MULTI-RESOLUTION ANALYSIS FOR MEDICAL IMAGE COMPRESSION

Mohammed Alhanjouri

Department of Computer Engineering, Islamic University of Gaza, Gaza, Palestine
mhanjouri@iugaza.edu.ps

ABSTRACT

The improvement in image compression filed is mainly related to the need of rapid and efficient techniques for the storage and transmission of data among individuals. To obtain the maximal capabilities of storage and transmission, different compression algorithms should be compared to find the optimal technique for medical image compression.

This work examines the coding properties of the Wavelet, Curvelet, and wave-atom transforms as multi-resolution analysis techniques. Also the comparative study is introduced to determine the best technique for medical image compression. MRI and CT are the images that used to achieve this work. Many parameters should be study for each technique to accomplish the best performance for each one.

In this work, Wave-atom is stated as the best multi-resolution analysis technique for image compression applications.

KEYWORDS

Wave-atom, Curvelet, Wavelet, Medical image compression, Compression Ratio.

1. INTRODUCTION

According to the rise of telemedicine and the use of digital medical images, the fast and efficient coding algorithms are needed for the medical field [1]. Therefore it is led to the development of several techniques that have revolutionized the field of image compression. However, the development of so many techniques has given rise to the problem of deciding any one of these methods possessed the best properties and potentials for effective coding. This problem is of importance task in the medical image processing field where the defacement of information may lead to inaccurate diagnosis. Thus, comparing of different coding algorithms should be needed in order to determine the advantages and disadvantages of each technique [2, 3].

To manipulate an image, we need to understand exactly how the computer stores the image. For a 100 x 150 pixel gray scale image, the image is stored as a 100 x 150 matrix, with each element of the matrix being a number ranging from zero (for black) to some positive whole number (for white). We can use this matrix, and some linear algebra to maximize compression while maintaining a suitable level of detail [4, 5, 6].

A periodic function into a sum of sines and cosines components oscillating functions can be represented by Fourier series. But a weakness of Fourier series is subverted due to discontinuities (Gibbs Phenomenon) and wherefore a large number of terms to reconstruct a discontinuity precisely are required. Development of new mathematical and computational tools based on multi-resolution analysis is a novel concept to overcome limitations of Fourier series. Many fields of contemporary science and technology benefit from multi-scale, multi-resolution analysis tools for maximum throughput, efficient resource utilization and accurate

DOI : 10.5121/ijcsit.2011.3617

computations. Multi-resolution tools render robust behavior to study information content of images and signals in the presence of noise and uncertainty.

Wavelet transform is a well known multi-resolution analysis tool capable of conveying accurate temporal and spatial information. Wavelet transform has been profusely used to address problems in; data compression, pattern recognition, image reconstruction and computer vision. Wavelets better represent objects with point singularities in 1D and 2D space but fail to deal with singularities along curves in 2D. Discontinuities in 2D are spatially distributed which leads to extensive interaction between discontinuities and many terms of Wavelet expansion. Therefore Wavelet representation does not offer sufficient sparseness for image analysis. Following the introduction of Wavelet transform, research community has witnessed intense efforts for development of ridgelets [7], contourlets [8], and Curvelets [9]. These tools have better directional and decomposition capabilities than Wavelets.

Wave-atoms are a recent addition to the collection of mathematical transforms for harmonic computational analysis. Wave-atoms are a variant of 2D Wavelet packets that retain an isotropic aspect ratio. Wave-atoms have a sharp frequency localization that cannot be achieved using a filter bank based on Wavelet packets and offer a significantly sparser expansion for oscillatory functions than Wavelets, Curvelets and Gabor atoms. Wave-atoms capture the coherence of patterns across and along oscillations whereas Curvelets capture coherence along oscillations only. Wave-atoms precisely interpolate between Gabor atoms [10] (constant support) and directional Wavelets [11] (wavelength ~ diameter) in the sense that the period of oscillations of each wave packet (wavelength) is related to the size of essential support by parabolic scaling i.e. wavelength ~ $(\text{diameter})^2$. This work uses three multi-resolution analysis techniques to compress the medical images: Wavelet, Curvelet, and Wave-atom transforms. The comparative study between them is introduced to determine the technique with the best performance.

2. RELATED WORK

Lossless JPEG (Joint Photographic Experts Group) (Wallace, 1991) and lossless Wavelet are the most popular compression algorithms in use today in the medical image compression community [12]. The Digital Imaging and Communications in Medicine (DICOM) group adopts JPEG in their widely file format, but later the wavelet compression algorithm is gaining ground. Actually in November of 2001, the DICOM Working Group added support for the JPEG 2000 standard into the DICOM format. It has also been adopted by ISO as a standard. JPEG 2000 is based on wavelet compression.

In spite of this, a many image compression researches examine the use of compression for applying to medical images. There are several common techniques that have been adopted in the literature to perform this redundancy reduction step including differential pulse code modulation, hierarchical interpolation, bit-plane encoding and multiplicative autoregression. Several popular approaches for encoding are Huffman encoding, Lempel-Ziv encoding, arithmetic encoding and run-length encoding.

Lempel-Ziv is used by Unix in the compress and gzip programs. It is also used in the GIF file format. The Huffman and Lempel-Ziv encoding approaches were tested as used to MRI images in Cohen (1991). It showed that Lempel-Ziv encoding methods achieve higher compression than compression ratios resulting from using Huffman encoding.

