Compression of Medical Images through DPCM Coding of Multi Resolution and Multidirectional Subbands

Sudha Krishnan and Sudhakar Radhakrishnan
Department of Electronics and Communication Engineering, Mahalingam College of Engineering and Technology, India

Abstract: This paper proposes a compression scheme for medical images through differential pulse code modulation coding of multi resolution and multidirectional subbands. Multi resolution representation of the medical images are obtained through laplacian pyramid which successfully decorrelates the image and thus reduces the redundant information by representing the image by a coarse signal at a lower resolution with several detail signals at successively higher resolutions. This multi scale transform is followed by directional transform to gather the nearby basis functions at the same scale into linear structures. Thus each image is decomposed into low pass subband and several band pass directional subbands that are encoded through DPCM. The proposed scheme was tested on various medical images and numerical results in this work shows the potential of various directional filter banks in the compression of medical images.

Keywords: Medical images, image compression, multi resolution, multi direction subbands, directional filter banks.

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1. Introduction

Medical imaging has a vital role in medicine, especially in the fields of diagnosis and surgical planning. However, imaging devices such as such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), X-rays, Ultrasound imaging etc., continue to generate large amounts of data per patient, which require long-term storage and efficient transmission. Raw data occupy large amounts of storage area and high bandwidth for transmission. These radiology images are of very huge size due to its high resolution and large number of images required for each examination. Studies have shown that the radiology department of a large hospital can produce more than 20 terabytes of image data per year. So, good compression algorithm which aims at reducing the bitrates becomes essential [12].

JPEG [10] is the widely used compression technique for medical images. Though it has become a standard, it suffers from blocking artifacts due to block processing that becomes more evident with increasing compression ratios. To minimize or prevent artifacts new compression technique JPEG2000 [7] based on wavelet transform arrived. Wavelet based image coding has witnessed great success in the past decade [3, 6, 9]. Being separable, conventional 2-D discrete wavelet transform efficiently captures point singularities [5, 8], but fails to capture 1-D singularities, such as edges and contours in images that are not aligned with the horizontal or vertical direction. Therefore, 2D DWT cannot provide efficient approximation for directional features of images. To incorporate directional representation and to exploit the characteristics of medical images for compression, we have adopted in this paper an efficient multi resolution and multidirectional representation of medical images to capture the intrinsic geometrical structures that are key features in visual information through directional filtering of the multi resolution subbands and have experimented on the potential of various filter banks in compressive activity on medical images.

2. Multi Scale Representation

Medical images have unique characteristics of more uniform gray levels compared to natural images i.e., adjacent pixels are highly correlated with lot of redundant information. So, any representation for such images should have small redundancy along with desirable properties such as multi resolution, localization, directionality and anisotrophy, so as to accomplish good compression results. One way of achieving multi scale decomposition is to use a laplacian pyramid as introduced by Burt and Adelson [2], which removes image correlation by combining predictive and transform coding techniques. In this approach, the image is low pass filtered and down sampled to construct a lower resolution coarse signal.
and a detail signal is constructed by computing the difference between original signal and the up sampled and interpolated form of coarse signal. This procedure is repeated on the coarse signal, so as to yield highly decor related detail signal for each iteration and a coarse signal at the end of last iteration.

Let \( X \) be the input image, after a level of LP decomposition, approximation (coarser) signal \( A_1 \) and detail signal \( B_1 \) are formed. If \( j \) level of decomposition is done then final stage output bands which has to be encoded are \( [A_j , B_1, B_2, B_3,...,B_j] \) i.e., at \( j^{th} \) level of decomposition \( A_{j,1} \) subband is decomposed into coarser signal \( A_j \) and detail signal \( B_j \). If all the Approximation bands are stacked one above the other in increasing order of decomposition levels, a pyramid like data structure will be formed which justifies its name.

Instead of encoding the original image, coarse and the detail signals are encoded. This gives a higher compression gain because the detail signal is highly décor related and contains lower dynamic range of values which are coded with fewer bits than the original image. Moreover, the coarse signal is sub sampled which gives further compression gain.

