)=1; % replacing 1’s %</td>
<td></td>
</tr>
<tr>
<td>% applying run length encoding %</td>
<td></td>
</tr>
<tr>
<td>[Enc o/p]= Run length encoder (a)</td>
<td></td>
</tr>
<tr>
<td>% transmit Enc o/p and non zero values vector b %</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decoding</th>
<th>% applying run length decoding %</th>
</tr>
</thead>
<tbody>
<tr>
<td>%Generate a sequence 010101/1010... of length (Enc o/p) and concatenate Enc o/p %</td>
<td></td>
</tr>
<tr>
<td>Seq=010101/1010...(length (Enc o/p)</td>
<td></td>
</tr>
<tr>
<td>t=[Seq Enc o/p]</td>
<td></td>
</tr>
<tr>
<td>[Dec o/p]= Run length decoder (t)</td>
<td></td>
</tr>
<tr>
<td>% create zero matrix with size Dec o/p vector %</td>
<td></td>
</tr>
<tr>
<td>Out= zeros(1, length of Dec o/p)</td>
<td></td>
</tr>
<tr>
<td>for i=1:length(Dec o/p) % length of Dec o/p %</td>
<td></td>
</tr>
<tr>
<td>if Dec o/p(i)=1 % identifying 1’s Dec o/p %</td>
<td></td>
</tr>
<tr>
<td>Out (i)= b (1); % replacing 1’s in Dec o/p with nonzero values in b %</td>
<td></td>
</tr>
<tr>
<td>b=b(2: end); % deleting the replaced values %</td>
<td></td>
</tr>
<tr>
<td>% out is the decoded vector and it should be reordered to get final matrix</td>
<td></td>
</tr>
</tbody>
</table>

**Algorithm for modified run length coding**

**VII. Simulation Results and Discussions**

In this proposed method, different types of images of size 512 x 512 pixels are used and grouped into natural like, animal, flower and plants, satellite, people, space/telescope etc. and synthetic like, Cartoon and computer generated images etc, these are taken arbitrarily from many sources. The proposed algorithm is implemented using MATLAB. The PSNR (peak signal to noise ratio) based on MSE (mean square error) is used as a measure of “quality”, MSE and PSNR are calculated by the following relations:

\[
MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (x_{i,j} - y_{i,j})^2
\]

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

Where M x N is the image size, \(x_{i,j}\) is the input image and \(y_{i,j}\) is the reconstructed image. MSE and PSNR are inversely proportional to each other and high value of PSNR guarantees Good image quality. Mean square error (MSE), visual quality, Compression ratio and PSNR of different images are calculated and compared [14] with existing lossless and lossy compression methods (fig.8). Performance of proposed compression system is varied by varying block size and threshold which is given in table4. Here the highest compression (191.53) with better visual quality, PSNR (78.38) and MSE (0.00094) are obtained. In SOFM, compression ratio, reconstructed image quality is poor. SPIHT and embedded zero wavelet (EZW) gives an acceptable visual quality but with poor compression ratio, and computationally expensive.

All these calculations are made based on single neural network of Fig.3, because no much of difference in quality, MSE, PSNR etc is observed. By using single neural network, training time is reduced dramatically and compression ratio is increased by many folds. Hence it is concluded that only one network is sufficient (fig. 3).

Modified run length encoder’s first part of the output sequence is 0101010101/101010…….Hence, it is not required to transmit because, same sequence can be generated at the receiver. However care must be taken for initial synchronization.
Table 2: I am and SF values for 8 images

<table>
<thead>
<tr>
<th>Image</th>
<th>BIOR6.8</th>
<th>BIOR5.5</th>
<th>DB10</th>
<th>DB9</th>
<th>SYM8</th>
<th>SYM7</th>
<th>COIF5</th>
<th>Best wavelet</th>
<th>Wavelet code</th>
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Table 3: PSNR Values Using Various Wavelets and Best Wavelet for 8 Image

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<th>SYM7</th>
<th>COIF5</th>
<th>Best wavelet</th>
<th>Wavelet code</th>
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<td>73.7118</td>
<td>73.8281</td>
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<td>65.7798</td>
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Table 4

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<th>PSNR</th>
<th>CR</th>
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Table 5

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<th>MSE</th>
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<th>CR</th>
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Figure 8: comparison of various methods with proposed method: (a) PSNR vs Method, (b) CR vs Method

(a) Input image   Reconstructed image with .2 & .3 threshold, 7x7 block size
(b) With .2 & .3 threshold, 7x7 block size

(d) With .2 & .4 threshold, 14 x14 block size  (e) Error image with .2 & .4 threshold, 14 x14 block size

Fig 9: Input, Reconstructed and Error images

Table 6

<table>
<thead>
<tr>
<th>Block size</th>
<th>Hard Threshold</th>
<th>MSE</th>
<th>PSNR</th>
<th>CR</th>
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</table>
Table 7: Performance Comparison of Different Compression Methods, for PS2 of Size 512 x 512

<table>
<thead>
<tr>
<th>Technique</th>
<th>MSE</th>
<th>PSNR</th>
<th>CR</th>
</tr>
</thead>
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<td>Proposed method</td>
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<td>191.53</td>
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<tr>
<td>SPIHT</td>
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<td>34.09</td>
<td>5.95</td>
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<tr>
<td>EZW</td>
<td>7.81</td>
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<td>14.79</td>
</tr>
</tbody>
</table>

Figure 10: comparison of various methods with proposed method: (a) PSNR vs Method, (b) CR vs Method

(a) Input image (ps2)       Reconstructed image (b) with .2 & .3 threshold, 7x7 block size
(c) with .2 & .45 threshold, 10x10 block size
d) With .2 & .4 threshold, 14 x 14 block size

(e) Error image with .2 & .4 threshold, 14 x 14 block size

Fig 11: Input, Reconstructed and Error images

VIII. Conclusion and Future Scope

In this paper a novel approach is proposed for dynamic selection of suitable wavelet for a given image under compression. It is done with counter propagation neural network because, it gives hundreds fold reduction in training time compared to error back propagation neural network and also gives better false acceptance ratio and false recognition ratios. After selecting suitable wavelet based on PSNR and MSE with the help of counter propagation neural network, effective color image compression is done with MLFFNN(Multilayer Feed forward Neural Network) with EBP(error Back propagation) training algorithm for LL2 component. Modified run length coding is applied on LH2 and HL2 components with hard threshold by discarding all other sub-bands (HH2, LH1, HL1 and HH1). Maximum compression ratio of 191.53, PSNR of 78.38 dB, minimum MSE of 0.00094 with hard threshold of 0.2 & 0.4 are obtained for image lena of size 512x512 and compared to SOFM(Self Organizing Feature Maps), EZW(Embedded Zero Wavelet), and SPIHT(Set partition in hierarchical tree) it is found that the proposed method is superior. Dynamic selection of suitable wavelet can be further enhanced with RBF(Radial Basis Functions) networks and effective compression is possible with BAM(Bidirectional Associative memory), to get better mapping accuracy, training time may be reduced and highest compression ratio is possible because, hidden and output layer weight matrices in BAM are transpose to each other.

References Références Referencias


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