As mentioned earlier in this paper, lossless methods are preferred in the medical community. Of these methods, JPEG and Wavelet are most popular. These two compression methods actually gained widespread acceptance as lossy methods. However, each can be made lossless which is the preferred style in medical imaging.

DeVore et al. (1992) showed that the wavelet transform is a promising tool for image compression providing high rates of compression while maintaining good image quality [13].

A comparison of three lossy compression methods (one wavelet and two JPEG) are tried as applied to a variety of 12-bit medical images in conjunction with the Department of Radiology at the Hershey Medical Center (Hershey, PA) (Iyriboz et al., 1999). This work shows the quality of JPEG and wavelet-based compression [14].

With regard to clinically relevant region encoding, not much has been published. In 1994, (Chen et al., 1994) made use of regions of interest using subband analysis and synthesis orvolumetric datasets using wavelets [15]. They followed up this work with (Chen et al., 1995) by using structure preserving adaptive quantisation methods as a means of improving quality for compression rates in the regions of interest [16]. But all of their effort was on lossy approaches.

In the most relevant work [17], (Storm and Cosman, 1997) developed a region based coding approach. They discussed two approaches: one uses different compression methods in each region such as 'contour-texture' coding and subband decomposition coding, and the other uses the same compression method in each region such as the discrete cosine transform but with varying compression quality in each region such as by using different quantisation tables. They used two multiresolution coding schemes: wavelet zerotree coding and the S-transform, and considered only 8 bit images. In their implementation, the regions of interest were selected manually.

A comparison of Curvelet with wavelet based compression was made for standard images like Lena, and Barbara by (Mansoor, 2005) [18]. Curvelet transform has resulted in high quality image compression for natural images. Our implementation offers exact reconstruction, prone to perturbations, ease of implementation and low computational complexity.

(Mohammed, 2009) applied the wave atoms based decomposition for fingerprint image compression, and compared his results with FBI's WSQ fingerprint compression standard. The improvements in PSNR are apparent and distinguished at higher compression ratios and verify the fact that wave atoms multiresolution analysis offers significantly sparser expansion, for oscillatory functions, than other fixed standard transformations such as wavelets, curvelets and Gabor atoms and captures coherence of pattern both along and across oscillations [19].

3. MEDICAL IMAGE COMPRESSION

Image compression [20, 21] aims at removing or at least reducing the redundancy present in the original image representation. In real world images, there is usually an amount of correlation among nearby pixels which can be taken advantage of to get a more economical representation. usually the compression ratio (CR) term is calculate to measure the degree of compression, i.e., the ratio of the total number of bits used for coding the original image to the total number of bits used to code the compressed image. The average number of bits per pixel (bpp) is referred to as the bit rate of the image. One can categorize the image compression schemes into two types:

(i) Lossless. These methods (also called reversible) achieve reduction of the inter-pixel correlation to the degree that the original image can be exactly reconstructed from its compressed image. It is this class of techniques that enjoys wide acceptance in the medical applications such as MRI, CT, Ultrasonic, and X-ray images, since it ensures that no data loss will accompany the compression/expansion process.

(ii) Lossy. The compression achieved via lossless schemes is often inadequate to cope with the volume of image data involved. Thus, lossy schemes (also called irreversible) have to be employed, which aim at obtaining a more compact representation of the image at the cost of some data loss, which however might not correspond to an equal amount of information loss. In other words, although the original image cannot be fully reconstructed, the degradation that it has undergone is not visible by a human observer for the purposes of the specific task. In general terms, one can describe an image compression system as a cascade of one or more of the following stages [22, 23]:

– Transformation. An appropriate transformation is applied to the image for achieving the target of converting it into a different domain where the compression process will be easier. Another way of viewing this is via a change in the basis images composing the original. Correlation and entropy can be lower in the transform domain, and the concentrated needs a small portion of the transformed image.

– Quantization. This is the stage that is mostly responsible for the 'lossy' character of the system. It entails a reduction for the number of bits that used to represent the pixels of the transformed image (also called transform coefficients). Coefficients of low contribution to the total energy or the visual appearance of the image are coarsely quantized (represented with a small number of bits) or even discarded, whereas more significant coefficients are subjected to a finer quantization. Usually, the quantized values are represented via some indices to a set of quantizer levels (codebook).

– Entropy coding (lossless). Further compression is achieved with the aid of some entropy coding scheme where the nonuniform distribution of the symbols in the quantization result is exploited so as to assign fewer bits to the most likely symbols and more bits to unlikely ones. This results in a size reduction of the resulting bit-stream on the average. The conversion that takes place at this stage is lossless, that is, it can be perfectly cancelled. The above process is followed in the encoding (compression) part of the coder/decoder (codec) system. In the decoding (expansion/decompression) part, the same steps are taken in reverse. That is, the compressed bit-stream is entropy decoded yielding the quantized transform coefficients, then 'de-quantized' (i.e., substituting the quantized values for the corresponding indices) and finally inverse transformed to arrive at an approximation of the original image [24].

