Lossy Compression of Medical Images Using Multiwavelet Transforms

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***Abstract*—In this paper, a new technique is developed for efficient medical image compression based on MWT transforms, which are employed with the VQ algorithm in different distribution. Lossy compression based on multi-wavelet transforms is considered a new technique for compression MRI and CT images. Medical image compression is crucial to reduce power consumption and improve data transmission efficiency. Particularly, the method can be categorized into time-domain and transform-domain groups. The proposed method offers a better compression performance for medical images with VQ. The codebook size refers to the total numbers of code vectors in the codebook. As the size of codebook increase the quality of the reconstructed signal improves. However, the compression ratio is reduced. Therefore, there is a tradeoff between the quality of the reconstructed signal and the amount of compression achieved. Hence, the extensive simulation confirms the improvement in compression performances offered by multi-wavelet transform over a single transform.**

***Index Terms*—Medical Image; Lossy Technique; Compression; Multi-Wavelet Transforms; Vector Quantization.**

I. Introduction

Medical imaging has been used greatly in recent years, especially with magnetic resonance images (MRI) and computed tomography (CT) which are both high in volumes and can be viewed as a succession of 2D images (slices). Such large data sets require efficient storage schemes adapted for navigation through a network [1].

Medical images compression is crucial to reduce power consumption and improve data transmission efficiency. Many medical data compression methods have been proposed to achieve a high compression ratio (CR) result and preserve clinical information. These methods can be categorized into time-domain, and transform-domain groups. An often-required compression features is lossless (even if sometimes near lossless would be sufficient) [2].

Recently, there has been considerable interest in applying lossy compression for medical data. In such approaches, however, the quality of reconstruction is the most important and specific compression ratios between of (5 to 20) are used. With these ratios, the difference between the quality of the original and the quality of the reconstructed image is hardly perceptible. Applications of lossy compression included storage of vast amounts of medical data, where real times processing may not be a major requirement, while accurate compressions is a major requirement. Most tomographic medical data are two-dimensionally (2-D) cross-sectional sequences of a three-dimensionally (3-D) object. Some of these sequences may also be obtained several times in time. This adds a temporal dimension to the data, thus making it four-dimensionally (4-D). Such signal characterization obviously requires huge amounts of storage space, thus requiring some means of compression, without compromising the quality [3].

Lossy signal compressions has been achieved by processing the signal in the spatial time domain or the transform domain. In the transform domain, an invertible transform maps the signal to a set of coefficients. The transform typically is required to converts the statistically correlated input samples to a set of uncorrelated coefficients. The dominant transform coefficients are retained and the remaining ones are discarded. The retained coefficients are then quantized and encoded for either transmission or storage. The process of representing signals with a limited set of transform coefficients are termed the constrained representations. A transform is favored if it can compact the energy in the fewest number of coefficients [2].

More recently, the wavelet transform has emerged as a cutting-edge technology, within the field of image compression. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios. Over the past few years, a variety of powerful and sophisticated wavelet-based schemes for image compression, have been developed and implemented. For better performance in compression, filters used in wavelet transforms should have the property of orthogonality, symmetry, shorter supported and higher approximation order. Due to implementation constraints, scalar wavelet do not satisfy all these properties simultaneously. A new class of wavelet called ‘Multi-wavelets’ which possesses more than one’s scaling filters overcomes this problem. This multi-wavelet offered the possibility of superior performance and high degree of freedom for image processing applications, compared with scalar wavelets. Multi-wavelets can achieve the best level of performances than scalar wavelets with similar computationally complexity [3].

This paper is organized to explain medical image compression techniques and the standard quantitative measurements that used for medical image compression and describe the proposed of compression algorithms. Finally, simulation results and discussion are concluded to test the performance.

II. Compression Techniques

Transform coding is one of the most widely used compression techniques. The main goal of any compression techniques is to achieve maximum data volume reduction while preserving the significant features [4]. A compression algorithm takes an input X and generates a representation XC that hopefully requires fewer bits. There is a reconstruction algorithm that operates on the compressed representation XC to generate the reconstructed presentation Y.

