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Medical Image Compression Using Multiwavelets for Telemedicine Applications

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Abstract— In this paper we propose an efficient region of interest (ROI) coding technique based on multiwavelet transform, set partitioning in hierarchial (SPIHT) algorithm of medical images. This new method reduces the importance of background coefficients in the ROI code block without compromising algorithm complexity. By using this coding method the compressed bit stream are all embedded and suited for progressive transmission. Extensive experimental results show that the proposed algorithm gives better quality if images using multiwavelets compared to that of the scalar wavelets. The performance of the system has been evaluated based on bits per pixel (bpp) , peak signal to noise ratio (PSNR)and mean square error (MSE).

Index Terms— Medical image compression, Multiwavelet, Region of interest (ROI), SPIHT, Telemedicine, Scalar wavelets, PSNR, MSE.

1 INTRODUCTION

ANALYSIS and compression of medical imagery is an important area of biomedical engineering. Medical image analysis and data compression are rapidly evolving field with growing applications in the healthcare services e.g teleradiology, teleconsultation, e-health, telemedicine and statistical medical data analysis[1]. For the telemedicine, medical image compression and analysis may even be more useful and can play an important role for the diagnosis of more sophisticated and complicated images through consultation of experts[2]. In medical image compression diagnosis and analysis are effective only when compression techniques preserve all the relavant and important image information needed. This is the case of lossless compression. On the otherhand lossy compression is more efficient interms of storage and transmission needs but there is no gauranty to preserve the characteristics needed in medical diagnosis [3]. To avoid the above problem, there may be third option that the diagnostically important region (ROI) of the image is lossless compressed. ROI, a segmentation approach can be used to extract the ROI. These regions are very useful for diagnosis.Hence, the ROI must be compressed by a lossless or a near lossless compression algorithm.

Wavelet based techniques are latest development in the field of medical image compression. In most cases, the wavelet transform produces floating point coefficients and although this allows perfect reconstruction of the original image in theory, the use of finite precision arithmetic together with quantization results in a lossy scheme.Another way to achieve improved compression results over wavelets is to use integer wavelets. Intger wavelet transform demonstrate a significant improvement in reconstructed image quality over the wavelet transform for medical images[4]. For best performance in image compression, wavelet transforms require filters that combine a number of desirable properties, such as orthgonality and symmetry. However, the design possibilities for wavelets are limited because they cannot simultaneously possess all of the desirable properties. The relatively new field of multiwavelets shows promise in obviating some of the limitations of wavelts. Multiwavelets offer more design options and are able to combine several desirable transform features.

This paper is organized as follows: section two region of interest section three describes wavelet and integer wavelet transforms, section four describes multiwavelet, section five describes SPIHT algorithm, section six experimental results section seven describes conclusion and future work.

2 REGION OF INTEREST (ROI)

ROI coding is one of the most important features provided by JPEG-2000. It allows, imposing heterogeneous fidelity constraints to different regions of the image rather than encoding the entire image as a single entity. This property is especially useful for image coding applications, where the image consists of regions that can be encoded at different bit rates, such as compression of medical images [5]. For most medical images, the diagnostically significant information is localized over relatively small regions of interest. In this case, region-based coding for better utilization of the available bit rate since the high quality should be maintained only for the aforementioned diagnostically significant regions and the rest of the image can be encoded at a lower bit rate. Once the region of interest is selected efficiently, the significant region is trans-

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formed using lossless integer multiwavelet transform filter. Then the transformed images are encoded using SPIHT algorithm.

3 Wavelet and integer wavelet transform

Wavelet based techniques are the latest development in the field of image compression. It offers multiresolution capability that is not available in any of the other methods. The low frequency components in the signal that are spread out in time, as well as the high frequency components that are localized in time are captured by a variable-length window[6]. The window is shifted by different units of time in a discrete manner, thus covering the entire signal. The wavelet transform (WT), in general, produces floating point coefficients. Although these coefficients can be used to reconstruct an original image perfectly in theory, the use of finite precision arithmetic and quantization results in a lossy scheme. Recently reversible integer wavelet transforms have been introduced [7]. Lifting is a technique used in constructing second generation wavelets, entirely in the spatial domain. The first generation wavelets are translates and dilates of a single mother wavelet, and Fourier techniques are essential in their construction. The lifting scheme does not use the Fourier technique. It is a very fast method compared to the first generation wavelets. Moreover, the inverse transform is obtained by replacing addition with subtraction and reversing the operations in the forward transform.