3.1. Scalar Quantization

Scalar quantization is the process of mapping the pixel values of an image into a smaller number of bins via a parameter called the bin-size. Bin-size refers to the size or number of pixel values that will be mapped into one bin. For instance, if a bin-size often is chosen for mapping an 8 bpp gray level image, then the pixel values 0 to 9 would be mapped into bin 0. Similarly, the pixel values 10 to 19 would be mapped into bin 1, 20 to 29 into bin 3, etc. Table 1 shows a pictorial example. Thus, the image would now be represented by 26 bins instead of 256 gray levels. In addition, this type of pixel mapping increases the correlation of the image. Therefore, scalar quantization allows the image to be further compressed [25].

Table 1. Example of scalar quantization of an excerpt 8 bpp gray level image

Excerpt of a 8 bpp gray level image											Scalar quantized excerpt with a bin-size=10										
13	15	17	19	29	26	23	58	55	57	57	1	1	1	1	2	2	2	5	5	5	5

3.2. Predictive Coding

If an image is highly correlated, then the pixels in a particular neighborhood should have similar values. Predictive coding takes advantage of this correlation by coding the difference between the current pixel value and the preceding pixel value.

Thus, if both pixels have similar values, the error to be coded is very small, and the number of bits per pixel needed to code the image is reduced. Algorithms such as differential pulse code modulation (DPCM) and delta modulation (DM) are based on the above concepts and can reduce the coded data of an 8 bpp image to 1-2 bpp with good quality [26, 27].

4. WAVELET TRANSFORM

Wavelet transform of a time dependent signal $f(t)$ consists of finding a set of coefficients $Cf(a,b)$ that measure the similarity between the signal and a set of scaled (compressed or dilated) and translated (shifted) versions of a function $\psi(t)$ called the mother Wavelet that given by:

$$\psi_{b,a}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

When *"a"* is the time dilation and *"b"* is translation, respectively. Depending on the application, we can selecting the mother Wavelet The coefficients *Cf(a,b)*, or the continues Wavelet transform, are defined by the following inner product:

$$CWT(a,b) = \int_{-\infty}^{+\infty} f(x).\psi^{*}_{b,a}(t)\ dt$$

Where "*" refers to complex conjugate. Wavelet transform of a sampled signal can be obtained by using the following discrete Wavelet transform:

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}}\sum_k f(x)\psi^{*}\left(\frac{n-ka_0^m}{a_0^m}\right)$$

where, a_0^m ,*k* represent a time exponential dilation and time shift, respectively, *n, k,* a_0 are integers; a_0 is the spacing factor (usually chosen equal to "2" for dyadic grid), and *m* (0,1,2,3…), is the dilation scaling (index).

The DWT involves pair of filters for each scaling stage: low-pass and high-pass filters. The large frequency range at the high frequency with the highest time resolution can be covered in the first scale. The higher scales cover the lower frequency ranges with progressively shorter bandwidths and increasingly longer time interval [28, 29].

4.1. Discrete Wavelet Decomposition

The Wavelet transform techniques [30, 31] for data compression have received a great deal of attention over the past several years. Already, image compression encoding standards based on Wavelet are developed, e.g. JPEG2000 that emerges to override traditional standards based on other image processing techniques. Recent researches show that it outperforms its counterparts in terms of image quality for higher compression ratios, up to 100:1. Therefore, we selected the Wavelet technology in the proposed access control system as it provides a cost-effective solution for a real-life application of our system.

4.1.1. Algorithm of the implementation of Wavelet decomposition and reconstruction

The generic step in the orthogonal Wavelet decomposition is splitting the approximation coefficients into two parts. Both approximation and detail coefficients vectors were obtained at a coarser scale after splitting. The detail coefficients assist us to capture the information that lost between two successive approximation coefficients.

Splitting the new approximation coefficient vector is the next step in this algorithm; there is no re-analyses due to successive details. For discrete signals, filter bank with different cutoff frequencies is applied to analyze the signal at different scales.

For analyzing existing high frequencies in the signal, it is passed through a series of high pass filters, while it is passed through a series of low pass filters for analyzing existing low frequencies in the signal.

By changing the filtering operations and the scale, we can state the resolution of the signal, which referring to the amount of detail information in the signal, this is can be obtained by up-sampling and down-sampling (sub-sampling) operations. The aim of sub-sampling a signal is reduction the sampling rate by eliminating some of samples from the signal. Firstly, the signal (sequence) is passing through a half band digital low pass filter with impulse response h[n].

4.1.2. Procedure

1) Loading the image on which decomposition will be performed.

2) Computing the decomposition and the reconstruction coefficients of the non causal filters which will be used in decomposition and reconstruction. Lo_D, Ho_D: low pass and high pass decomposition filters coefficients respectively.

3) Decomposition process which can be described as follows:

Firstly, performing convolution (*circular convolution)* between the input rows and the low pass and high pass decomposition filters coefficients. Secondly, down sampling the columns by keeping the even indexed columns. Thirdly, performing convolution (*circular convolution)* between the input columns and the low pass and high pass decomposition filters coefficients. Finally, down sampling the rows by keeping the even indexed rows.

The previous steps are repeated once for second level decomposition, and twice for third level decomposition which we used in our system.

