Journal of Engineering and Development, Vol. 15, No. 1, March (2011) ISSN 1813-7822

Investigation Image Compression Using Nondyadic Wavelet Transform and Fast Zero Tree Algorithm

M. Sc. Ali Majeed Mohammed
Al-Mustansriyha University
Department of computer & software Eng.
E-Mail: ali2_majeed@yahoo.com

Abstract

Nondyadic Wavelet decomposition of Daubechies–4 orthogonal filter banks was used in this paper of image compression scheme that based on this type of transform . and zero tree data structured is which used to quantized the output coefficients of Discrete Wavelet Transform (DWT).

This scheme gives good results , and high quality of image that called (MRI), with Peak Signal to Noise Ratio (PSNR) about (33.13 dB) at bit rate (br) equal (0.114)

Keywords : Image Compression, Nondyadic Wavelet Transform, Zero Tree Algorithm.

الخلاصة

تم استخدام مخطط ضغط الصورة والذي يستند على

Nondyadic Wavelet decomposition of Daubechies–4

والذي يكون متعامد على filter banks حيث تعتمد هذه الطريقة وبشكل كبير على هذا النوع من تحويل المويجة وكذلك تعتمد أيضا على الشجرة الصفرية للبيانات والتي يتم تكميمها فيما بعد.

وهذه الطريقة أعطت نتائج جيدة وبجودة عالية للصورة الطبية ألمسماه (MRI) وبقمة الإشارة نسبتاً إلى قمة الضوضاء (PSNR) بحدود (33.31) ديسبل عند معدل بت (br) بحدود (0.114) بت لكل ثانية.

1- Introduction

Wavelet image has been an exciting and fertile area of research in the image processing community in recent years particularly in relation to image compression. It does not only provide a good compression result, but it is also suitable for transmissions and provides a multireslution capability. However, applying the wavelet transform on image for compression alone does not reduce the amount of data to be compressed, since it may remove some of the redundancy and decorrelate the neighbour pixels. A common way to reduce the number of bits required for compression is to quantize the resulting coefficients from the transformation [1].

In recent years, there has been a surge of interest in wavelet transforms for image and video coding applications. This is mainly due to the nice localization properties of wavelets in both space and frequency. Zerotree quantization, proposed by Shapiro (1993), is an effective way of exploiting the self-similarities among high-frequency subbands at various resolutions. The main thrust of this quantization strategy is in the prediction of corresponding wavelet coefficients in higher frequency subbands at the finer scales, by exploiting the parent-offspring dependencies. This prediction works well, in terms of efficiently coding the wavelet coefficients, due to the statistical characteristics of subbands at various resolutions, and due to the scale-invariance of edges in high frequency subbands of similar orientation [2].

This paper is organized as follows. In the next section, a brief review of the Dyadic and Non-Dyadic Wavelet Analysis. A general and fast zerotree structure are described in Section 3. The Proposed Compression Algorithm is explained in Section 4, and the experimental results are presented in Section 5. Finally, we discuss this results.

2- Dyadic and non – dyadic wavelet analysis

The statistical analysis of time series can be pursued either in the time domain or in the frequency domain, or in both. A time-domain analysis will reveal the sequence of events within the data, so long as the events do not coincide. A frequency-domain analysis, which describes the data in terms of sinusoidal functions, will reveal its component sequences, whenever they subsist in separate frequency bands. The analyses in both domains are commonly based on the assumption of stationarity. If the assumption is not satisfied, then, often, a transformation can be applied to the data to make them resemble a stationary series. For a stationary series, the results that are revealed in one domain can be transformed readily into equivalent results in the other domain [3].

The revolution in statistical Fourier analysis that occurred in the middle of the twentieth century established the equivalence of the two domains under the weak assumption of statistical stationarity. Previously, it had seemed that frequency-domain analysis was fully applicable only to strictly periodic functions of a piecewise continuous nature. However, the additional flexibility of statistical Fourier analysis is not sufficient to cope with phenomena that are truly evolving through time. A sufficient flexibility to deal with evolutionary phenomena can be achieved by combining the time domain and the frequency domain in a so-called wavelet analysis [3].

The replacement of classical Fourier analysis by wave packet analysis occurred in the realms of quantum mechanics many years ago when Schr odinger's time-dependent wave equation became the model for all sorts of electromagnetic phenomena. (See Dirac 1958, for example.) This was when the dual wave-particle analogy of light superseded the classical wave analogy that had displaced the ancient corpuscular theory. It is only recently, at the end of the twentieth century, that formalisms that are similar to those of quantum mechanics have penetrated statistical time-series analysis. The result has been the new and rapidly growing field of wavelet analysis [3].