4 Multiwavelet transform

Multiwavelets are defined using several wavelets with several scaling functions. Multiwavelets have several advantages in comparision with scalar wavelet. The features such as compact support, orthogonality, symmetry, and higher order approximation are known to be mportant in signal processing. Multiwavelets provide one alternative to the wavelet transform. Multiwavelets are very similar to wavelets but have some important differences. In particular, where as wavelets but have an associated scaling function and wavelet function, multiwavelets have two or more scaling and wavelet function. Multifilter construction methods are already being developed to exploit the useful properties such as ortogonality, symmetry and high order of approximation [8]. However, the multi-channel nature of mutiwavelets also means that the sub band structure resulting from passing a signal through a multifilter bank is different. A single level of standard wavelet decomposition splits the input signal into lowpass and highpass coefficients through filtering and down sampling. A multi-level wavelet filter bank involves iterating the low pass - high pass filtering and down sampling procedure only on the output of the lowpass branch of the previous stage. During a single level of decomposition using a scalar wavelet transform, the 2D image data is replaced with four blocks corresponding to the sub bands. The multiwavelets used here have two channels, so there will be two sets of scaling coefficients and two sets of wavelet coefficients since multiple iterations over the lowpass data are desired, the scaling coefficients for the two channels are stored together. Likewise, the wavelet coefficients for the two channels are also stored together.

3.1 Multi rate Filter Bank

The main idea of multi filter bank is same as filter bank of scalar wavlets.A time scale representation of digital signal is obtained by using different filtering techniques.In case of scalar wavelets the signal is passed through the highpass and lowpass filters to analyze the high and low frequency components.The resolution of signal, which is measure of detail information in the signal, is changed by the filtering operations and the scale is changed by upsampling and downsamplingoperations.On the other hand a multi filter bank is a combination N ordinary filters,each operating on the separate data stream.

3.2 Iteration of Decomposition

Wavelt produces one lowpass subband and one highpass subband in each dimension. Since multiwavelets produces two lowpass subband and two highpass subband in each dimension.The multiwavelets used here have two channels, so ther will be two sets of scaling coefficients and two sets of wavelet coefficients.During a single level of decomposition using a scalar wavelet transform, 2D image data is replaced by four blocks corresponding to the subbands representing either lowpass or highpass filtering in each direction.

5 SPIHT Algorithm

The set partition in hierarchical trees (SPIHT) coding algorithm was proposed by said and Pearlman [9]. SPIHT quantizer achieves good performance by exploiting the spatial dependencies of pixels in different sub bands of a scalar wavelet transform. The method deserves good image quality, high PSNR, Especially for color images. It has been noted [10] that there exists a spatial dependence between pixels in different sub bands in the form of a child-parent relationship. The coder starts with a threshold value that is the largest integer power of two that does not exceed the largest pixel value. Pixel values are evaluated in turn to see if they are larger than the threshold; if not, these pixels are considered insignificant. If a parent and all of its descendents are insignificant, then the coder merely records the parent’s coordinates. Since the children’s coordinates can be inferred from those of the parent, those coordinates are not recorded, resulting in a potentially great savings in the output bit stream. The parent- child relationship in this scheme shown in fig.1. After locating and recording all the significant pixels for the given threshold, the threshold is reduced

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of each stage, all coefficients that have been found to be significant will have their most significant bits recorded.

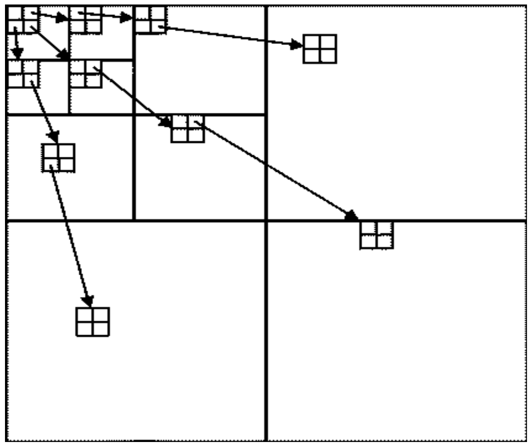

Fig.1.Illustration of parent-child relationship

6 Experimental Results

The original MRI image is taken as test image.Fig.2. (a), (b), and(c) shows that the original image, mask, and background suprresed images.The multiwavelet filters are used in this work are 'GHM','SA4','CL' and also used 'HAAR' scalar wavelet.Table 1 gives the result of comparision of different multiwavelet and scalar wavelet at different bpp interms of PSNR.Table 2 gives the result of comparision of different multiwavelet and scalar wavelet at different bpp interms of MSE.Fig.3 shows the comparision of PSNR values using sacalar wavelet and multiwavelet at different bpp.Fig.4 shows the comparision of MSE values using scalar and multiwavelet at different bpp.