After carrying out the multiresolution Wavelet decomposition, we used scalar quantizers in order to quantize the coefficients of the decomposed image and map them into different bins. Since the detail images contain the high frequency content of the image (i.e., harder to see visually), their coefficients were coarsely quantized by using only a few bins for mapping the pixel values after the Wavelet Transform (WT). However, we applied a more accurate scalar quantizer to the low pass image which simply truncated and mapped, if necessary, the pixel values of the low pass image to values between 0 and 255. Since the low pass image contains the information which is more critical to visual interpretation of the image, this approach maintained good image quality in the reconstructions. Finally, a combination of Run Length Coding (RLC) and Huffman Coding was applied to the coefficients to get the final compression as shown in figure 1. The number of decompositions (levels in the pyramid) and coarseness of scalar quantizers (i.e., binsize) were varied in order to find the maximum compression ratio that gave reasonable PSNR values.

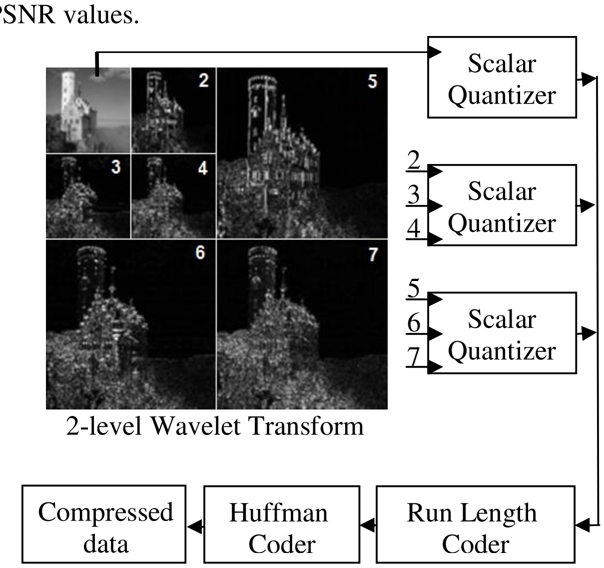

Figure 1. Multi-resolution WT pyramid coding

5. CURVELET TRANSFORM

The Curvelet transform is a higher dimensional generalization of the Wavelet transform designed to represent images at different scales and different angles [32].

There are two implementation of Curvelet: The first digital transformation is based on unequally spaced fast Fourier transforms (USFFT) many times, while the second is based on the wrapping of specially selected Fourier samples. Those two implementations essentially are different by the choice of spatial grid that used to translate Curvelets at each scale and angle. Both digital transformations return a table of digital Curvelet coefficients that indexed by a scale parameter, an orientation parameter, and a spatial location parameter. Curvelet via wrapping has been used for this work since it is the fastest Curvelet transform currently available [33].

If we *have* $g[t_1,t_2]$, $t_1 \geq 0$, $t_2 < n$ as Cartesian array and $\hat{g}[n_1,n_2]$ to denote its 2D Discrete Fourior Transform, then the architecture of Curvelets via wrapping is as follows[32]:

1. 2D FFT (Fast Fourier Transform) is used to extract Fourier samples $\hat{g}[n_1,n_2]$.
2. For each scale j and angle l, the product $\tilde{U}_{j,l}[n_1,n_2]\,\hat{g}[n_1,n_2]$ is formed, where $\tilde{U}_{j,l}[n_1,n_2]$ is the discrete localizing window.
3. This product is wrapped around the origin (*eight angles around origin are used in this paper*) to obtain $\breve{g}_{j,l}[n_1,n_2] = W(\tilde{U}_{j,l}\,\hat{g})[n_1,n_2]$; where the range for n_1,n_2 is now $0 \leq n_1 < L_{1,j}$ and $0 \leq n_2 < L_{2,j}$; $L_{1,j} \approx 2^j$ and $L_{2,j} \approx 2^{j/2}$ are constants.
4. Inverse 2D FFT is applied to each $\breve{g}_{j,l}$, hence creating the discrete Curvelet coefficients.

5.1. Curvelet based feature extraction

Curvelet transform has been developed for representing the objects with 'curve-punctuated smoothness' i.e. objects which display smoothness except for discontinuity along a general curve; a good example of this kind of objects is an images with edges. Two adjacent regions can often have differing pixel values in a two dimensional image. Such a gray scale image will have a lot of "edges" i.e. discontinuity along a general curve and consequently Curvelet transform will capture this edge information. It is crucial to collect these interesting edge information which in turn increases the discriminatory power of a recognition system for forming an efficient feature set [34].

The images are decomposed into its approximate and detailed components using two level of Curvelet transform. These sub-images thus obtained are called *curvefaces*. These *curvefaces* greatly reduce the dimensionality of the original image. Figure 2 shows the Curvelet coefficients for an image decomposed at scale = 2 and angle = 8, we can note that the first image in the first row is the approximate coefficients and others are detailed coefficients at eight angles. The approximate coefficients to feed the first scalar quantizer, while first four detailed coefficients to feed the second scalar quantizer, and last four detailed coefficients to feed the third quantizer like as illustrated in Figure 1

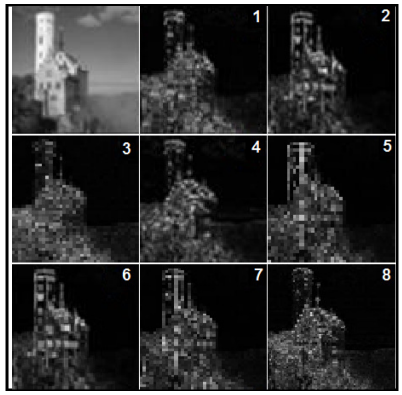

Figure 2: Curvelet Coefficients (approximate and details)

6. WAVE-ATOM TRANSFORM

Laurent Demanety and Lexing Ying presented a new member in the family of oriented, multi-scale transforms for image processing and numerical analysis. This is called Wave-atom transform [35].

