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MULTIWAVELET TRANSFORM IN COMPRESSION OF MEDICAL IMAGES

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Abstract

This paper analyses performance of multiwavelets - a variant of wavelet transform on compression of medical images. To do so, two processes namely, transformation for decorrelation and encoding are done. In transformation stage medical images are subjected to multiwavelet transform using multiwavelets such as Geronimo-Hardin-Massopust, Chui Lian, Cardinal 2 Balanced (Cardbal2) and orthogonal symmetric/antsymmetric multiwavelet (SA4). Set partitioned Embedded Block Coder is used as a common platform for encoding the transformed coefficients. Peak Signal to noise ratio, bit rate and Structural Similarity Index are used as metrics for performance analysis. For experiment we have used various medical images such as Magnetic Resonance Image, Computed Tomography and X-ray images.

Keywords:

Wavelets, Multiwavelets, Medical Image and SPECK

1. INTRODUCTION

Modern medical imaging modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), X-rays, Ultrasound imaging etc., creates images of the internal parts of human body which is of great help to clinicians in diagnosing and treating diseases. The data generated by these modalities in hospitals are of high resolution and large size. Due to its huge size, it requires lot of storage space in its raw state. In telemedicine, teleradiology and teleconsultation, these images have to be transmitted to distant areas through telecommunication links. Due to large size of these medical images, transmission of it necessitates large bandwidth and transmission time. So, medical data has to be compressed before storage or transmission [1]-[2]. Compression algorithms exploit the redundancy and irrelevancy present in the image so as to make a compact representation of the data. There are different types of redundancies such as

- Spatial redundancy – It is the correlation between neighbouring pixel values
- Spectral redundancy – It is the correlation between different spectral bands.
- Temporal redundancy – It is the correlation between adjacent frames.
- Compression algorithms try to remove one or more these redundancies.

Transform based compression schemes which generally comprises of three stages such as, transformation, quantization and coding are more popular in recent days because the transform decorrelate the spatially distributed energy into fewer data samples. Widely used compression standards for medical images are JPEG [3]-[4] and JPEG2000 [5]-[6] which are transform based compression schemes. In JPEG the image is divided into 8 × 8 blocks, each and every block is Discrete Cosine Transformed and quantized using standard quantization table. The blocks are zig-zag scanned and entropy coded using Huffman coding. Here, due to block separation blocking artifacts arises. It does not support resolution or SNR scalability and error resilience. The next evolved standard JPEG2000 was based on Discrete Wavelet Transform, scalar quantization and arithmetic coding. Discrete wavelet transform operates globally on the image and has excellent time frequency localization. This standard supported lot of functionalities such as region of interest coding, error resilience, random access, multicomponent images, resolution and SNR scalability. It had better compression compared to JPEG.

The filter banks used to implement wavelet transform, if satisfies properties such as orthogonality, symmetry, short support and higher approximation order simultaneously then the compression performance improves considerably. Unfortunately due to implementation constraint wavelets do not satisfy all these properties simultaneously. A new class of wavelets, called multiwavelets surmounts this problem. So, this paper analyses the performance of various reported multiwavelets on the compression of medical images.

This paper is organized as follows: Section 2 discusses some key points on multiwavelets and its implementation using filter banks. Results and discussions are presented in section 3 and section 4 concludes the paper

2. MULTIWAVELETS

Like wavelets [7], multiwavelets were also based upon multiresolution analyses (MRA). MRA using wavelets comprises of one scaling function $\phi(t)$ and one wavelet function $\omega(t)$, where as multiwavelets possess many number of scaling functions under one vector denoted as, $\Phi(t) = [\phi_1(t), \phi_2(t)\ldots \phi_N(t)]^T$ and many wavelet functions denoted by $W(t) = [\omega_1(t), \omega_2(t)\ldots \omega_N(t)]^T$ satisfying matrix dilation Eq.(1) and wavelet Eq. (2)

$$\Phi(t) = \sum_k H[k]\phi(2t-k) \tag{1}$$

$$W(t) = \sum_k G[k]\phi(2t-k) \tag{2}$$

So far reported multiwavelets all have N to be 2 i.e., two scaling functions and two wavelet functions [8]-[11]. The coefficients $H[K]$ and $G[K]$ are $N \times N$ matrices instead of scalar values. Fig.1 shows a filter bank that decomposes the image one level. As these filterbanks have taps that are $N \times N$ matrices, the input to the multifilter has to be vectors.