The object of the wavelet analysis is to associate an amplitude coefficient to each of the wavelets. The variation in the amplitude coefficients enables a wavelet analysis to reflect the changing structure of a non-stationary time series. By contrast, the amplitude coefficients that are associated with the sinusoidal basis functions of a Fourier analysis remain constant throughout the sample.(Accounts of wavelet analysis, which place it within the context of Fourier analysis, have been given by Newland (1993) and by Boggess and Narcowich (2001). Other accessible accounts have been given by Burrus, Gopinath and Guo (1998) and by Misiti, Misiti, Oppenheim and Poggi (1997) in the user's guide to the MATLAB Wavelets Toolbox.) [3].

The fact that the Daubechies wavelets are know only via their dilation coefficients is no impediment to the discrete wavelet transform. This transform generates the amplitude coefficients associated with the wavelet decomposition of a data sequence; and it is accomplished via the pyramid algorithm of Mallat (1989). The continuous-time wavelets are, in reality, a shadowy accompaniment—and, in some ways, an inessential one—of a discrete-time analysis that can be recognised as an application of the techniques of multi-rate filtering, which are nowadays prevalent in communications engineering. (For examples, see Vaidyanathan 1993, Strang and Nguyen 1997 and Vetterli and Kovacevi c 1995.) In this perspective, the dilation coefficients of the wavelets and of the associated scaling functions are nothing but the coefficients of a pair of quadrature mirror filters that are applied in successive iterations of the pyramid algorithm. This uncommon relationship between the continuous-time and the discrete-time aspects of the analysis is undoubtedly the cause of many conceptual difficulties [3].

The Daubechies–Mallat paradigm has been very successful in application to a wide range of signal processing problems, particularly in audioacoustic analysis and in the analysis of digitised picture images, which are two-dimensional signals in other words. There are at least two reasons for this success. The first concerns the efficiency of the pyramid algorithm, which is ideal for rapid processing in real time. The second reason lies in the Daubechies wavelets themselves. Their restricted supports are a feature that greatly assists the computations. This feature, allied to the sharp peaks of the wavelets, also assists in the detection of edges and boundaries in images [3]. The system of Daubechies and Mallat is not suited to all aspects of statistical signal extraction. For a start, the Daubechies wavelets might not be the appropriate ones to select. Their disjunct nature can contrast with the smoother and more persistent motions that underlie the data.

The non-availability of their discretely sampled versions may prove to be an impediment; and the asymmetric nature of the associated dilation coefficients might conflict with the requirement, which is commonly imposed upon digital filters, that there should be no phase effects. (The absence of phase effects is important when, for example, wavelets are used as an adjunct to transfer-function modelling, as in the investigations of Ramsey and Lampart 1998 and of Nason and Sapatinas 2002.) A more fundamental difficulty lies in the nature of the dyadic decomposition.

In statistical analyses, the structures to be investigated are unlikely to fall neatly into dyadic time and frequency bands, such as those of Figure 1; and the frequency bands need to be placed wherever the phenomena of interest happen to be located [3].

3- Fast Zero Three Algorithm

The zero tree idea is first introduced by Lewis and Knowles , A Zerotree-Based Image Coding it is important to define and understand the hierarchical structures in the wavelet domain for the following review. The tree structure, called a tree, is a set of wavelet coefficients corresponding to the same spatial location and orientation . The assembly of three trees, which specifies the same spatial location, is called a total tree. The union of three trees (a total tree) and one coefficient in the LFS, called a square tree, corresponds to a square block in the image domain. In other words, a square tree has the complete information about the corresponding square block.

It is noted that most of the zerotree-based encoders could be modified to encode each square tree, total tree or tree independently. It is very efficient to encode with square trees from a rate-distortion standpoint, because these are good for exploiting the correlation among square blocks.

However, as mentioned before, it is not desirable for a noisy channel. The zerotree-based image coders assume that if there are insignificant coefficients in the low-frequency subbands in a tree, then there are most likely insignificant coefficients in the corresponding positions in the higher frequency subbands. This is the zerotree with respect to a given threshold. Most trees can be efficiently represented by using the zerotree. However, when this assumption does not hold, considerable bits are required to specify nonzerotree structures. For example, relatively large coefficients in high-frequency subbands cost lots of bits to specify their values and locations [4].

