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

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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 in to linear structures. Thus each image is decomposed in to 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 amount 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 décor 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.

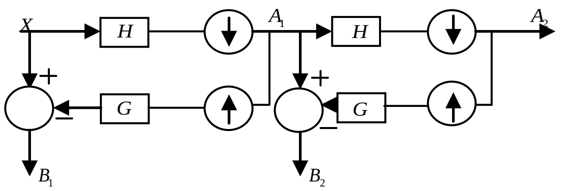


Figure 1. Laplacian pyramid signal flow graph.

The decimation blocks here, indicate decimation by a factor of two. For an input image X the approximation and detail signal are determined as follows:

$$A=HXH^T \quad (1)$$

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

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.

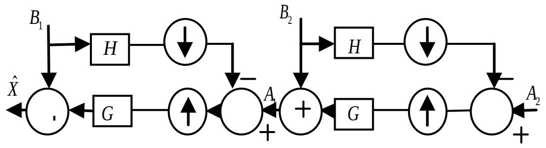


Figure 2. Reconstruction signal flow graph.

$$\hat{X} = G\,(A-HBH^T)\,G^T+B \quad (3)$$

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.

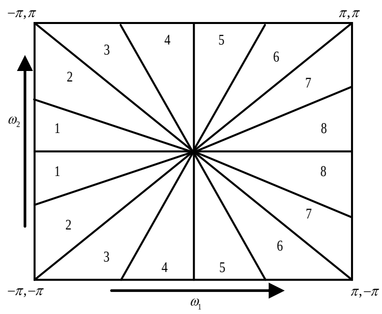


Figure 3. Wedge-shaped frequency response for 8-band decomposition.

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

1. Input is modulated by π in the frequency variable ω_1.
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.

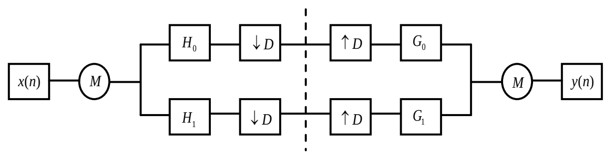


Figure 4. Analysis and synthesis bank for 2-band decomposition.

a) Frequency response of H_0. b) Frequency response of H_1.

Figure 5. Frequency response of analysis filters.

3. The two sub band outputs are decimated by Quincunx sampling matrix as given by Equation 4

$$D = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \tag{4}$$

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

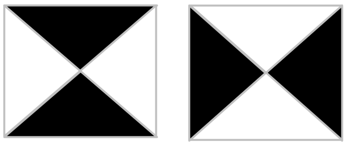


Figure 6. Wedge-shaped frequency response of two sub-band outputs.

5. These four sub bands 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.

$$R_1 = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}, \quad R_2 = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, R_3 = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix}, \quad R_4 = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}. \tag{5}$$

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,

$$H_0(Z)=H_1(-Z) \tag{6}$$

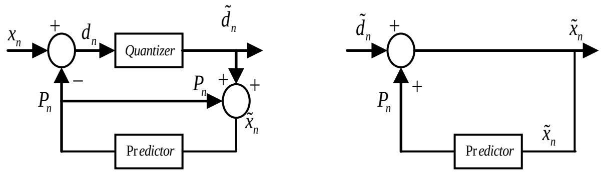
and, the polyphase representation matrix $H_p(Z)$ of analysis filter and polyphase representation matrix $G_p(Z)$ of synthesis filter should satisfy the following condition.

$$H_P(Z)G_P(Z)=I \tag{7}$$

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.



a) Encoder. b) Decoder.

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 $\tilde{d}_n$, which is the n^{th} value of the new sequence to be entropy coded. Simultaneously, $\tilde{d}_n$ and the prediction P_n are added up to yield $\tilde{x}_n$, which is the reconstructed value of x_n. $\tilde{x}_n$ 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 $\tilde{x}_n$ is calculated from $\tilde{d}_n$ 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:

$$PSNR\ in\ dB = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{8}$$

$$MSE = \frac{\sum_i \sum_j (X(i,j) - Y(i,j))^2}{M * N} \tag{9}$$

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.

$$SSIM(X, Y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_X^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{10}$$

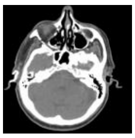
$$\mu_x = \frac{1}{MN}\sum_{i=1}^{MN} x_i \tag{11}$$

$$\sigma_x = \left(\frac{1}{MN}\sum_{i=1}^{MN}(x_i - \mu_x)^2\right)^{\frac{1}{2}} \tag{12}$$

$$\sigma_{xy} = \frac{1}{MN}\sum_{i=1}^{MN}(x_i - \mu_x)(y_i - \mu_y) \tag{13}$$

Here, μ is the mean, σ 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, $K_2 \ll 1$ (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.

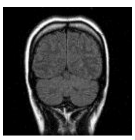


a) CT image of brain.

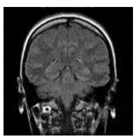
b) CT scan of brain.

c) Chest X-ray.

d) Hand X-ray.



e) MRI of human



f) MRI scan of

Figure 8. Test images used for experiment.

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

Bitrate (bpp)	Filter Banks			
	HAAR	PKVA	9/7	5/3
0.4	24.08	24.62	25.73	27.31
0.6	25.41	26.08	27.87	29.23
0.8	28.42	29.92	31.44	34.25
1.0	31.17	32.63	33.19	35.88
1.2	32.13	33.43	35.16	37.97
1.5	35.84	36.98	37.57	40.24
2.0	38.75	39.24	41.46	43.19

Table 2. PSNR values at different bit rates of test image 8-c.

Bitrate (bpp)	Filter Banks			
	HAAR	PKVA	9/7	5/3
0.4	23.72	24.31	25.65	26.72
0.6	25.46	26.59	26.62	29.91
0.8	27.70	28.30	30.15	32.85
1.0	30.26	30.47	32.23	35.83
1.2	31.05	32.75	33.81	36.70
1.5	34.08	34.63	35.89	39.03
2.0	37.83	38.15	39.68	42.16

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

Bitrate (bpp)	Filter Banks			
	HAAR	PKVA	9/7	5/3
0.4	24.37	26.15	27.20	27.96
0.6	27.54	28.09	28.83	29.19
0.8	28.84	30.13	31.68	33.08
1.0	32.45	33.46	33.87	35.33
1.2	33.38	34.91	35.93	37.10
1.5	36.44	37.57	38.74	41.16
2.0	39.27	40.38	41.51	43.64

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.

Bitrate (bpp)	Filter Banks			
	HAAR	PKVA	9/7	5/3
0.4	0.2516	0.2635	0.2918	0.4626
0.6	0.5164	0.5429	0.5942	0.7652
0.8	0.5241	0.5713	0..6101	0.7986
1.0	0.6032	0.6210	0.6899	0.8421
1.2	0.6248	0.6581	0.7358	0.8934
1.5	0.6567	0.6930	0.7435	0.9786
2.0	0.6957	0.7125	0.7815	0.9960

Table 5. Structural SIMilarity index values at different bit rates for test image 8-c.

Bitrate (bpp)	Filter Banks			
	HAAR	PKVA	9/7	5/3
0.4	0.2862	0.3005	0.3096	0.4851
0.6	0.5217	0.5357	0.5442	0.7746
0.8	0.5833	0.5951	0..6682	0.8981
1.0	0.6335	0.6415	0.6933	0.8712
1.2	0.6512	0.6795	0.7491	0.9654
1.5	0.6897	0.6973	0.7644	0.9868
2.0	0.7014	0.7546	0.7928	0.9987

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.

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