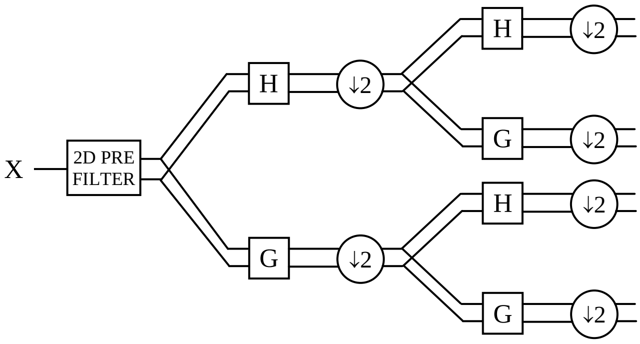

Fig.1. Analysis filter bank for 1 level decomposition

When *N* is two, the input has to be two vectors. This could be achieved by either splitting odd and even sample separately from input or repeating single stream of input into two streams or prefiltering the given scalar input to find a consistent approximation that yields two streams of length half of the input. When prefiltering is done before decomposition a post filter after the synthesis filter bank is applied for de-approximation that yields single stream of input length [12]-[15].

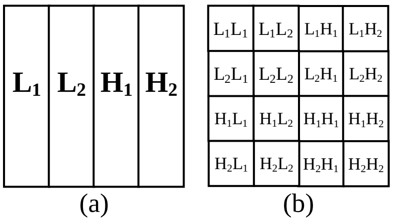

Fig.2. Image subband structure for first level of decomposition (a). filtering along horizontal direction (b). filtering along vertical direction after horizontal direction

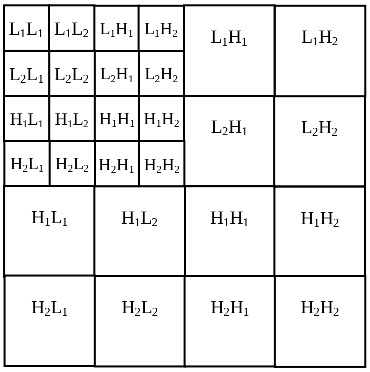

Fig.3. Multiwavelet decomposition subbands for 2-level

Multiwavelets decomposition produce two low pass subbands and two high pass subbands in each dimension. Fig.2 shows the subband structure after one level of multiwavelet decomposition. Wavelet decomposition yields four subbands after one level of decomposition, whereas in multiwavelets sixteen subbands result after first level of decomposition. The next step of the cascade will decompose the low-low-pass sub-matrices L_1L_1, L_2L_1, L_1L_2 and L_2L_2 in a similar manner. Fig.3 shows the two level decomposition subband structure.

Multiwavelet system can simultaneously provide perfect reconstruction while preserving length due to orthogonality of filters, good performance at the boundaries (via linear-phase symmetry), and a high order of approximation (vanishing moments) [11].

3. RESULTS AND DISCUSSION

Various medical images such as Magnetic Resonance Images, Computed Tomography images and X-ray images were used in the experiment. Few such images are shown in Fig.4. The images in the first stage were decomposed 3 levels using multiwavelet filter banks. The multiwavelets considered here are Geronimo-Hardin-Massopust (GHM), Chui Lian (CL), Cardinal 2 Balanced (Cardbal2) and Orthogonal Symmetric/Antisymmetric (SA4). Decompositon using multiwavelets leads to good energy compaction, but after a certain level of decomposition there is no advantage gained due to decomposition except for additional computational complexity. So, we have used in our work only three level of decomposition in all systems. In second stage, for progressive encoding of the coefficients, Set Partitioned Embedded Block Coder (SPECK) [16] is used. It is used in common for encoding all multiwavelet decomposed coefficients. Performance analysis of various multiwavelets in compressing medical images was done through the metrics Peak Signal to Noise Ratio and Structural SIMilarity Index (SSIM) [17] as given by Eq.(3) and Eq.(5),

