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ORIGINAL ARTICLE

Medical Image Compression Using Orthogonal And Biorthogonal Wavelets Transform

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Abstract:

This paper offers a lossless compression method for medical image. The goal is to achieve higher compression ratio by applying different wavelet coefficient of Discrete Wavelet Transform (DWT) and investigate the impact quality of orthogonal and biorthogonal wavelet filters. Selection of wavelet filters to achieve the coding performance of the medical image. Orthogonal wavelet filter are Haar, Debauchees 4, Symlet. The experimental results have been compared and qualitative analysis is done on the basis of time taken for compression and error after decompression for medical image.

KEYWORD:

Discrete wavelets transform Image compressions, orthogonal, biorthogonal

INTRODUCTION

Medical images are required and stored digitally. These images may be very large in size and number and compression offers a means to reduce the cost of storage and increase the speed of transmission. Compression methods are important in many medical applications to ensure fast interactivity through large sets of images. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image. The resolution in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or download [1-2].

Medical data are increasingly represented in digital form. Imaging techniques like magnetic resonance (MR), computerized tomography (CT) and positron emission tomography (PET) are available. The limitations in transmission bandwidth and storage space on one side and the growing size of image datasets on the other side has necessitated the need for efficient methods and tools for implementation. Lossless compression includes Run length coding, dictionary coding, transform coding, entropy coding The entropy coding includes Huffman coding which is a simple entropy coding and commonly used as the final stage of compression, arithmetic coding which is a simple entropy coding for infinite input data with a geometric distribution and finally the universal coding which is also an entropy coding for infinite input data with an arbitrary distribution. Lossless compression includes Discrete Cosine transform (DCT), fractal compression, wavelet compression, vector quantization, linear predictive coding. Lossless image compression schemes often consist of two distinct and independent components which are modeling and coding. The modeling part can be formulated as one in which an image is observed pixel by pixel in some predefined order [3-4].

DWT provides a multiresolution image representation and has become one of the most important tools in image analysis and coding over the last two decades. Image compression algorithms based on DWT [5–8] provide high coding efficiency for natural (smooth) images. In medical image compression, diagnosis is effective only when compression techniques preserve all the relevant information needed without any appreciable loss of information, in case with lossless compression. Lossy compression

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techniques are more efficient in terms of storage and transmission needs because of high compression ratio and the quality. In lossy compression, image characteristics are usually preserved in the coefficients of the domain space in to which the original image is transformed. The quality of the image after compression is very important and it must be within the tolerable limits which vary from image to image and method to method, hence the compression becomes more interesting as a part of qualitative analysis of different types of medical image compression techniques

LOSSLESS IMAGE COMPRESSION:

In lossless compression scheme, the reconstructed image after compression is numerically identical to original image. However lossless compression can only achieve a modest amount of compression. Lossless coding guaranties that the decompressed image is absolutely identical to the image before compression. This is an important requirement for some application domain, e.g. medical imaging, where not only high quality is in demand but unaltered archiving is a legal requirement. The loss of information is not acceptable for medical image compression. Lossless technique also used for the image compression was described in literature [9-11].

WAVELETS IN IMAGE COMPRESSION:

The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the FT and DCT. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem was discussed in [12-13]. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter or longer window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions. Because of this collection of representations we can speak of a multiresolution analysis. In the case of wavelets we normally do not speak about time-frequency representations but about time-scale representations, scale being in a way the opposite of frequency, because the term frequency is reserved for the FT.

A block diagram of a wavelet based image compression system is shown in Figure1. The analysis or compression stage of the system is the forward DWT. Here, the input image is mapped from a spatial domain, to a scale-shift domain. This transform separates the image information into octave frequency subbands. The expectation is that certain frequency bands will have zero or negligible energy content thus, information in these bands can be thrown away or reduced so that the image is compressed without much loss of information. The DWT coefficients are then quantized to achieve compression. Information lost during the quantization process cannot be recovered and this impacts the quality of the reconstructed image. Due to the nature of the transform, DWT coefficients exhibit spatial correlation, those are exploited by quantization algorithms like the EZW and SPIHT for efficient quantization. The quantized coefficients may then be entropy coded this is a reversible process that eliminates any redundancy at the output of the quantizer.