Although there are some minor differences among the zerotree- based image coders, their encoding procedures can be summarized as consisting of three categories of operations: 1) the significance map pass; 2) the zerotree map pass; and 3) the refinement pass. In the significance map pass, the significance function, with respect to a given threshold, is applied to each wavelet coefficient using a predefined scanning order. The two possible results for each coefficient are significant (1 symbol) or insignificant (0 symbol).

This is a form of simple binary quantization. Usually, the initial threshold T_0 is given by the following [4]:

$$T_0 = 2^{\left[\log_2\left(\max_{i,j}|c(i,j)|\right)\right]} \quad \text{.............(1)}$$

where $c(i, j)$ is the wavelet coefficient at location (i, j) and $\max_{i,j}$ denotes the largest integer less than or equal to x . In the next pass, the threshold is generally decreased to $T_0 / 2$.

In the zerotree map pass, the zerotree function, which also has two possible outputs with respect to a given threshold, is applied to the trees. If there are no significant coefficients in a tree, the zerotree function outputs the insignificant symbol. Otherwise, this function outputs the significant symbol and the positions of the significant coefficients in the tree should be specified by an appropriate method at a given threshold. The choice of the specifying method determines the computational efficiency and rate-distortion performance of the particular zerotree-based encoder.

In fact, the SPIHT coder improves its performance compared to most other zerotree-based encoders by applying a more sophisticated tree set in the zerotree map pass. In the refinement pass, each coefficient that turned out to be significant in the zerotree map pass, approaches its exact value. One bit is allocated for each coefficient. It is noted that the refinement pass is applied to the coefficients that are significant with respect to the former thresholds, not those that are significant with respect to the given threshold. The algorithm that creates the bitstream in an embedded and progressive manner can be terminated at any time [4].

The zerotree-based encoders show good rate-distortion performance with very low computational complexity. However, their performances are greatly dependent on several factors, such as the set of wavelets, the normalization unit in the wavelet transform, a scan order, and the first threshold T_0. Among these, the normalization unit, which multiplies successively the coefficients in the same decomposition level, might cause significant loss (about 3–5 dB). The first threshold may reduce the performance up to 1 dB. The number of decomposition levels can also make some differences in image compression performance [4].

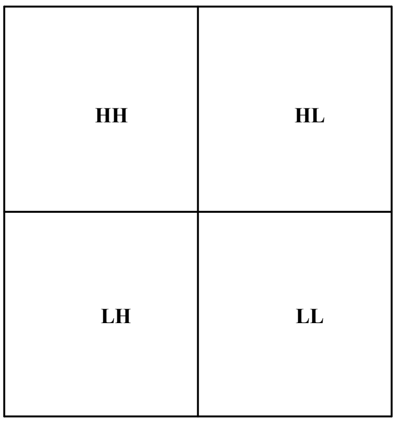


Figure (1) One Level DWT

4- The Proposed Compression Algorithm

The original image is passed through multi-resolution wavelet transformation (Nondyadic wavelet Transform) to produce transform coefficients that are decorrelated and energy backed. The basic idea of the DWT is that of successive approximation, together with that of added detail. At each stage, the input signal is decomposed into a coarse approximation signal, and an added detail signal. In this regard, the DWT decomposes the input signal into a set of frequency subbands [5].

Then quantize the transformation coefficients , that step is mapping of a large set of possible inputs into a smaller set of possible output. Practically the rounding to the nearest integer operation could be represented as the simplest quantization approach. The implemented model in this paper is Fast Tree-Structured and Zero Tree Quantization scheme. which shown in figure (2). The quantization goal is to produce transform coefficients, with entropy of resulting distribution of quantized coefficient symbols is small enough so that the symbols can be entropy-coded at low bit rate.

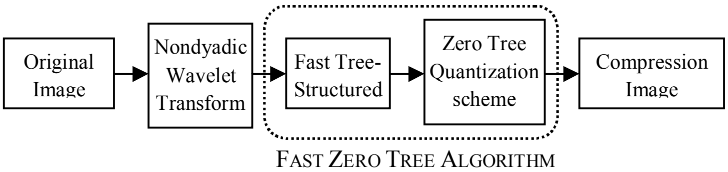


Figure (2) Block Diagram of the Proposed Compression Algorithm

5-Result of this algorithm

MRI gray scale image with size 256×256 was obtained in this compression scheme for multi bit rates in terms of PSNR that seen in figure (3), a large range of compression ratio is achieved such as (61.53:1) at PSNR of (38.74 dB), (65.57:1) at PSNR of (38.34 B), and a (72.72:1) compression ratio at PSNR of (33.13 dB) Figure (4) shows some examples of the decompression MRI image. This algorithm will implement using Visual Basic version 6 (VB.6).