$$\text{PSNR in dB} = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{3}$$

$$MSE = \frac{\sum_i \sum_j \left(X(i,j) - Y(i,j)\right)^2}{M * N} \tag{4}$$

where, *MSE* stands for Mean Squared Error, *X* is the original image, *Y* is the reconstructed image and $M \times N$ is the dimension of the image.

$$SSIM(X,Y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{5}$$

$$\mu_x = \frac{1}{MN}\sum_{i=1}^{MN} x_i \tag{6}$$

$$\sigma_x = \left(\frac{1}{MN}\sum_{i=1}^{MN}\left(x_i - \mu_x\right)^2\right)^{\frac{1}{2}} \tag{7}$$

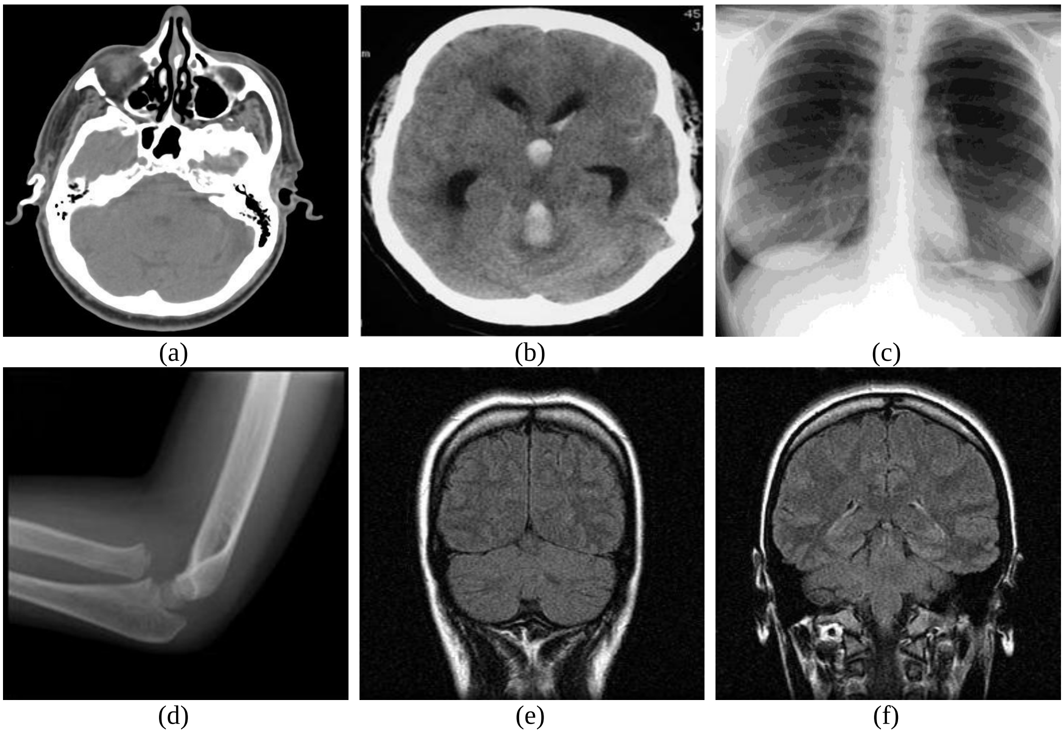

Fig.4. (a) and (b) CT scan of brain (c) Chest X-ray (d) Hand X-ray (e) and (f) MRI scan of head

$$\sigma_{xy} = \frac{1}{MN}\sum_{i=1}^{MN}(x_i - \mu_x)(y_i - \mu_y) \tag{8}$$

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<<1 (we have used in our experiment K_1 = 0.01 and K_2 = 0.03).