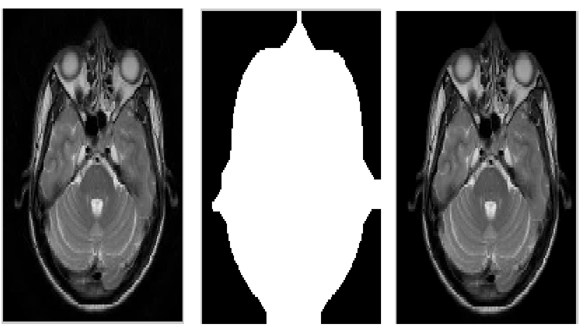

Fig.2 (a) Original image (b) Mask (c) Background suppresed image

TABLE 1
Comparision of PSNR values for wavelet and multiwavelet at differetn BPP

PEAK SIGNAL TO NOISE RATIO				
Bits per pixel	GHM	CL	SA4	HAAR
1.0	33.18	33.50	33.47	27.51
1.2	33.77	34.21	34.38	27.51
1.4	34.44	35.18	35.26	27.51
1.6	35.14	36.10	36.31	27.53
1.8	36.25	37.32	37.54	27.54
2.0	37.14	38.59	38.80	27.54

TABLE 2
Comparision of MSE values for wavelet and multiwavelets at different BPP

MEAN SQUARE ERROR				
Bits per pixel	GHM	CL	SA4	HAAR
1.0	31.24	28.97	29.23	115.26
1.2	27.25	24.63	23.66	115.26
1.4	23.35	19.71	19.34	115.12
1.6	19.88	15.93	15.20	114.72
1.8	15.41	12.03	11.43	114.53
2.0	12.55	8.99	8.55	114.53

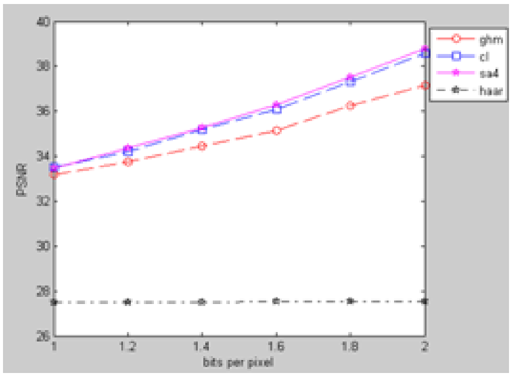

Fig.3.Comparision of PSNR values using scalar wavelets and multiwavelets at level 3

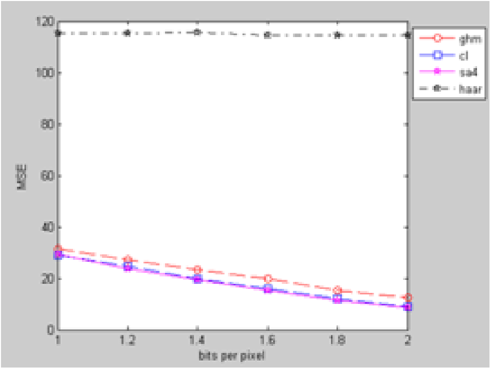

Fig.4. Comparision of MSE values using scalar wavelets and multiwavelets at level 3

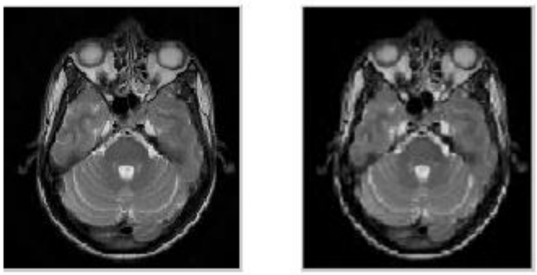

Fig.5 (a) Original image (b) Reconstructed image using SA4 multiwavelet at level 3

6 Conclusion

The performance of the multiwavelets in general depends on image characteristics.Multiwavelets is superior to capture the edges than wavelets.SA4 multiwavelet gives good PSNR at low bitrates.Futurework includes multiwavelets coefficients are implemented via lifting scheme i.e integer multiwavelet transform.

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