The signal flow graph of the Laplacian Pyramid for two levels is shown in Figure 1, where \( X \) is our original image, \( H \) is an FIR decimation filter, \( G \) is an FIR interpolating filter, \( A \) is the coarse signal and \( B \) is the detail signal.

\[
A = HXH^T \quad (1)
\]

\[
B = X - GAG^T \quad (2)
\]

Superscript \( T \) denotes matrix transpose operation. Given \( A \) and \( B \) we can reconstruct [4] the image \( X \) as follows if the decimation and interpolation filters are orthogonal. The reconstruction signal flow graph is shown in Figure 2.

\[
\hat{X} = G (A - H B H^T) G^T + B \quad (3)
\]

Thus, the image is represented as a series of band-pass filtered images, each sampled at successively sparser densities. When compared to critically sampled wavelet scheme, Laplacian pyramid has the drawback of oversampling. However, frequency scrambling which happens in the wavelet filter bank when a high pass channel after down sampling is folded back into the low frequency band is avoided in each level band pass image of laplacian pyramid as it down samples only the low pass channel.

3. Multidirectional Representation

Among the bands \( [A_j , B_1, B_2, B_3,...,B_j] \) generated after \( j^{th} \) level of decomposition by laplacian pyramid, \( B_1, B_2, B_3,..., B_j \) are subjected to directional filter bank [1] which captures high frequency components representing directionality of images. DFB can maximally decimate the input subbands with perfect reconstruction. It is realized through tree structured two band decomposition systems. For \( n \) level of decomposition, the input is split into \( 2^n \) sub-bands with each sub-band having a wedge-shaped frequency response. Figure 3 shows the wedge-shaped frequency partition for 3 level of decomposition. An increase in the number of levels leads to an increase in the number of wedge-shaped bands and a corresponding increase in the angular resolution of the directional decomposition.

4. Conclusion

Following are the steps to obtain eight directional subbands from each bandpass image of the LP.

1. Input is modulated by \( \pi \) in the frequency variable \( \omega _j \).
2. Modulated output is subjected to two band decomposition filter bank system \( H_0, H_1 \) as shown in Figure 4, whose frequency responses (Diamond shaped) are as shown in Figure 5.
3. The two subband outputs are decimated by Quincunx sampling matrix as given by Equation 4

\[
D = \begin{bmatrix}
1 & -1 \\
-1 & 1
\end{bmatrix}
\]  

(4)

4. Frequency response of the two subband outputs are as shown in Figure 6. Steps 1 to 3 are repeated on these two subbands to form four subbands.

![Frequency response](Image)

Figure 6. Wedge-shaped frequency response of two sub-band outputs.

5. These four subbands are subjected to resampling matrices as given by Equation 5 respectively, which only rearranges the samples and steps 2 to 3 are repeated on each subband to yield eight directional subbands.

\[
R_1 = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}, \quad R_2 = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \quad R_3 = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix}, \quad R_4 = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}
\]  

(5)

Directional decomposition is thus done by the DFB, it is also designed to have perfect reconstruction property [14, 15] or alias free reconstruction. If sum of the decomposed subbands equals the input image then the filter bank is said to possess Perfect Reconstruction. For PR,

\[
H_0(Z) = H_1(Z)
\]  

(6)

and, the polyphase representation matrix \( H_0(Z) \) of analysis filter and polyphase representation matrix \( G_0(Z) \) of synthesis filter should satisfy the following condition.

\[
H_0(Z)G_0(Z) = I
\]  

(7)

If PR is satisfied by the filter pair \( H_0 \) and \( H_1 \) for two band decomposition then the filter bank is PR for any number of cascades of this filter pair.

4. DPCM Coding

Here, we discuss the basic concept behind differential pulse code modulation [13], which has been used for coding the multi resolution and multidirectional subbands obtained. This scheme consists of a DPCM system followed by entropy coder. DPCM possesses good compression capability, simple implementation and highly suitable for lossless compression schemes [17]. DPCM system consists of two main blocks, prediction and quantization. In prediction block, present and previous inputs are used to predict the future data. The difference between predicted and present input called predictor residue is quantized in quantization block. Output sequence of the quantizer, has values around zero and small variance. This is the one which has to be entropy coded. If actual input values are used to predict the future values, it might lead to accumulated errors as process continues. So, in DPCM system, the reconstructed data sample is used to predict the future value. Thus DPCM system transforms the original data sequence into a new sequence with a much smaller variance and dynamic range, which can be coded with fewer bit rates than original data sequence.