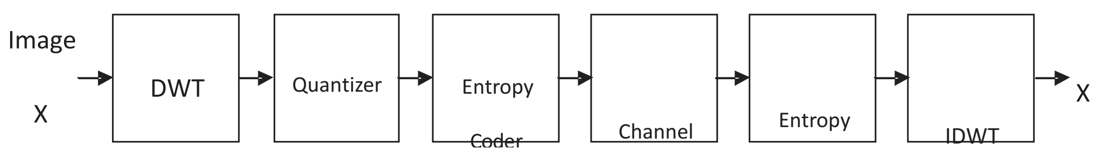


Figure 1; A wavelet based image compression system.

The more an image is compressed, the more information is discarded by the quantizer, the result is a reconstructed image that exhibits increasingly more artifacts. Certain integer wavelet transforms exist that result in DWT coefficients that can be quantized without any loss of information. These result in lossless compression, where the reconstructed image is an exact replica of the input image.

However from literature it is not always clear what is meant by small and large scales image, the large scale is the big picture, while the small scales show the details of image was reported in literatures [14-16].

ORTHOGONAL AND BIORTHOGONAL DWT:

In an orthogonal DWT filter bank, lowpass and highpass filters are related by alternating flip as follows:

$$j(n) = (-1)^n f(N-n) \quad \leftrightarrow \quad J(z) = -z^{-N} F(-z^{-1}). \qquad 1$$

The analysis filters are simply time reversals of the filters:

$$h(n) = f(-n) \quad \leftrightarrow \quad H(z) = F(z^{-1})$$

$$g(n) = j(-n) \quad \leftrightarrow \quad G(z) = J(z^{-1}). \qquad 2$$

Thus all filters in an orthogonal filter bank, can be defined by just one filter the lowpass analysis filter H(z).

An FIR filter bank cannot have both orthogonal and symmetric filters with length greater than 2. In image compression applications it is essential to have symmetric filters for efficient handling of image boundaries. Hence instead of using the orthogonal DWT, the biorthogonal DWT is used where the input function is mapped onto biorthogonal subspaces. Here, the wavelet function used in the analysis stage is different from another. The FIR filters are no longer orthogonal but they are symmetric, the design of discrete liner phase for FIR filter, which is handy for image compression. The equations for the biorthogonal DWT of any x(t) ϵ L2(R) are the biorthogonal basis functions.

$$\tilde{a}_{j,k} = \int x(t) 2^{j/2} \tilde{\phi}(2^j t - k) dt, \qquad \tilde{b}_{j,k} = \int x(t) 2^{j/2} \tilde{\psi}(2^j t - k) dt$$

$$x(t) = 2^{N/2} \sum_k \tilde{a}_{N,k} \phi(2^N t - k) + \sum_{j=N}^{M-1} 2^{j/2} \sum_k \tilde{b}_{j,k} \psi(2^j t - k).$$

$$\{\phi_{i,j}(t), \psi_{i,j}(t)\} \text{ and } \{\tilde{\phi}_{i,j}(t), \tilde{\psi}_{i,j}(t)\} \qquad 3$$

ãj,k and *b?,k* are the scaling and wavelet coefficients respectively together they form the biorthogonal DWT coefficients of *x(t)*.

Fast Wavelet Transform (FWT) can be used for computing the biorthogonal DWT coefficient was discussed in [17, 18]. The lowpass analysis filter *h[n] ? H(z)* corresponds to the analysis scaling function *ϕ(?t)*, the highpass analysis filter *g[n] ? G(z)* corresponds to the analysis wavelet function *ψ?(t),* the lowpass synthesis filter *f[n] ? F(z)* corresponds to the synthesis scaling function *ϕ(t),* the highpass analysis filter *j[n] ? J(z)* corresponds to the synthesis wavelet function *ψ (t).*

The forward and inverse biorthogonal FWT is given by:

$$\tilde{a}_{j,k} = \sum_l h(l-2k) \tilde{a}_{j+1,l}, \qquad \tilde{b}_{j,k} = \sum_l g(l-2k) \tilde{a}_{j+1,l} \qquad \text{(FWT)}$$

$$\tilde{a}_{j+1,k} = \sum_l [f(k-2l) \tilde{a}_{j,l} + j(k-2l) \tilde{b}_{j,l}]. \qquad \text{(IFWT)} \qquad 4$$

In a Perfect Reconstruction (PR) filter bank, the reconstructed scaling coefficients $a_{j+1,k}$ will be equal to the scaling coefficients input to the filter bank, if the biorthogonal filters satisfy the following PR conditions:

$$F(z)H(z) + J(z)G(z) = 2z^{-d} \quad \text{(no-distortion)}$$
$$F(z)H(-z) + J(z)G(-z) = 0 \quad \text{(no-aliasing)} \qquad 5$$