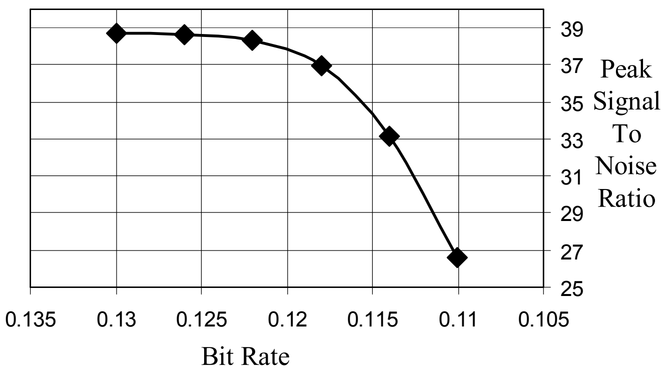
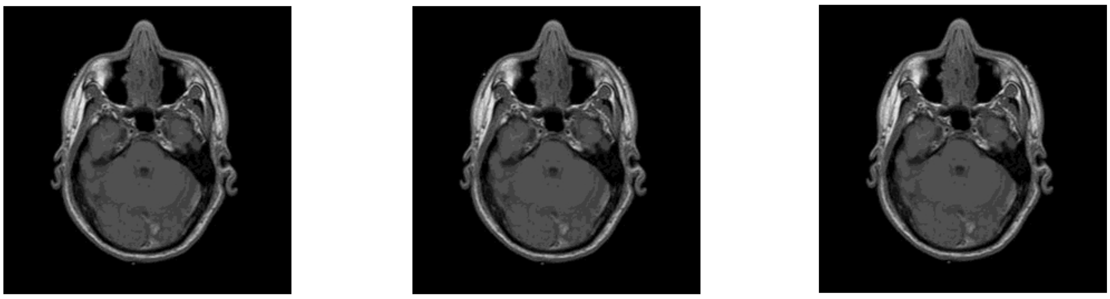


Figure (3) The Relation Ship between Bite Rate (br) and PSNR



(a) br=0.130, PSNR=38.74 CR=61.53

(b) br=0.122, PSNR=38.34 CR=65.57

(c) br=0.114, PSNR=33.13 CR=72.72

Figure (4) Decompression MRI image at different Bit Rates and PSNR

6- The discussion

From the previous results some remarkable, concerning the behavior and performance of the proposed compression scheme. The following is the important coclusions.

1. The use of the Nondyadic Wavelet Transform. This transform provides an attractive tradeoff between spatial and frequency resolution. This unique property of wavelet transform does not exist in other transform.
2. The coarsest level, LL contains the most important coefficients. Thus, a great care should be given to this subband in quantization to obtain high decompression quality.
3. Fast and spatial quantization was used to coded the remaining coefficient and achieve good results.

7- References

1. Othman khalifa, "wavelet coding design for image data compression", international arab journal of information technology, vol. 2, no. 2, april 2005.
2. Nasir Rajpoot, Francois Meyer, Ronald Coifman , and Roland Wilson, "ProgressiveWavelet Packet Image Coding Using Compatible Zerotree Quantization", e-mail: rajpoot-nasir@cs.yale.edu.
3. D.S.G. Pollock and Iolandalo Cascio, "NON-DYADIC WAVELET ANALYSIS", Department of Economics, Queen Mary College, University of London, Mile End Road, London E1 4NS, UK, 2006.
4. Taekon Kim, Seungkeun Choi, Robert E. Van Dyck, and Nirmal K. Bose, "Classified Zerotree Wavelet Image Coding and Adaptive Packetization for Low-Bit-Rate Transport", IEEE Transactions on circuits and systems for video technology, Vol. 11, No. 9, September 2001.
5. Sviram, P., and M. Marcellin, “Image Coding Using Wavelet Transform and Entropy Constrained Trellis Coded Quantization”, IEEE Transaction on Image Processing, Vol.4, No.6, pp.725-733, June 1995.