Wave-atoms are a recent addition of mathematical transforms of computational harmonic analysis. They come either as an orthonormal basis or a tight frame of directional wave packets, and are particularly well suited for representing oscillatory patterns in images. The name of Wave-atoms is coming because they also provide a sparse representation of wave equations.

6.1. Wave-atom Transform Theory

Consider a one-dimensional family of wave packets $\psi^j_{m,n}(x), j \geq 0, m \geq 0, n \in \mathbb{N}$, centered in frequency around $\pm\omega_{j,m} = \pm\pi 2^j m$ with $c_1 2^j \leq m \leq c_2 2^j$ where $c_1 < c_2$ are positive constants, and centered in space around $x_{j,n} = 2^{-j}n$. One-dimensional version of the parabolic scaling states that the support of each bump of $\psi^j_{m,n}(\omega)$ is of length $O(2^j)$ while $\omega_{j,m} = O(2^{2j})$. Dyadic dilates and translates of $\hat{\psi}^0_m$ on the frequency axes are combined and basis functions, written as:

$$\psi^j_{m,n}(x) = \psi^j_m(x - 2^{-j}n) = 2^{j/2}\psi^o_m(2^j x - n)$$

The transform $WA : L^2(\mathbb{R}) \to l^2(\mathbb{Z})$ maps a function u onto a sequence of Wave-atom coefficients

$$c_{j,m,n} = \int_{-\infty}^{\infty} u(x)\,\psi^j_{m,n}(x)\,dx = \frac{1}{2\pi}\int_{-\infty}^{\infty} e^{-i2^{-j}n\omega}\overline{\hat{\psi}^j_m(\omega)}\;\hat{u}(\omega)\,d\omega$$

If the function *u* is discretized at *xk* = *kh*, *h*=1/*N*, *k* =1....*N* , then with a small truncation error is modified as:

$$C^D_{j,m,n} = \sum_{k=2\pi(-\mathrm{N}=2+1:1:\mathrm{N}=2)} e^{-i2^{-j}nk}\overline{\hat{\psi}^j_m(k)}\,\hat{u}(k)$$

A simple wrapping trick is used for the implementation of discrete Wavelet packets and the steps involved are:

1. Perform an FFT of size *N* on the samples of (*k*).

2. For each pair (*j*, *m*) wrap the product $\hat{\psi}_m^j \hat{u}$ by periodically inside the interval $[-2^j \pi, 2^j \pi]$ then perform inverse FFT of size 2^j of the result to obtain $C_{j,m,n}^D$.
3. Repeat step 2 for all pairs (*j*, *m*).

The positive and negative frequency components represented by:

$$\hat{\psi}_{m,n}^j(\omega) = \hat{\psi}_{m,n}^+(\omega) + \hat{\psi}_{m,n}^-(\omega)$$

Hilbert transform $H\hat{\psi}_{m,n}^j(\omega)$ of the equation represents an orthonormal basis $L^2(R)$ and is obtained through a linear combination of positive and negative frequency bumps weighted by ***i*** and ***–i*** respectively.

$$H\,\hat{\psi}_{m,n}^j(\omega) = -i\hat{\psi}_{m,n}^+(\omega) + i\hat{\psi}_{m,n}^-(\omega)$$

To extend Wave-atom to be 2D, let $\mu = (j, \mathbf{m}, \mathbf{k})$, where $\mathbf{m} = (m_1, m_2)$ and $\mathbf{n} = (n_1, n_2)$, so from equation 1.

$$\psi_\mu^+(x_1, x_2) = \psi_{m_1}^j(x_1 - 2^{-j}n_1)\psi_{m_2}^j(x_2 - 2^{-j}n_2)$$

A dual orthnormal basis, which is defined from the Hilbert-transformed,

$$\psi_\mu^-(x_1, x_2) = H\,\psi_{m_1}^j(x_1 - 2^{-j}n_1)\,H\psi_{m_2}^j(x_2 - 2^{-j}n_2)$$

By now, combine the primal and dual (Hilbert-transformed) basis. More precisely, the recombination

$$\psi_\mu^{(1)} = \frac{\psi_\mu^+ + \psi_\mu^-}{2} \quad , \psi_\mu^{(2)} = \frac{\psi_\mu^+ - \psi_\mu^-}{2}$$

This combination provides basis functions with two bumps in the frequency plane, symmetric with respect to the origin, hence purely directional Wave-atoms. Together, $\psi_\mu^{(1)}$ and $\psi_\mu^{(2)}$ form the Wave-atom frame and may be denoted jointly as ψ_μ [36, 37].

The frequency tiling of 2D Wave-atoms is illustrated in Figure 3, only the first quadrant is shown.

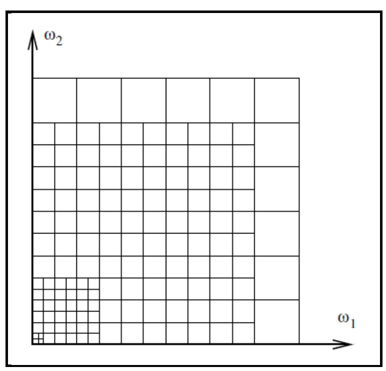

Figure 3. Wave-atom tiling of the frequency plane.