A. Discrete Wavelet Transform

Wavelets are mathematically functions that provides the time-frequency representation. It cuts up data into differently frequency components, and then study each component with a resolution matched to its scale [3]. Most interesting dissimilarities between wavelet and Fourier transforms is that individual wavelet functions are localized in space, Fourier sine and cosines functions are not. In discrete wavelets transforms (DWT) the scales and translated parameters are chosen such that the resulting wavelet set forms an orthogonal set, i.e. The inner product of the individual wavelets ψ (j, k) is equals to zero. To this ends, dilation factors are chosen to be powers of 2. For DWT, the set of dilation and translation of the mother wavelet is defined as [5]:

$$\psi_{j,k}(t) = 2^{j/2}\,\psi(2^j\, t - k) \qquad (1)$$

Where j is the scaling factor and k is the translation factor. It is obvious that the dilation factor is a power of 2. Forward and inversed transforms are then calculated using the following equations [5].

$$C\,\tau, s = \int_{-\infty}^{+\infty} \mathrm{f}\,(\mathrm{t})\,\psi\,\tau, s\,(t)\,dt \qquad (2)$$

$$f(t) = \sum\nolimits_{\tau,s} \mathrm{C}\tau, \mathrm{s}\,\psi\,\tau, s\,(t) \qquad (3)$$

For efficient décor-relations of the data, an analysis, wavelet set ψ (j, k) should be chosen which matches the features of the data well. This together with orthogonally of the wavelet set will result in a series of sparse coefficients in the transforms domains, which obviously will reduce the amount of bits needed to encode it [6]. Figure 1 shows the wavelet subband decomposition of an image. The subbands' labels in this figure indicated how the subband data are generated. For example, the data in subband LH are obtained from high pass filtering for the rows and then low-pass filtering the columns.

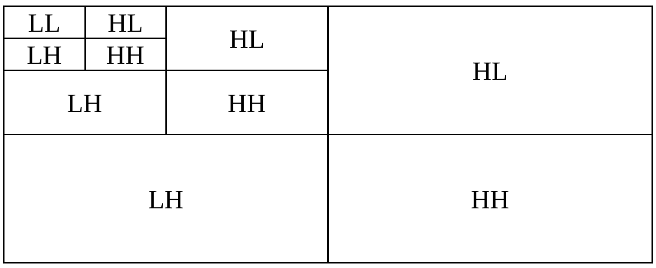

Figure 1: Pyramid structure of wavelet decomposition [6]

B. Multi-wavelet Transform

Multi-wavelet has been introduced as a more powerful multi-scale analysis tool. A scalar wavelet system is based on a single scaling function and mother wavelet. On the other hand, a multi-wavelet uses severally scaling functions and mother wavelets. Multi-wavelets, namely, vector-valued wavelet functions, are a new additional to the classical wavelets theory that has revealed to be successfully in practically applications, such as signal and image compression. In fact, multi-wavelets possess severally advantages in comparison to scalar wavelet, since a multi-wavelet system can simultaneously provide perfect reconstruction while preserving orthogonality, symmetry, a high order of approximation (vanishing moments), etc. Nevertheless, multi-wavelets differ from scalar wavelet systems in requiring two or more input streams to the multi-wavelet filter bank [7].

The multi-wavelet idea originates from the generalization of scalar wavelets; instead of one scaling function and one wavelet, multiple scaling functions and wavelets are used. This leads to more degree of freedom in constructing wavelets. Therefore, opposed to scalar wavelets, properties such as compacted support, orthogonality, symmetry, vanishing moments, and short supporting can be gathered simultaneously in multi-wavelets, which are fundamental in signal process. The increase in the degree of freedom in multi-wavelets is obtained at the expense of replacing scalars with matrices, scalar functions with vector functions and single mattresses with a block of matrices. Also, pre-filtering is an essential task which should be performed for any use of multi-wavelet in the signals processing [8].

