CHAPTER 2

HYBRID COMPRESSION SCHEME USING PRECODING BLOCK AND FAST STATIONARY WAVELET TRANSFORMATION

2.1 INTRODUCTION

The previous chapter discuss about the various fundamentals compression techniques and overview of the proposed research work. In this chapter a hybrid compression using precoding block and Fast Stationary Wavelet Transformation have been proposed for standard and compound images. The proposed method is the extension of transformation based compression process. It has two operations 1. precoding, 2. transformation. The first process is precoding in which the original image is divided into \((n \times n)\) non overlapping blocks then each block is combined with the precoding block, which have different level of gray values. When the original pixel value is nearer to the precoding block element, then the original pixel value is rounded near the precoding element data. Secondly the precoded image data has been transformed by FSWT (Fast Stationary Wavelet Transformation) and got the energy compaction .The proposed technique is dually reduce the size of the information by precoding block and transformation. So it is very much suitable for compressing all types of images.

2.2 PREVIOUS ARTS

A lot of previous methods have been implemented for image compression; a discrete cosine transform (Oizumi 2006) express a sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. But it can be done by using real numbers only.
DCTs are equivalent to DFTs of twice the length, operating on real data with even symmetry.

Marpe et al (2000) propose wavelet based compression algorithm. In each iteration DWT decomposes its input into four spatial frequency subbands. However, this method contains smaller code-block dimensions which gives reduced compression performance. It results in increased packet signaling overhead and increased disk thrashing.

Then the Vector quantization (VQ) works by Dividing a large set of points (vectors) into groups having same number of points closest to them. The density matching property of vector quantization is powerful, especially for identifying the density of large and high-dimensioned data. Since data points are represented by the index of their closest centroid, then the Predictive coding estimates a pixel color value based on the pixel color values of its neighboring pixels. To enhance the accuracy of the estimation, the prediction scheme can help to minimize the upper bound of the residual errors from the prediction.

Talukder & Harada (2007) have proposed a Discrete Wavelet Transform for Image Compression and A Model of Parallel Image Compression Scheme for Formal Verification. They used a model of the scheme of verification of parallelizing the compression. It is well known that wavelet transform is especially useful to transform images. They applied it twice: first on rows, second on columns. Upon this, the image matrix was deinterleaved and recursively transformed each sub-band individually further for the compression.
Averbuch et al (1996) Proposed a compression scheme using wavelet and the decomposition has been done using pyramidal multiresolution scheme.

Daechul park Moon Ho Lee (1994) proposed a compression using a best wavelet packet bases exhibit a SFFT (short-time fast Fourier transform) subband decomposition at one source, a wavelet decomposition at another source, or any intermediate wavelet packet decomposition. Based on wavelet analysis adaptive method has been proposed by Hao (2001).

Antonini et al (1992) proposed a method based on two steps. At first the original image was decomposed by the wavelet transform and then according to the Shannon's rate distortion theory, the wavelet coefficients are vector quantized using a multiresolution codebook.

Jong-Han et al (1998) proposed a region based wavelet transform to overcome a problem that wavelet transform is not applicable to the arbitrarily shaped in images.


Jiaxian et al (2007) proposed a data analysis algorithm which analysis the observed data. A 2-dimension data decomposition framework and makes modifications of contexts used by Embedded Block Coding with Optimized Truncation.

Huang et al (1992) proposed a compression technique in which three fast search routines are used in encoding phase of vector Quantization. Shen En Qian (2004) proposed A fast vector quantization algorithm for data compression of hyperspectral imagery.
Hao Xu et al (2007) Proposed a new directional DCT-like transform, whose transform matrix is dependent on directional angle and interpolation used there.

Bo Li et al (2011) proposed a 2-D Oriented Wavelet Transform which can perform integrative oriented transform in arbitrary direction and achieve a significant transform coding gain. To maximize the transform coding gain, two separable 1-Dimensional transforms are implemented in the same direction for local areas with direction consistency. Sub pixel interpolation rules are designed for rectangular subbands generation. In addition, semidirection displacement is adjusted to handle direction mismatch after the first 1-D transform.