Wave-atoms can be implemented using the wrapping strategy in the frequency plane, along the same line of thought as Curvelets [37].

The search for a low redundancy transform is however complicated by the Wavelet packet curse, a well documented phenomenon that filter bank ideas provide provably suboptimal time-frequency localization [38].

Wave-atom transform is a fast transform, isometric up to round-off errors, and invertible with inversion algorithm of the same complexity. Wave-atoms have redundancy 2, i.e., there are twice more Wave-atom coefficients than samples on the Cartesian grid [37].

The Wave-atom transform is an $N^2 \log N$ operation, and needs to be applied once to the initial condition. The inverse Wave-atom transform is also $N^2 \log N$, and needs to be applied once to the final solution [37].

An appropriate global threshold is used to achieve desired transmission bit rate. After thresholding significance map matrix and a significant coefficient vector is generated. Significance map is a matrix of binary values that indicates the presence or absence of significant coefficient at a specific location. The significance map is processed with a sequence of dilation and closing operations. Dilations and erosions were performed to minimize the loss of potentially important coefficients due to thresholding [38]. And the algorithm as the following steps:

1. Apply 2D discrete Wave-atoms decomposition to the original image.
2. Use appropriate threshold for Wave-atoms coefficients to get required compression ratio.
3. Generate binary significance map and significant coefficients.
4. Dilate and erode the significance map.
5. Divide significance map into non-overlapping block
6. Quantize each block with desired number of codewords.
7. Apply scalar quantization for significant coefficients with required quantization levels.
8. Use arithmetic entropy coding to encode significance map and significant coefficients.
9. Reconstruct image by decoding, un-quantizing and performing inverse 2D Wave-atoms decomposition and obtain mean square error and peak signal to noise ratio.

7. PERFORMANCE EVALUATION

Each technique's performance was measured by calculating the mean square errors (MSE), normalized MSE (NMSE), the peak signal to noise ratio (PSNR) in dB, and root mean square signal to noise ratio (SNRrms). The equations which describe these performance evaluation functions are:

$$MSE = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(\hat{x}_{i,j} - x_{i,j}\right)^2}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(x_{i,j}\right)^2}$$

$$NMSE = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(\hat{x}_{i,j} - x_{i,j}\right)^2}{255^2 * N^2}$$

$$PSNR = 10log_{10}\frac{255^2}{\frac{1}{N^2}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(\hat{x}_{i,j} - x_{i,j}\right)^2} = 10log_{10}\frac{1}{NMSE}$$

$$SNR(rms) = \sqrt{\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(\hat{x}_{i,j}\right)^2}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(\hat{x}_{i,j} - x_{i,j}\right)^2}}$$

Where $\hat{x}_{ij}$ and x_{ij} represent the pixel value at location (i,j) of the reconstructed and original image, respectively, and N^2 is the total number of pixels in the image. It was found that the performance evaluation criteria which best matches the human visual quality of the image was the PSNR. For this reason, a heavy emphasis will be placed on the PSNR over the other techniques as a criterion for performance evaluation.

8. EXPERIMENTAL RESULTS

In order to compress the medical images, as shown in Figure 4, used in this work efficiently, the appropriate Wavelet coefficients needed to be chosen. To avoid randomly choosing one set of coefficients, the performance evaluation measurements were applied to a small sample of 512×512 images which were compressed and reconstructed using Daubechies 6, Daubechies 12, and to Adelson tap Wavelet coefficients.

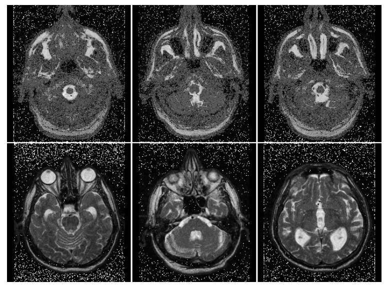

Figure 4 samples of MRI Images

After comparing the compression capabilities of the Daubechies 6, Daubechies 12, and Adelson Wavelet coefficients, we found that Adelson coefficients worked best for compressions requiring more than three levels of decompositions, as shown in Table 2. This is generally the case when higher compression ratios are required since Adelson tap Wavelet filter coefficients do not add artifacts as is the case with Daubechies coefficients [2, 18]. Then, we use scalar quantization, run length coding, and Huffman coding to achieve its final image compression.

Table 2. CR and PSNR for different Wavelet coefficients of 8 bpp MRI image (binsize=10)

	Daubechies 6		Daubechies 12		Adelson	
Level	CR	PSNR	CR	PSNR	CR	PSNR
1	3.8	36.2	1.8	35.3	3.7	35.2
2	6.2	36.1	3.0	35.6	7.6	35.6
3	5.8	35.7	3.2	35.1	11.2	35.8

As can be noted from Table 2, the Daubechies coefficients perform better than Adelson's coefficients when one level decomposition of MRI image were used for compression. However, for the third level decomposition of the MRI image, by using Adelson's coefficients, produced a better CR as well as superior PSNR. Since the purpose of the Wavelet algorithm is to achieve a high CR with a high PSNR, Adelson's Wavelet coefficients are the optimal coefficients out of the three compared. Thus, for the rest of this research, they will be used in the Wavelet compression algorithm. And it will be compared with Curvelet and Wave-atom transforms for medical images compression.