Many types of multi-wavelets such as Geronimo-Hardin Massopust (GHM) and Chui-Lian (CL) multi-wavelets have been developed [9]. To implements the multi-wavelet transforms, a new filter bank structure is required where the low-pass and high-pass filter banks are matrices rather than scalars. That is, the GHM two scaling and wavelet functions satisfy the following two-scale dilation equations [9]

$$\begin{bmatrix}\phi_1(t)\\ \phi_2(t)\end{bmatrix} = \sqrt{2}\sum_k H_k \begin{bmatrix}\phi_1(2t-k)\\ \phi_2(2t-k)\end{bmatrix} \qquad (4)$$

$$\begin{bmatrix}\psi_1(t)\\ \psi_2(t)\end{bmatrix} = \sqrt{2}\sum_k G_k \begin{bmatrix}\psi_1(2t-k)\\ \psi_2(2t-k)\end{bmatrix} \qquad (5)$$

The (2×2) matrix filters in the multi-wavelet filter bank required vector inputs. Thus, a 1-D inputs signals must be transformed into two 1-D signals. This is transformation is called preprocessing. For some multi-wavelet, the preprocessing must be accompanied by an appropriate prefiltering operation that depends on the spectral characteristics of the multi-wavelet filters [10].

C. Vector Quantization

Vector quantization (VQ) is used for both image and sound compression. In practices, VQ is commonly used to compressed data that have been digitized from an analog source, such as sampled sound and scanned images. Vector quantization is based on two facts [11]:

i. The compression method that compress strings, rather than individual symbols can, in principle, produced better results.
ii. Adjacent data items in an image (i.e., pixels) and digitized sound (i.e., samples) are correlated. There is a good chance that the nearest neighbors of a pixel P will have the same values as P or very similar values. Also, consecutives sound samples rarely differed much.

For signal compression, VQ divide the signal into small blocks of pixels, typically 2×2 or 4×4. Each block is considered a vector. The encoder maintains a list (called a codebook) of vectors and compresses each block by writing to the compressed stream a pointer to the block in the codebook. The decoder has the easy task of reading pointers, following each pointer to a block in the codebook, and joining the block to the image so far (see Figure 2). Vector quantization is thus an asymmetric compression method [11].

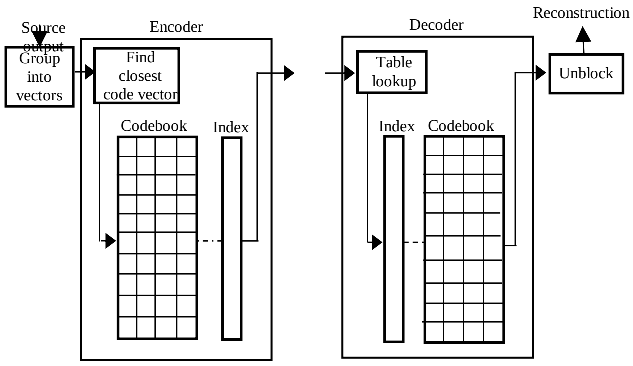

Figure 2: Encoder and decoder in a vector quantization [11]

An improved algorithm of VQ codebook generation approaches such as the LBG algorithms has been developed. LBG algorithm designing a codebook that best represent the set of input vectors is very-hard. That means that it requires an exhaustive search for the best possible codewords in space, and the search increases exponentially as the number of codewords increases, therefore, we resort to suboptimal codebook design schemes, and the first one that comes to mind is the simplest. It is named LBG algorithm for Linde-Buzo-Gray and it is known as K-means clustering [12].

This algorithm is in fact designed to iteratively improve a given initial codebook. The design of a codebook with N-codewords can be stated as follows [12]:

i. Determine the number of codewords, N, or the size of the codebook.
ii. Select N codewords at random, and let that be the initial codebook. The initial codewords can be randomly chosen from the set of input vectors.
iii. Use the Euclidean distance measures to cluster size the vectors around each codeword. This is done by taking each input vector and finding the Euclidean distance between it and each codeword. The input vector belongs to the cluster of the codeword that yields the minimum distance.
iv. Compute the new set of codewords, by obtaining the average of each cluster. Add the component of each vector and divide by the number of vectors in the cluster [12].

$$y_i = \frac{1}{m}\sum_{j=1}^{m} x_{ij} \qquad (6)$$

Where i is the components of each vector (x, y, z, directions) and m is the number of vectors in the cluster.

v. Repeat steps 1, 2 and 3 until either the codewords do not change or the change in the codewords is small.

This algorithm is by far the most popular, and that is due to its simplicity. Although it is locally optimal, yet it is very slow. The reason it is slow is because for each iteration, determining each cluster requires that each input vector be compared with all the codewords in the codebook.