Azam Karami et al (2012) Proposed a algorithm based on Discrete Wavelet Transform and Tucker Decomposition (DWT-TD), exploits both the spectral and the spatial information in the images. The core idea behind this technique is to apply TD on the DWT coefficients of spectral bands of HSIs.

The hybrid method used for optimize spatial prediction and the choice of subsequent transform in image compression. Image compression scheme with pruning proposal based on Discrete Wavelet transformation has been proposed by Mozammel & Amina (2012).

The two dimensional discrete wavelet transform has been applied by Kamrul & Koichi (2007) and the detail matrix from the information matrices have been estimated. The reconstructed image is synthesized using estimated detail matrices and information matrix provided by the wavelet transform.
Alarcon et al (2013) proposed a compression method using DWT and thresholding. The image was divided into sub images and each one was decomposed in a vector following a Hilbert Fractal Curve. Wavelet transform was applied to each vector and high frequency components are suppressed based on thresholding.

The hybrid compression using precoding and FSWT (Fast Stationary Wavelet Transform) has been proposed. This method gives the optimal compression by combining the precoding block and Fast wavelet transform for all kind of still images, it is the extension of transformation based compression process. Here the initial compression has been done by precoding matrix then the precoded data has been compressed using FSWT (Fast Stationary Wavelet Transform). So the optimal performance has been achieved, when compared to other methods. The compression ratio can be achieved depend upon the precoding matrix elements. So it is very much suitable to get good compressed data by adjusting the precoding matrix elements.

2.3 PROPOSED HYBRID SYSTEM

The proposed method is the extension of transformation based compression process. It has two operations 1. precoding, 2. transformation. In precoding the original image is divided into (n x n) non overlapping blocks then each block is combined with the precoding block, which have different level of gray values.

The proposed algorithm has been illustrated in block diagram as shown in Figure 2.1.
When the original pixel value is nearer to the precoding block element, the original pixel value is rounded near the precoding element data. Then the precoded image data has been transformed by FSWT (Fast Stationary Wavelet Transform), then the soft Thresholding will be parallely operated on the transformed coefficients and got the energy compaction.

In the decoding section the compressed data is regenerated using Inverse FSWT and get the original image. This proposed technique will dually
reduce the size of the information by precoding block and transformation. So it is very much suitable for compressing all types of still images and achieve high PSNR value. The main compression had been done on the precoding process design.

**Algorithm 1 - for precoding**

**Step 1**: Read the input image I(x,y) And divide it in to NXN matrix

**Step 2**: Construct the MXM precoding block mask which is equal to dividend input image

**Step 3**: Initialize the precoding matrix element by zero

**Step 4**: Update the left diagonal element of the precoding matrix based upon the weight vector value

**Step 5**: Weight value of the precoding matrix element can be calculated by NXN of the original dividend matrix by the formulae

**Step 6**: Update only the diagonal element of the matrix of the precoding block rest of the elements will be added with the original image matrix

**Step 7**: Slide the window for whole image and get the compressed Image.

**Algorithm 2 - for transformation**

**Step1**: Get the precoded image P(x,y)

**Step2**: Perform a single-level Fast Stationary Wavelet Decomposition.

**Step3**: Construct the level 1 approximation and details (A1, H1,V1 and D1) from the coefficients

**Step4**: Perform a decomposition at level 3 of the image (again using the haar wavelet),

**Step5**: Reconstruct approximation at Level 3 and details from coefficients.

**Step 6**: Do the soft Thresholding for the coefficients.

**Step 7**: Regenerate the image by taking Inverse Stationary Wavelet Transform.
2.3.1 Precoding Design

The precoding is nothing but a predefined block holding the different gray level values based upon the weight parameter and the precoding block gray values varies from 2 to 256

Construction of precoding block:

The precoding block is constructed based upon the weight parameter and if the weight parameter value is high means, the precoding block element value will be high and the precoding block element value will be changing based on the weight value for each pixel in the original image non overlapping block. The precoding block is defined in matrix form (2.1).

\[ P = \begin{pmatrix}
    P_{1,1} & P_{1,2} & \ldots & P_{1,r} \\
    P_{2,1} & P_{2,2} & \ldots & P_{2,r} \\
    \vdots & \vdots & \ddots & \vdots \\
    P_{r,1} & P_{r,2} & \ldots & P_{r,r}
\end{pmatrix} \]  

(2.1)

For example 3x3 precoding block given by

\[ P(3,3) = \begin{pmatrix}
    P_{1,1} & P_{1,2} & P_{1,3} \\
    P_{2,1} & P_{2,2} & P_{2,3} \\
    P_{3,1} & P_{3,2} & P_{3,3}
\end{pmatrix} \]  

(2.2)

Weight parameter:

The weight parameter value will be determined based upon the neighborhood pixel values of the original image. The non overlapping blocks weight value will be computed based upon the average value of upper diagonal and lower diagonal pixel value of the original block.

The weight parameter for precoding block element is given by \( W_n = \text{Average (Upper diagonal and lower diagonal value of the original image)} \)
2.3.2 Transformation

To encode a $2^J \times 2^J$ image, an analyzing wavelet $\psi$ and a minimum decomposition level $J-P$ are selected and used to compute DWT of the image. If the wavelet has the complementary scaling function $\phi$, then fast wavelet transform can be used. The transform converts a large portion of the original image to horizontal, vertical, and diagonal coefficients with zero mean and Laplacian-like distribution. Many of these coefficients carries little visual information. It can be quantized and coded to reduce inter-coefficient and coding redundancy. Since the wavelet transform is both computationally efficient and inherently local (since basis functions have a limited duration). So, image subdivision into block is not needed, which eliminate the blocking artifact and it is the major difference compared to the transform coding.

We use a class of orthogonal wavelet bases generalizing the Daubechies functions this is well adapted to numerical calculations. In these bases (for a given accuracy) integral operators satisfying certain analytical estimates have a band-diagonal form, and can be applied to arbitrary functions in a fast manner. In particular, Dirichlet and Neumann boundary value problems for certain elliptic partial differential equations can be solved in $N$ order calculations, where $N$ is the number of nodes in the discretization of the boundary region.

Effectively, this paper provides two schemes for the numerical evaluation of integral operators. The first is a straight forward realization (standard form) of the matrix in the wavelet basis. This scheme is an order $N \log (N)$ procedure (even for such simple operators as multiplication by a function).

Haar Wavelet: The haar function $h_{j, k}$ with integer indices $j$ and $k$ are defined by
Clearly the Haar function $h_{j,k}(x)$ is supported in the dyadic interval $J$

$$h_{j,k} = [2^j(k - 1), 2^j k]$$  \hspace{1cm} (2.4)$$

To obtain a numerical method for calculating the haar coefficients, given $N=2^n$ samples of a function for simplicity it is represented in scaled values as in equation 2.5.

$$S^0_k = 2^{n/2} \int_{2^{k-1}}^{2^k} f(z) dz$$  \hspace{1cm} (2.5)$$

Off an interval of length $2^k$ the haar coefficients interval length is obtained. Then the coefficients can be written as

$$d^l_k = \frac{1}{\sqrt{2}} (s^0_{2^{k-1}} - s^0_{2^{k}})$$  \hspace{1cm} (2.6)$$

We also compute the average

$$S^1_k = \frac{1}{\sqrt{2}} (s^0_{2^{k-1}} - s^0_{2^{k}})$$  \hspace{1cm} (2.7)$$

On the interval of length $2^{n+1}$ repeating this we get the haar coefficients

$$d^{l+1}_k = \frac{1}{\sqrt{2}} (s^l_{2^{k-1}} - s^l_{2^{k}})$$  \hspace{1cm} (2.8)$$

And the averages are,

$$S^{l+1}_k = \frac{1}{\sqrt{2}} (s^l_{2^{k-1}} - s^l_{2^{k}})$$  \hspace{1cm} (2.9)$$
Figure 2.2 Fast stationary wavelet transform

For adaptation here we interchange the row to column and column to row for getting the right information in all approximation, horizontal, vertical and diagonal details. So each of the filter output have different information from the original image.