Table 3 shows the CR and PSNR for three level of Curvelet decomposition for MRI image that decomposed at scale = 2, and angle = 8.

Table 3. CR and PSNR for three level of Curvelet decomposition for MRI image.

level	CR	PSNR
1	3.6	37.2
2	11.9	37.6
3	12.2	36.3

As can be noted from Table 3, the best CR is produced using three levels of Curvelet decomposition but with the worst PSNR, while the best PSNR is achieved by two levels of

Curvelet decomposition but not the best CR. Although CR is important performance but still PSNR is most interested for medical field applications, because that the second level coefficients of curevelet is chosen to complete the comparative study.

The discrete 2D Wave-atom decomposition is applied on the original MRI/CT medical image; to efficiently capture coherence patterns along and across the oscillations. Table 4 illustrates CR and PSNR for different scales (j in equations 2, 3) by using Wave-atom transform.

Table 4. CR and PSNR for different scales of Wave-atom transform for MRI image.

Scale	CR	PSNR
2	5.4	37.1
3	16.3	38.8
4	17.6	37.4

The coefficient at scale = 3 gives the best PSNR while at scale = 4 gives the best CR. As we say before, the PSNR is most important for medical image compression if there is small difference in CR. From all these results, the comparative study can be achieved in table 5 that summarizes the best result for each used method.

Table 5 illustrate the comparison of the CR and PSNR for MRI image compression by using three level Adelson Wavelet, two level Curvelet, and Wave-atom coefficients. Can be noted that Wavelet gives CR = 11.2 and PSNR = 35.8 as the lowest values, while the Curvelet produces 11.9 of CR, not make important difference, and 37.6 for PSNR as an important improved value. Wave-atom achieves the best improvement for CR and PSNR, in spite of Wave-atom is the newest member in multi-resolution methods and still under consideration.

Table 5. CR and PSNR for different three methods for MRI image compression.

Method	CR	PSNR
Three level Wavelet	11.2	35.8
Two level Curvelet	11.9	37.6
Wave-atom with scale=3	16.3	38.8

9. CONCLUSION

Despite advances in lossy compression, lossless compression remains useful for many medical imaging applications. So this work tried to improve and investigate lossless compression techniques and compare them to determine the best modern multi-resolution analysis technique. For achieving that, three modern techniques for medical image compression are introduced; Wavelet, Curevelet, and Wave-atom transforms. Also comparative study is achieved to determine the best technique for medical image compression.

This work introduces Wave-atom, with scale 3, as the best technique with CR of 16.3, and PSNR of 38.8, although more studies for Wave-atom are needed to select the optimal parameters values that needed to accomplish the best lossless medical compression algorithm. On the other hand, Curvelet transform also needs for additional studies to improve the results by selecting the suitable level of transformation. May be the combining with other techniques for quantization and coding explores improved results.

REFERENCES

[1] Stephen Wong, Loren Zaremba, David Gooden, and H.K. Huang, "Radiologic image compression - a review," *Proc. of the IEEE,* vol 83, no. 2, pp. 194-219, Feb. 1995.

[2] I. Daubechies, "Orthonormal bases of compactly supported Wavelets," *Commun. Pure Appl Math.,* vol 41, pp. 909-996, Nov 1988.

[3] Stephane G. Mallat, "A theory for muhiresolution signal decomposition: the Wavelet representation," *IEEE Trans, on Pattern Analysis and Machine Intelligence,* vol 11, no. 7, pp 674-693, July 1989.

[4] Marc Antonini, Michel Bariaud, Pierre Mathieu, and Ingrid Daubechies, "Image coding using Wavelet transform," *IEEE Trans, on Image Proc.,* vol. 1, no. 2, pp. 205-220, April 1992.

[5] H. J. Barnard, *Image and Video Coding Using Wavelet Transforms,* Ph.D. Dissertation, Technische Universiteit Delft, May 1994.

[6] Ali N. Akansu, "Wavelets and Fiher Banks," *IEEE Circuit and Devices,* pp 14- 18, November 1994.

[7] M.N. Do and M. Vetterli, “The Finite Ridgelet Transform for Image Representation”, *IEEE Trans Image Processing,* vol. 12(1), pp. 16-28, 2003.

[8] M.N. Do and M. Vetterli, “The Contourlet Transform: An Efficient Directional Multiresolution Image Representation”, *IEEE Trans. Image Processing*, vol. 14(12), pp. 2091-2106, 2005.

[9] E.J. Candès, L. Demanet, D.L. Donoho and L. Ying, "Fast Discrete Curvelet Transforms", *Multiscale* Model. Simul., pp. 861-899, 2005.

[10] S. Mallat, “A Wavelet Tour of Signal Processing”, Second Edition, Academic Press, Orlando-SanDiego, 1999.

[11] J.P. Antoine and R. Murenzi, “Two-dimensional Directional Wavelets and the Scale-Angle Representation”, Sig. Process., vol. 52, pp. 259-281, 1996.

[12] Wallace, Gregory K. "The JPEG Still Picture Compression Standard", *Communications of the ACM,* April 1991 (vol. 34 no. 4), pp. 30-44.