III. PROPOSED METHOD

It consists mainly of applying the multi-wavelet, wavelet transforms in a cascaded manner to the MRI image or medical data. This proposed transform is implemented by applying MWT first, this in turn introduced the four approximation subbands (L1L1, L1L2, L2L1 and L2L2) which have approximated information to the original signal, and then VQ algorithm are applied in different procedure.

The description of the procedure used in the compression process for this method transforms schemes, are as follows:

i. Apply the MWT to the approximation band (LL) which results four square bands as shown in Figure 3. The four square bands results are splits and each is processed individually.
ii. Apply the MWT to the 1'st approximation square which consists of four approximation subbands (L1L1, L1L2, L2L1 and L2L2) which in turn introduce four square subbands (1st, 2nd , 3rd and 4th), as shown in Figure 3. The 1st subband have important information which is approximated to the original signal, since VQ is a lossy compression so that the 1st subband will not be treated by VQ. The three subbands (2nd, 3rd and 4th) will be treated by VQ technique.
iii. Apply VQ to the three details square remains from applying MWT in step 1. Figure 4 shows the proposed scheme of using the multi-wavelet transforms and VQ on medical images.

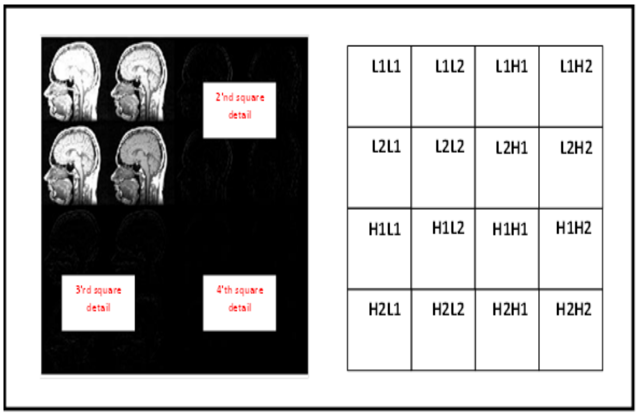

Figure 3: Resultant multi-wavelet transform bands

IV. PERFORMANCE MEASUREMENTS

Evaluations of Medicals images encoders uses measurements related to the amplitude differences between the original and the reconstructed signals. The compression ratios (CR) is a measure of the amounts of data sizes reduction achieved and it is calculated by [2]:

$$CR = \frac{uncompressed\ size}{compressed\ size} : 1 \qquad (7)$$

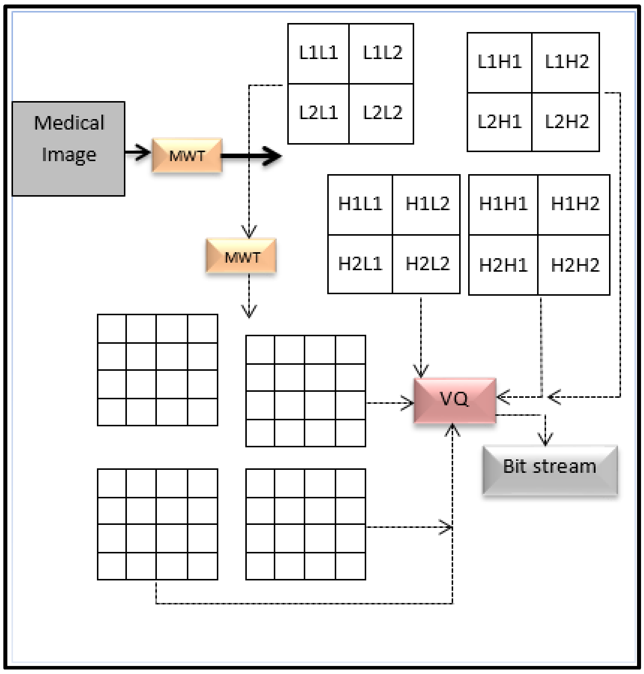

Figure 4: Proposed scheme of MWT and their compression processing

Evaluations of images compressions methods needs a standard metric to measure the quality of reconstructed images compared with the originals ones. A common measured used for this purposed is the peak signals to noise ratio (PSNR). It has only a limited and approximated relationship with the perceived errors noticed by the human visual systems. Denoting the pixels of the original images by x (n) and the pixels of the reconstructed image from $\tilde{x}(n)$, the mean square error (MSE) between the two images is defined as [6]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x(n) - \tilde{x}(n))^2 \tag{8}$$