2.3.3 FSWT

Replacing the haar basis S with vanishing moment S and assuming the coefficient $S_k^o$, $k=1,\ldots,N$ are given, then we can replace the expression with the formulae as in 2.10 and 2.11.

\[
S_k^j = \sum_{n=1}^{2M} h_n S_{n+2k-2}^{j-1} \quad (2.10)
\]

\[
d_k^j = \frac{1}{\sqrt{2}} (d_{2k-1}^0 - d_{2k}^0) \quad (2.11)
\]

Where $S_k^j$ and $d_k^j$ are periodic sequences with the period $2^{n-j}$

After the first, second or third level decomposition has been done, soft thresholding will be parallel operated on the transformed coefficients. Soft thresholding is a wavelet shrinkage in which the values are reduced.
2.4 RESULT AND ANALYSIS

In this section we have almost verified 15 data sets with our proposed methods from that we could find out the MSE, and PSNR. Here two of the error metrics are used to compare the various image compression techniques are Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the MSE and PSNR are given in equation (2.12) and (2.13) respectively.

\[
MSE = \frac{1}{MN} \sum_{y=1}^{N} \sum_{x=1}^{M} [I(x) - I(y)]^2
\]

\[
PSNR = 20 \times \log_{10} \frac{255}{\sqrt{MSE}}
\]

where I(x) is the original image, I(y) is the approximated version (which is actually the decompressed image) and M, N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher.

Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a lower MSE (and a high PSNR), you can recognize that it is a better one. The following output results showing the performance of the proposed compressed technique for different precoding matrix with the transformation.
Visual assessment of the compression results

(a) original, (b) 3x3 precoded image, (c) 1st level compression (d) 2nd level compressed image

(a) original, (b) 5x5 precoded image, (c) 1st level compression (d) 2nd level compressed image

(a) original, (b) 9x9 precoded image, (c) 1st level compression (d) 2nd level compressed image

Figure 2.3 Visual assessment of the compression results

Comparison is performed using various techniques and tabulated in Table 2.1.
Table 2.1 Comparison table for test image

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Compression Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard Image (LENA)</td>
</tr>
<tr>
<td>DCT</td>
<td>28.5</td>
</tr>
<tr>
<td>SPHIT with 3 level Wavelet</td>
<td>30.53</td>
</tr>
<tr>
<td>Fractal Image compression using Quadtree</td>
<td>9.4566</td>
</tr>
<tr>
<td>JPEG 2000</td>
<td>24.926</td>
</tr>
<tr>
<td>PROPOSED</td>
<td>39.99</td>
</tr>
</tbody>
</table>

Figure 2.4 Comparison between compression ratio

2.5 DISCUSSION

The hybrid compression using precoding and FSWT (Fast Stationary Wavelet Transform) has been proposed. This method gives the optimal compression by combining the precoding block and Fast stationary wavelet transform for all kind of still images, it is the extension of transformation based compression process. The initial compression has been done by the precoding matrix then the precoded data has been compressed using FSWT (Fast Stationary Wavelet Transform). It dually reduces the size
of the information by precoding block and transformation. So the optimal performance has been achieved compared to other methods. The compression ratio can be achieved depend upon the precoding matrix elements. So it is very much suitable to get good compressed data by adjusting the precoding matrix elements.

2.6 SUMMARY

The new hybrid compression scheme using precoding block and Fast Stationary Wavelet Transformation have been implemented for standard images and compound images. Results indicated that the proposed method delivered better compression for various image data base. With regard to further improvement to the established system, the next chapter discusses the improved hybrid image compression schemes for compound images.