Medical Image Compression Using Biorthogonal Spline Wavelet With Different Decomposition

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***Abstract*—With extensive digitization of data and increasing use of telemedicine, most of image data in hospitals are stored in digital form using picture archiving and communication systems. The need for data storage and bandwidth requirements is increasing and lossy compression techniques have become a necessity. The successful use of the wavelet transform in the field of image compression has been extensively studied in literature. In this paper we investigate the performance of Biorthogonal spline wavelet as an effective mode for medical image compression.**

Keywords-Wavelet, Image compression, Medical images, Biorthogonal spline wavelet, Lossy compression

I. Introduction

Image compression is a necessity for most telematic applications and plays a crucial role to ensure good quality of service[1]. It is necessary that medical images be transmitted fast with high reliability so that medical diagnosis at remote locations with poor network connectivity can be easily facilitated. To this end, image compression plays an important role to reduce the bandwidth required during the connection. The challenge however is that while high compression rates are desired, the usability of the reconstructed images depends on certain significant characteristics of the original images which need to be preserved after the compression process has been finished[2].

Image compression reduces the amount of data required to represent an image with close resemblance to the original image by removing redundant information. Three types of redundancies for digital images are generally exploited by compression algorithms. These are, coding redundancy that arises from the representation of the image gray levels, inter pixel redundancy as there is a high similarity between neighboring pixels in a major percentage of the image, and visual redundancy that is based on Human perception of the image information [3]. An image compression system consists of an encoder that exploits the redundancies to represent the image data in a compressed manner. Whereas the decoder is used to reconstruct the original image from the compressed data.

Compression algorithms for image compression can either be lossless or lossy. Images compressed in a lossless manner can be reconstructed without any change in the pixel intensity which limits the amount of compression. However, many applications such as satellite image processing and certain medical and document imaging, cannot afford any losses in their data and are normally compressed using lossless compression methods. Lossy encoding methods are based on trading off achieved in either compression or bit rate with the distortion of the reconstructed image. Lossy encoding for images is usually obtained using transforms which can be converting data from spatial domain to frequency domain. Transform domain removes the redundancies by mapping the pixels into the transform domain before encoding. This results only in a few transform coefficients. For compression, only the few significant coefficients need be encoded, while a majority of the insignificant coefficients can be removed without significantly affecting the quality of the reconstructed image. An ideal transform mapping should be reversible and able to completely decor relate the transform coefficients.

Compressing an image is significantly different than compressing raw binary data[4]. General purpose compression programs can also be used to compress images, but the result obtained are typically less than optimal as images have certain statistical properties which can be exploited by encoders specifically designed for them. Two of the error metrics used to compare the various image compression techniques are the 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

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

measure of the peak error. The mathematical formulae for the two are

and

PSNR = 20 * log10 (255 / sqrt(MSE))

where I(x,y) is the original image, I'(x,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 lower error, and as seen from the inverse relation between the MSE and PSNR, which 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.

An image can be represented as a two-dimentional array of coefficients, each coefficient representing the brightness level of the pixel. Looking from a general perspective, we can't differentiate between coefficients which are important and which are not. Most natural images have smooth colour variations, with the fine details being represented as sharp edges in between the smooth variations. The smooth variations in colour can be termed as low frequency variations and the sharp variations as high frequency variations which can be a prime source for encoding algorithms.

The low frequency components constitute the base of an image, and the high frequency components add upon them to refine the image, thereby giving a detailed image. Separating the smooth variations and details of the image can be achieved using a Discrete Wavelet Transform (DWT). In DWT a low pass filter and a high pass filter are chosen, such that they exactly halve the frequency range between themselves. This filter pair is called the Analysis Filter pair. The process starts by applying the low pass filter for each row of data, thereby getting the low frequency components of the row[5]. But since the low pass filter is a half band filter, the output data contains frequencies only in the first half of the original frequency range, thus by Shannon's Sampling Theorem, they can be subsampled by two, so that the output data now contains only half the original number of samples. Next, the high pass filter is applied for the same row of data, and similarly the high pass components are separated, and placed by the side of the low pass components. This procedure is done for all rows. The reverse is applied to reconstruct the image. For reconstruction the filter pair is called the Synthesis Filter pair. The filtering procedure is exactly the opposite of the decomposition method.

This paper is organized into the following sections. Section II deals with the Biorthogonal spline wavelet, Section III describes the experimental setup with obtained results for medical images and Section IV draws conclusions of our work.

II. BIORTHOGONAL SPLINE WAVELET

The biorthogonal wavelets introduced by Cohen, Daubechies, and Feauveau contain in particular compactly supported biorthogonal spline wavelets with compactly supported duals.In biorthogonal wavelets, separate decomposition and reconstruction filters are defined and hence the responsibilities of *analysis* and *synthesis* are assigned to two different functions (in the biorthogonal case) as opposed to a single function in the orthonormal case [6,7,8].

The biorthogonal scaling function is given by

$$\phi(t) = 2\sum_{n=-\infty}^{\infty} h(n)\phi(2t-n) \qquad \underline{dual} \ \tilde{\phi}(t) = 2\sum_{n=-\infty}^{\infty} \tilde{h}(n)\tilde{\phi}(2t-n)$$

$$\left\langle \phi(t), \tilde{\phi}(t-k) \right\rangle = \delta(k) \qquad \left\langle \phi(2^{-k}t), \tilde{\phi}(2^{-k}t-n) \right\rangle = 2^k \delta(n)$$

Where $h(n)$ and $\tilde{h}(n)$ serve as impulse response of FIR filters and two sets of scaling functions $\phi(t)$ and $\tilde{\phi}(t)$ generate subspaces V_k and $\tilde{V}_k$ respectively. Unlike the orthogonal case, it is possible to synthesize biorthogonal wavelets and scaling functions which are symmetric or antisymmetric and compactly supported.