The root mean square error (RMSE) is defined as the square root of the MSE, therefore the PSNR is defined as [8]:

$$PSNR = 20\log\frac{\max|\mathrm{x(n)}|}{\mathrm{PMSE}} \tag{9}$$

The absolute values are normally not needed, since pixel values are rarely negatives. The PSNR is dimensionless, since the units of both numerator and denominator are pixel values. However, because of the uses of the logarithms, the PSNR is expressed in decibel (dB).

The simulation results of the proposed algorithms are presented using a MATLAB (R2013a). It is used to run on a PC with 2.2 GHz processor, 320 GHz hard disk with 2 GHz main memory.

V. Results and Discussion

The results of MRI image compression using proposed multi-wavelet transforms algorithms are shown in Figure 5.

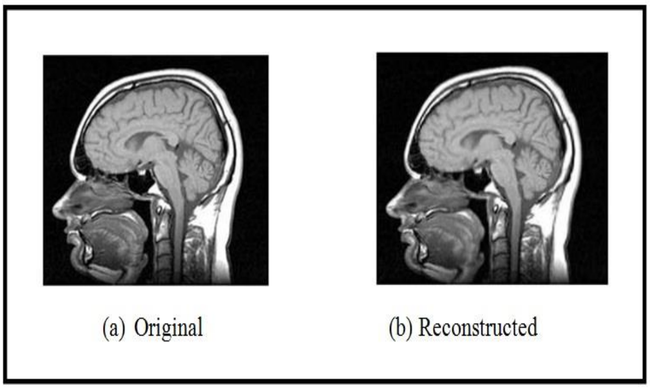

Figure 5: Original and reconstructed MRI image using MWT for CR = 14.6 and PSNR = 54.4 dB

Table 1 illustrates the comparison of CR and PSNR for MRI image compression by using different methods such as multi-resolution analysis [5] and wavelet transform [6]. It can be noted that the proposed algorithm achieved better improvement for CR and PSNR than other methods.

Table 1:
CR and PSNR for different methods for MRI image compression

Algorithm	CR	PSNR(dB)
Reference [5]	5.4	37.1
	16.3	38.8
Reference [6]	13.606	34.454
	12.217	35.019
Proposed Method	14.6	54.4

It is noticeable that the CR for proposed method is nearly closed for reference [5] and reference [6] while PSNR for proposed method is higher than the reference [5] and reference [6] which means all algorithms achieve close CR to reduce power consumption, while PSNR for proposed method achieve better resolution than other methods.

VI. Conclusion

A new technique is developed for efficient medical image compression based on MWT transforms, which are employed with the VQ algorithm in different distribution. This distribution was exploited by cascading manner. The following points are the summary of the important conclusions:

i. The proposed method offers a better compression performance for medical data than using wavelet transform.
ii. The codebook size refers to the total numbers of code vectors in the codebook. As the size of codebook increase the quality of the reconstructed signal improves, but the compression ratio reduces. Therefore, there is a tradeoff between the quality of the reconstructed signal and the amount of compression achieved.
iii. Extensive simulations confirm the improvement in compression performances offered by the proposed MWT transform over a single transform. Sample results are presented to illustrate the improvement.

ABBREVIATIONS

The following abbreviations are used in this manuscript:

CT	Computed Tomography
MRI	Magnetic Resonance Imaging
VQ	Vector Quantization
1-D	One – Dimensional
2-D	Two – Dimensional
3-D	Three – Dimensional
4-D	Four – Dimensional
CR	Compression Ratio
DWT	Discrete Wavelet Transform
LL	Low Low Subband
HL	High Low Subband
LH	Low High Subband
HH	High High Subband
GHM	Geronimo-Hardin-Massopust
CL	Chui-Lian
LGB	Linde-Buzo-Gray
MWT	Multiwavelet Transform
PSNR	Peak Signal to Noise Ratio
MSE	Mean Square Error
RMSE	Root Mean Square Error

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