In a biorthogonal filter bank, the no-aliasing PR condition is satisfied by design:

$$g(n) = (-1)^n f(n) \quad \leftrightarrow \quad G(z) = F(-z)$$
$$j(n) = -(-1)^n h(n) \quad \leftrightarrow \quad J(z) = -H(-z). \qquad 6$$

Since the highpass filters are related to the lowpass filters by equation 6, the no distortion PR condition is determined by the frequency response of only the lowpass filters H(z) and F(z). Thus the biorthogonal filter bank is represented by two filters H(z) and F(z).

5.2 Biorthogonal Wavelets:

A biorthogonal wavelet is a wavelet where the associated wavelet transform is invertible but not necessarily orthogonal. Designing biorthogonal wavelets allows more degrees of freedom than orthogonal wavelets. One additional degree of freedom is the possible to construct symmetric wavelet function, biorthogonal wavelet filter and its applications to image compression was discussed in literatures [19-21].

In the biorthogonal case, there are two scaling functions, which may generate different multiresolution analyses, and accordingly two different wavelet functions. So the numbers M and N of coefficients in the scaling sequences may differ. The scaling sequences must satisfy the following biorthogonal condition.

The orthogonality condition is relaxed allowing semi-orthogonal, biorthogonal or non-orthogonal wavelet bases. Biorthogonal Wavelets are families of compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function. In the biorthogonal case, rather than having one scaling and wavelet

function, there are two scaling functions $\phi, \tilde{\phi}$, that may generate different multiresolution analysis and accordingly two different wavelet functions, $\psi, \tilde{\psi}$. $\tilde{\psi}$ is used in the analysis and ψ is used in the synthesis. In addition, the scaling functions $\phi, \tilde{\phi}$ and the wavelet functions $\psi, \tilde{\psi}$ are related by duality in the following equation 7 and 8.

$$\int\int_{j,k}(x)\tilde{\int}_{j,k}(x)\,dx \int 0$$

as soon as $j \neq \acute{j}$ or $k \neq \acute{k}$ and even

$$\int\int_{o,k}(x)\tilde{\int}_{o,k}(x)\,dx \int 0$$

as soon as $k \neq \acute{k}$. (7&8)

5.2.1. Biorthogonal Wavelet Systems:

Figure 5.6 show a one level filter bank associated with a biorthogonal wavelet expansion. By iterating on the lowpass output (e.g., the h0 branch) a multiscale wavelet expansion can be obtained.

Associated with the analysis filter h0 and synthesis filter g0 are the scaling function -(x) and the dual e-(x) respectively defined by

$$\int (x) \int \sqrt{2} \int_n h_o(n) \int (2x \int n)$$

$$\int (x) \int \sqrt{2} \int_n h_o(n) \int (2x \int n) \qquad (9\&10)$$

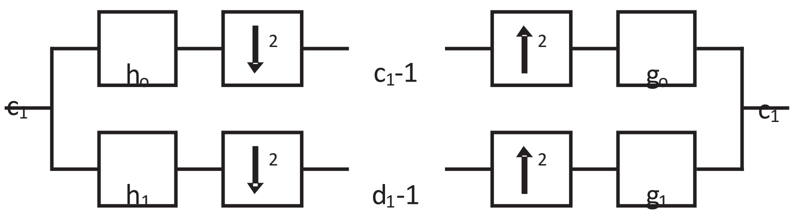


Figure 2 One level biorthogonal filter bank for implementing the biorthogonal wavelet analysis and synthesis

.

Equations (5.14) and (5.15) converges to compactly supported basis functions if both

$$\int_n h_o(n) \int \sqrt{2}$$

And

$$\int_n g_o(n) \int \sqrt{2} \qquad (11\ \&12)$$

are satisfied. Associated with the scaling function f(x) and its dual ef(x) are the wavelets (x) and e (x) defined by

$$\int (x) \int \sqrt{2} \int_n h_1(n) \int (2x \int n)$$

$$\tilde{\int} (x) \int \sqrt{2} \int_n g_1(n) \tilde{\int} (2x \int n)$$

$$(13\&14)$$

The system is then said to be biorthogonal if the following three conditions holds:

$$\int_n \int (x) \tilde{\int} (x \int k)\, dx \int \int (k)$$

$$\int_n \int (x) \tilde{\int} (x \int k)\, dx \int 0$$

$$\int_n \tilde{\int} (x) \int (x \int k)\, dx \int 0$$

(15, 16&17)