III. EXPERIMENTAL SETUP

Matlab was used to incorporate the functionality of biorthogonal wavelet and the compression efficiency were computed for the following medical images for various low and high decomposition levels. Images used for our work is displayed below along with some reconstructed image for decomposition and reconstruction values as given in table 1 below.

Table 1: Different values for decomposition and reconstruction used in our experimental setup.

Nr	Nd	Nd	Nd
2	2	4	6
3	5	7	9

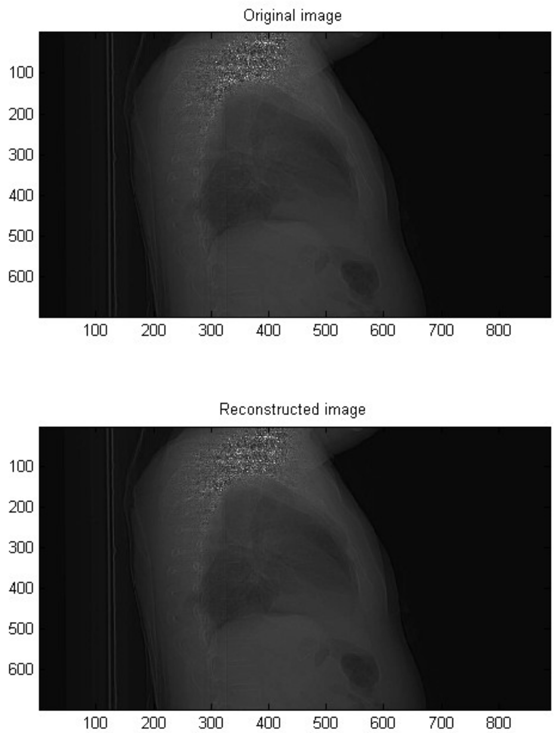

Figure 1: Image 1, Decomposition =2 and Reconstruction =4.

IV.

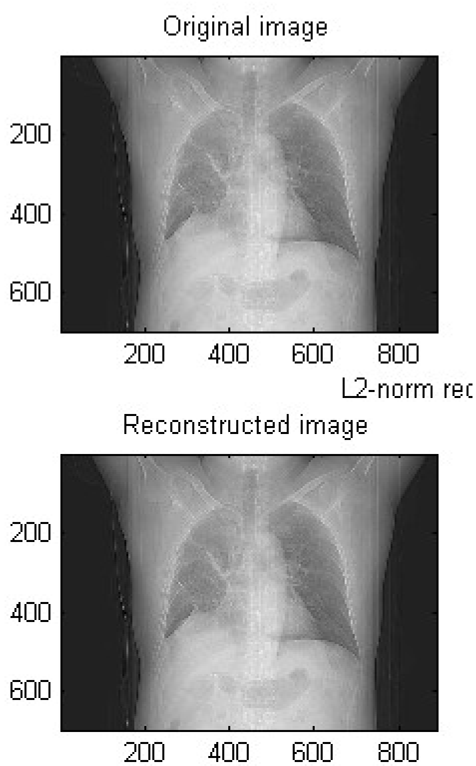

Figure 2 :Image 2, Decomposition =3 and Reconstruction = 5

Table 2 :Compression % for image type 1 and 2 under various decomposition

	Nr	Nd	Compression ratio (%)	L2-Normal Recovery(%)
Image 1	2	2	84.2671	99.9876
Image 1	2	4	84.0343	99.9879
Image 1	2	6	83.8026	99.9885
Image 1	3	5	83.925	99.9924
Image 1	3	7	83.7947	99.9926
Image 1	3	8	83.4675	99.9928
Image 2	2	2	84.2726	99.9949
Image 2	2	4	84.0337	99.995
Image 2	2	6	83.8026	99.995
Image 2	3	5	83.9246	99.9967
Image 2	3	7	83.6947	99.9967
Image 2	3	8	83.4675	99.9966

and reconstruction methods.

V. CONCLUSION

An experimental setup to compare the efficiency of medical image compression using biorthogonal wavelet was implemented. The output of the experimental set up to various reconstruction and decomposition values a fairly stable compression ratio. However the proposed methodology need to be tested with different images. The experimental results are plotted in figure 3.

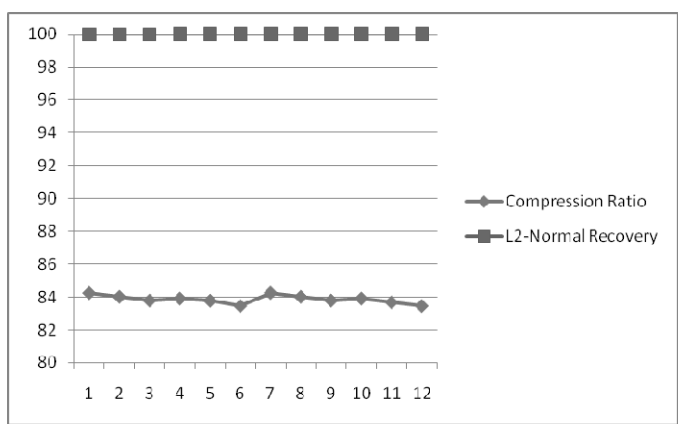

Figure 3 : Compression ratio and L2 Normal recovery plot.

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