![DPCM system](Image)

Figure 7. DPCM system.

Shown in Figure 7 is the DPCM system. Here \( x_n \) is the input at \( n^{th} \) time step, \( P_n \) is the predicted value of the data sample \( x_n \) at the same time instant. The difference between the prediction value \( P_n \) and the input \( x_n \) is the predictor residue \( d_n \). The \( d_n \) is then subjected to quantization. The quantizer output is \( \hat{d}_n \), which is the \( n^{th} \) value of the new sequence to be entropy coded. Simultaneously, \( \hat{d}_n \) and the prediction \( P_n \) are added up to yield \( \hat{x}_n \), which is the reconstructed value of \( x_n \). \( \hat{x}_n \) is the value saved for the prediction of the next data sample. The reconstruction process is as shown in Figure 7-b, the reconstructed value \( \hat{x}_n \) is calculated from \( \hat{d}_n \) and \( P_n \). For our experiment linear predictor, Jayant quantizer and arithmetic coding (entropy coding) were used.

5. Experimental Results

Various medical images such as MRI, CT, X-ray images were subjected to proposed scheme. The LP was constructed through 9/7 biorthogonal wavelet. Haar filter bank, 5/3 filter bank, 9/7 filter bank, PKVA [11] filter bank were used for directional decomposition. Performance analysis of various filter banks in compressing medical images was done through the metrics bit rate (bits per pixel), Peak Signal to Noise Ratio (PSNR) and Structural SIMilarity index (SSIM) [16] as given by:
Using different filter banks. When evaluated that 5/3 filter bank performed a minimum of 6% to maximum of 14% better than other filter banks. Evaluating PSNR values for a large dataset of medical images, it becomes near lossless compression. It can be noted from the tables "evaluation of PSNR there is no perceptible difference between reconstructed and original image and becomes near lossless compression. It can be noted from the tables that at higher ranges of PSNR, 5/3 filter bank consistently performs better than the other filter banks. Evaluating PSNR values for a large dataset of medical images, it was found that 5/3 filter bank performed a minimum of 6% to maximum of 14% better than other filter banks at near lossless compression.

**Figure 8** shows a few test images used in the experiment. Tables 1, 2 and 3 gives PSNR values at different bit rates for images shown in Figures 8-a, c and e respectively using different filter banks. When the quantization step size is varied PSNR values changes. At low quantization step size, bit rate increases along with PSNR values. Above 40 dB of PSNR there is no perceptible difference between reconstructed and original image and becomes near lossless compression. It can be noted from the tables that at higher ranges of PSNR, 5/3 filter bank consistently performs better than the other filter banks. Evaluating PSNR values for a large dataset of medical images, it was found that 5/3 filter bank performed a minimum of 6% to maximum of 14% better than other filter banks at near lossless compression.

Where Mean Squared Error (MSE), X is the original image, Y is the restored image and M x N is the dimension of the image.

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

(9)

\[
\text{PSNR in dB} = 10 \log \left( \frac{255^2}{\text{MSE}} \right)
\]

(8)

Here, \( \mu \) is the mean, \( \sigma \) is the standard deviation, \( C_1=(K_1L)^2 \) and \( C_2=(K_2L)^2 \). L is the dynamic range of pixel values and \( K_1, K_2<<1 \) (we have used in our experiment \( K_1=0.01 \) and \( K_2=0.03 \)).

- **Figure 8** shows a few test images used in the experiment. Tables 1, 2 and 3 gives PSNR values at different bit rates for images shown in Figures 8-a, c and e respectively using different filter banks. When the quantization step size is varied PSNR values changes. At low quantization step size, bit rate increases along with PSNR values. Above 40 dB of PSNR there is no perceptible difference between reconstructed and original image and becomes near lossless compression. It can be noted from the tables that at higher ranges of PSNR, 5/3 filter bank consistently performs better than the other filter banks. Evaluating PSNR values for a large dataset of medical images, it was found that 5/3 filter bank performed a minimum of 6% to maximum of 14% better than other filter banks at near lossless compression.