[13] DeVore, R. et al, "Image compression through wavelet transform coding", *IEEE Transactions on Info. Theory*, 38 (1992) 719-746.

[14] Iyriboz T, Zukoski M, Hopper K et al. (1999), "A compression of wavelet and Joint Photographic Experts Group lossy compression methods applied to medical images", *J. Gigit Imaging 12*, pp. 14-17.

[15] Chen W, Hsieh L, and Yuan S.(2004), "High performance data compression method with pattern matching for biomedical ECG and arterial pulse waveforms", *Comp. Method Prog. Biomed 74*, pp 11-27.

[16] Chen Y, and TAIS "Enhancing ultrasound by morphology filter and eliminating ringing effect", *Eur. J. Radiol 53*, 2005, pp.293-305.

[17] J. Strom and P.C. Cosman, "Medical image compression with lossless regions of interest," *Signal Processing, 59*, *Special issue on medical image compression*, June 1997, pp. 155-171

[18] Mansoor, A., Mansoor, A.B., "On Image Compression using Digital Curvelet Transform", *9th International Multitopic Conference*, *IEEE INMIC* 2005, Karachi, pp. 1-4

[19] Majid Rabbani and Paul W Jones, *Digital Image Compression Techniques*, Washington DC: SPIE Optical Engineering Press, 1991.

[20] A.K. Jain, P.M. Farrelle, V.R. Algazi, *Image data compression*, in: M.P. Ekstrom (Ed.), *Digital Image Processing Techniques*, Academic Press, New York, 1984, pp. 171–226.

[21] N. Jayant, "Signal compression: Technology targets and research directions", *IEEE J. Selected Areas in Commun.* 10 (5) (1992) 796–818.

[22] P. Roos, et al. "Reversible intraframe compression of medical images", *IEEE Trans. Med. Imag*. 7(4) (1988) 328–336.

[23] P.C. Cosman, R.M. Gray, R.A. Olshen, "Evaluating quality of compressed medical images: SNR, subjective rating, and diagnostic quality", *Proc. IEEE* 82 (6) (1994) 919–932.

[24] J.W. Woods (Ed.), *Subband Image Coding*, Kluwer, Dodrecht,1991.

[25] Khalid Sayood, *Introduction to Data Compression*, Morgan Kaufmann Publishers, 2000, ISBN 1-55860-558-4

[26] Anil K. Jain, *Fundamentals of Digital Image Processing*, Englewood Cliff, NJ: Prentice Hall, 1989.

[27] R. J. Clarke, *Transform Coding of Images*, London: Academic Press, 1985.

[28] Rioul, O. and Vetterli, M., "Wavelet and signal processing", *IEEE SPM, Vol. 8, No. 4, Oct. 1991, pp. 14-38.*

[29] Robertson, D. C. and Camps O. I., "Wavelets and electromagnetic power system transients", *IEEE Trans. on Power Delivery, Vol. 11, No. 2, April 1996, pp. 1050-1058.*

[30] S. Mallat , " A Theory of Multiresolution Signal Decomposition: The Wavelet representation", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 11, 1989, pp. 674-693.

[31] M. Vetterli and J. Kovacevic, "*Wavelets and Subband Coding*", New Jersey: Prentice Hall, 1995.

[32] Tanaya Mandal, Q. M. Jonathan Wu,"Face Recognition using Curvelet Based PCA", *Pattern Recognition, ICPR 2008, 19th international conference*, Tampa, FL, pp. 1- 4.

[33] E. J. Candes, L. Demanet, D. L. Donoho, and L. Ying, "Fast Discrete Curvelet Transforms", *Technical Report, Cal Tech*, March, 2006

[34] Emmanuel Candes, and Laurent Demanet, (Aug. 24, 2007), "Curvelet", available at: www. Curvelet.org

[35] Demanety, L., and Ying, L. "Wave-atoms and Sparsely of Oscillatory Patterns", *appear in Appl. Comput. Harm. Anal.* , February 2007.

[36] Demanet, L., 2006, "*Curvelets, Wave-atoms, and wave equations*," Ph.D. Thesis, California Institute of Technology

[37] Villemoes, L., 2002, "Wavelet packets with uniform time-frequency localization," *Comptes Rendus Math,*. 335-10, pp. 793-796.

[38] Abdul Adeel Mohammed, Rashid Minhas, Q. M. Jonathan Wu, Maher A. Sid-Ahmed: "Fingerprint image compression standard based on Wave-atoms decomposition and self organizing feature map". *IEEE International Conference on Electro/Information Technology*, June 7-9, 2009, Canada, pp. 367-372.

Authors

Dr. Mohammed Ahmed Alhanjouri received Bachelor of Electrical and Communications Engineering (honor) (1998), Master of Electronics Engineering (excellent) (2002) and Ph.D. in 2006. he is working as Assistant Professor and head of computer Engineering department, Islamic University of Gaza, Palestine. His primary research interest is in the area of Artificial Intelligence. He also carries out research in many other areas such as: Microcontroller applications, Cryptogaphy, Advanced digital signal processing, Pattern recognition (Image and Speech), Modern classification techniques (neural networks, Hidden Markov Models, Ant colony and Genetic Algorithm). Tel: 009708-280600 Ext: 2883. Email: mhanjouri@iugaza.edu.ps