PSNR can be used only as an indicator of quality, so we have used SSIM Index to have a closer look at the quality of reconstructed image. Here we have split the image into 8 × 8 subimages and computed SSIM values for all subimages and taken an average of all these values to give an index value between 0 and 1, indicating the quality of reconstructed image.

Table.1. PSNR values for CT image

Bitrate	Multiwavelets			
	GHM	**CL**	**Cardbal2**	**SA4**
0.2	23.52	23.68	25.89	26.92
0.4	26.40	26.43	27.41	28.94
0.6	28.67	29.02	31.67	33.13
0.8	31.03	31.68	33.24	34.96
1.0	33.37	33.79	35.31	36.73
1.5	36.10	36.26	37.85	39.42
2.0	38.64	39.21	40.58	42.86

Table.1 to Table.3 gives the PSNR values of reconstructed images at various bitrates for different multiwavelet systems. It can be noted that Cardbal2 performed better than GHM and CL, whereas SA4 had still better than Cardbal2. At different bitrates the percentage of performance improvement was varying. On an average over all bitrates SA4 had a minimum of 6% to maximum of 12% improvement in its PSNR compared to other multiwavelets. Table.4 shows the SSIM Index values for different reconstructed medical images of various sizes. SSIM index values of SA4 multiwavelet system were also on an average over all bitrates, 3% to 7% better than other multiwavelet systems.

Table.2. PSNR values for MR image

Bitrate	Multiwavelets			
	GHM	**CL**	**Cardbal2**	**SA4**
0.2	22.13	22.74	23.07	24.93
0.4	24.83	25.19	25.86	27.06
0.6	26.75	27.05	29.22	30.91
0.8	29.23	29.94	31.69	33.18
1.0	30.71	30.87	32.84	34.70
1.5	33.19	33.52	34.78	37.03
2.0	36.72	37.04	38.85	40.71

Table.3. PSNR values for X-ray image

Bitrate	Multiwavelets			
	GHM	**CL**	**Cardbal2**	**SA4**
0.2	25.26	25.42	26.31	27.17
0.4	27.43	27.51	28.04	29.27
0.6	29.73	30.02	31.87	33.29
0.8	31.81	32.34	33.84	35.05
1.0	34.06	34.97	35.93	37.10
1.5	36.67	37.14	38.12	40.16
2.0	39.19	39.26	41.28	43.52

Table.4. SSIM Index values for various medical images at a bitrate of 1 bpp

Images (size)	Multiwavelets			
	GHM	CL	Cardbal2	SA4
Brain MR 1 (256 × 256)	0.8358	0.8360	0.8768	0.9104
Brain MR 2 (256 × 256)	0.8362	0.8406	0.8771	0.9133
Brain CT 1 (600 × 650)	0.8634	0.8683	0.9014	0.9309
Brain CT 2 (600 × 650)	0.8643	0.8716	0.9027	0.9383
Chest X-ray (400 × 480)	0.8919	0.8927	0.9264	0.9449
Hand X-ray (400 × 480)	0.8936	0.8950	0.9305	0.9456

4. CONCLUSION

This paper discusses the efficiency of various multiwavelets on compression of medical images. Multiwavelets have the capability of possessing properties such as orthogonality, symmetry, short support and higher approximation order simultaneously. So, they seem to be very good candidate for decorrelation in compression process. Our experiment with various muliwavelets like Geronimo- Hardin-Massopust, Chui Lian, Cardinal 2 Balanced (Cardbal2) and orthogonal symmetric/antsymmetric multiwavelet (SA4) on a variety of medical images such as Magnetic Resonance Imaging, Computed Tomography and X-ray has revealed that GHM and CL were having more or less the same performance, whereas Cardbal2 was performing slightly better. Orthogonal SA4 had the best performance among all the multiwavelets considered. Its PSNR and SSIM Index performance was 6% - 12% and 3% - 7% better than other multiwavelets respectively.

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