Equations (5.20 - 5.22) are equivalent to the following two conditions on the scaling and wavelet filters and their duals

$$\int_n h_o(n)\, g_o\,(n \int 2l) \int \int (l)$$

$$\int_n h_o(n)\, g_1\,(n \int 2l) \int 0$$

$$\int_n h_o(n)\, h_1\,(n \int 2l) \int 0 \qquad (18, 19\&20)$$

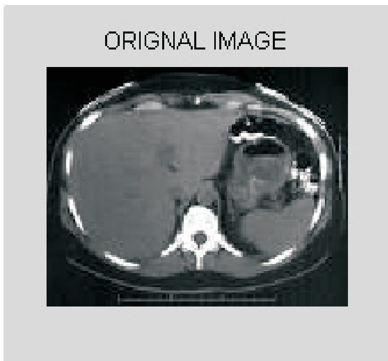
Hence, using the conditions in equation (18-20) a nonlinear constrained optimization problem for designing biorthogonal wavelets can be posed over the free filter parameters. Furthermore, by imposing that the filters be symmetric, linear phase solutions can be obtained.

5.2.4 Biorthogonal is better than Orthogonal Wavelets:

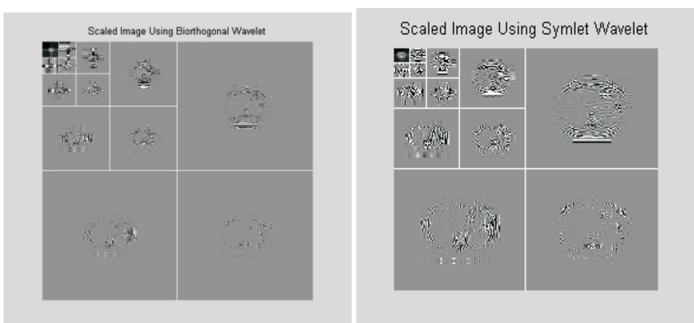
The symmetry property of biorthogonal wavelet is also exploited for the detection. It improves the rate of missed objects as they were centered in the extracted. The results obtained from the orthogonal wavelets are inferior compared to both previous wavelets, because the irregularity of the wavelet affects the detection of objects to a far extent. More pixels from the right areas to the pixels that are processed currently are taken into consideration by the analysis. This leads to a misestimating of these parts. As a result the extracted regions become bigger than the objects and are shifted to the left. This is clearly seen by the results of the data set. The objects are from the right end of the scene to the left end.

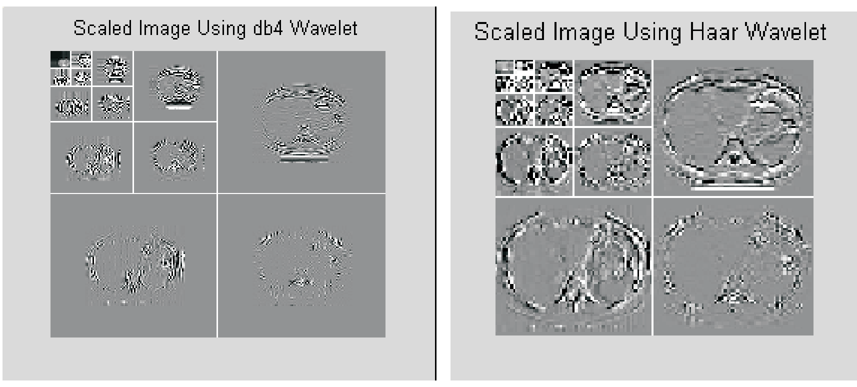
RESULTS:

Original Image

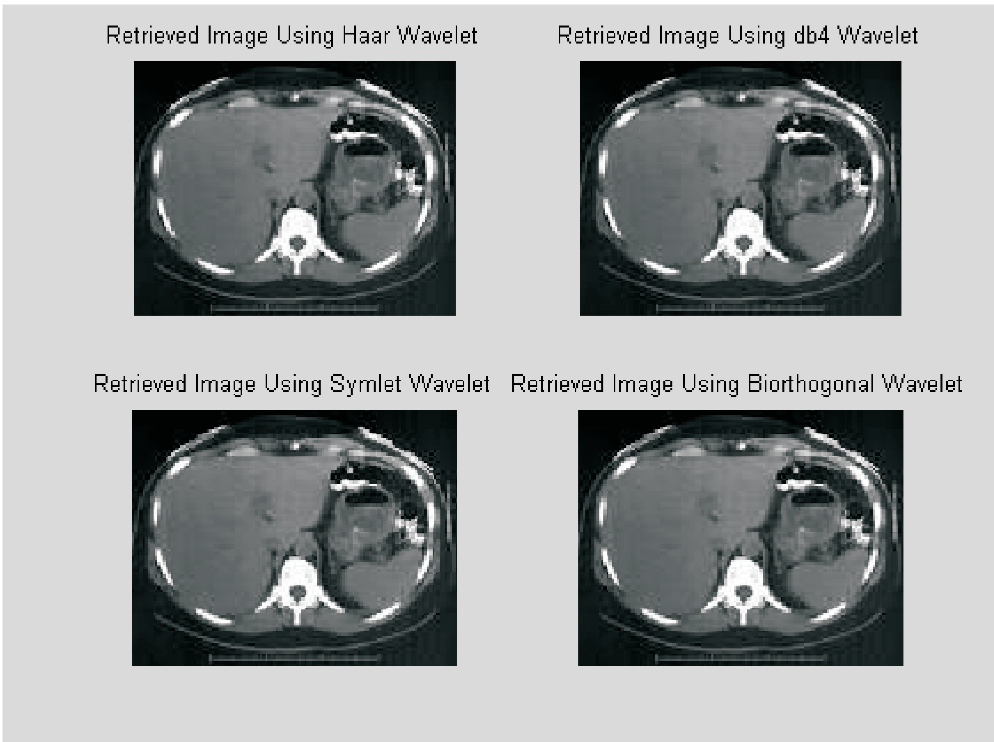


Scale Image of orthogonal & Biorthogonal

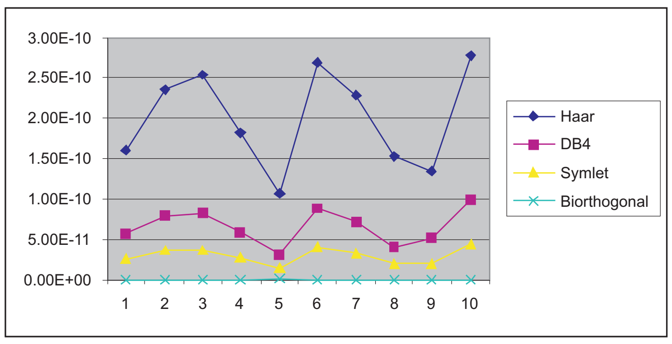




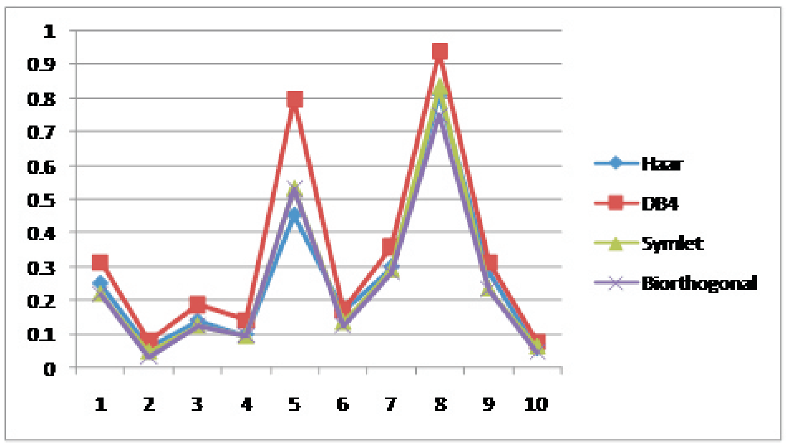
Retrieved Image of Orthogonal & Biorthogonal Wavelet



Time taken for Compression (ms)



Error after Decompression



CONCLUSION:

An experimental setup to compare the efficiency of medical image compression using biorthogonal wavelet was implemented. The result of various reconstructed and decomposition of medical images. The performance of the resulting Orthogonal and Biorthogonal with different coder was studied, the biorthogonal wavelet perform gain over orthogonal wavelets for low and high frequency medical images.

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