**Table 1. PSNR values at different bit rates of test image 8-a.**

<table>
<thead>
<tr>
<th>Bitrate (bpp)</th>
<th>HAAR</th>
<th>PKVA</th>
<th>9/7</th>
<th>5/3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4</td>
<td>39.24</td>
<td>39.20</td>
<td>39.21</td>
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<tr>
<td>0.8</td>
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<td>33.34</td>
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<tr>
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<td>30.22</td>
<td>30.28</td>
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**Table 2. PSNR values at different bit rates of test image 8-c.**

<table>
<thead>
<tr>
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<td>1.5</td>
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<td>17.38</td>
<td>17.44</td>
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</table>

**Table 3. PSNR values at different bit rates of test image 8-e.**

<table>
<thead>
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<th>Bitrate (bpp)</th>
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<th>5/3</th>
</tr>
</thead>
<tbody>
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<tr>
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<tr>
<td>0.8</td>
<td>23.26</td>
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<tr>
<td>1.2</td>
<td>17.35</td>
<td>17.32</td>
<td>17.39</td>
<td>17.45</td>
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<tr>
<td>1.5</td>
<td>14.39</td>
<td>14.36</td>
<td>14.42</td>
<td>14.48</td>
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</table>

**MSE measures are adequate for giving an idea of global compression quality, since they are not differentiated enough and measure only one quantity over the whole (large) dataset. PSNR can be used as an indicator for quality, but it is not enough for drawing detailed conclusions on the proposed compression method. So, we have also assessed the scheme through another metrics SSIM Index, whose values lie between 0 and 1. A window of size 8 x 8 was run on the image and SSIM was calculated for every window location. Obtained SSIMs were averaged to give a single index representing the quality of the image. Tables 4 and 5 gives the SSIM index values for image 8-a and c at different bit rates respectively. This again reiterates the same results.**

**Table 4. Structural SIMilarity index values at different bit rates for test image 8-a.**

<table>
<thead>
<tr>
<th>Bitrate (bpp)</th>
<th>HAAR</th>
<th>PKVA</th>
<th>9/7</th>
<th>5/3</th>
</tr>
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<td>0.2635</td>
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</tr>
<tr>
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<tr>
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<td>0.6930</td>
<td>0.7435</td>
<td>0.9786</td>
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<tr>
<td>2.0</td>
<td>0.6957</td>
<td>0.7125</td>
<td>0.7815</td>
<td>0.9960</td>
</tr>
</tbody>
</table>

a) CT image of brain.  b) CT scan of brain.  c) Chest X-ray.  d) Hand X-ray.  e) MRI of human  f) MRI scan of
Table 5. Structural SIMilarity index values at different bit rates for test image 8-c.

<table>
<thead>
<tr>
<th>Bitrate (bpp)</th>
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<th>5/3</th>
</tr>
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</tr>
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<td>0.6512</td>
<td>0.6795</td>
<td>0.7491</td>
</tr>
<tr>
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<td>0.6897</td>
<td>0.6973</td>
<td>0.7644</td>
</tr>
<tr>
<td>2.0</td>
<td>0.7014</td>
<td>0.7546</td>
<td>0.7928</td>
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</table>

6. Conclusions

This paper proposes a compression scheme for medical images through which efficiency of different filter banks in compression activity has been analysed. Medical images which have highly correlated data are décor related, preserving the edge information by multi resolution and multidirectional representation. The DFB served as a valuable tool for carrying out directional decomposition of images. Perfect reconstruction provides robustness to the scheme, as no information is lost during the decomposition process. The proposed scheme also takes the advantage of simplicity of the DPCM encoder. The numerical results shows that 5/3 filter bank had better performance on medical images than other filter banks used in the experiment.

References


**Sudha Krishnan** is currently, Associate Professor in the Department of Electronics and Communication Engineering, Mahalingam College of Engineering and Technology, Pollachi. She holds PhD degree in Information and Communication Engineering from Anna University, Chennai. She has published papers in international, national journals and conference proceedings. Her research areas include digital signal processing, digital image processing and medical image compression.

**Sudhakar Radhakrishnan** is currently, Professor and Head of Electronics and Communication Engineering Department, Mahalingam College of Engineering and Technology, Pollachi, India. He holds a PhD degree in Information and Communication Engineering from PSG College of Technology, Anna University, Chennai since 2007. He has published books and papers in international, national journals and conference proceedings in the area of image processing. His areas of research include digital image processing, wavelet transforms and digital signal processing.