P. Vijayalakshmi et al Int. Journal of Engineering Research and Applications www.ijera.com
ISSN : 2248-9622, Vol. 4, Issue 4(Version 1), April 2014, pp.120-124

RESEARCH ARTICLE OPEN ACCESS

An Analysis of 2D Bi-Orthogonal Wavelet Transform Based On Fixed Point Approximation

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ABSTRACT
As the world advances with technology and research, images are being widely used in many fields such as biometrics, remote sensing, reconstruction etc. This tremendous growth in image processing applications, demands majorly for low power consumption, low cost and small chip area. In this paper we analyzed 2D bi-orthogonal wavelet transform based on Fixed point approximation. Filter coefficients of the bi-orthogonal wavelet filters are quantized before implementation. The efficiency of the results is measured for some standard gray scale images by comparing the original input images and the reconstructed images. SNR and PSNR value shows that this implementation is performed effectively without any loss in image quality.
Key Words— Bi-orthogonal wavelet Transform, Fixed Point Approximation

I. INTRODUCTION

Recent advances in medical imaging and telecommunication systems require high speed, resolution and real-time memory optimization with maximum hardware utilization. The 2D Discrete Wavelet Transform (DWT) is widely used method for many medical imaging systems because of perfect reconstruction property. DWT can decompose the signals into different sub bands with both time and frequency information and to arrive high compression ratio. DWT architecture, in general, reduces the memory requirements and increases the speed of communication by breaking up the image into the blocks.

A wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components. Usually one can assign a frequency range to each scale component. Each scale component can be studied with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets. The wavelets are scaled and translated copies known as daughter wavelets of a finite-length or fast-decaying oscillating waveform known as the mother wavelet. Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals.

Both Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT) are continuous-time transforms. They can be used to represent continuous-time signals. CWT's operate over every possible scale and translation whereas DWT's use a specific subset of scale and translation values or representation grid. There are a large number of wavelet transforms each suitable for different applications. The discrete wavelet transform (DWT) has generated a great deal of interest recently due to its many applications across several disciplines, including signal processing. Thus wavelets provide a time-scale representation of signals as an alternative to traditional time-frequency representations.

RELATED WORK

Many architectures have been proposed to perform DWT, but few address the precision of the coefficients necessary to ensure perfect reconstruction. The goal of work is to determine the precision of the filter coefficients (for an orthogonal wavelet) needed to compute the 2-D DWT without introducing round-off error via the filter. It needs at least 14 bits for 1 octave of decomposition if both DWT and IDWT are fixed-point operation, while 13 bits are enough to come up with the same result if only the transform DWT is fixed-point [2]. The implementation of 2D DWT using fixed point representation are shown and the results shown that this can be performed without any loss [3]. "VLSI Architectures for the 4-Tap and 6-Tap 2-D Daubechies Wavelet Filters Using Algebraic Integers," presented an algebraic integer (AI) based multi-encoding of Daubechies-4 and -6 2-D wavelet filters having error-free integer-based computation. It also guarantees a noise-free computation throughput the multi-level multi-rate 2-D filtering operation. Comparisons are provided between Daubechies-4 and -6 designs in terms of SNR, PSNR, hardware structure, and power consumptions, for different word lengths [1].

II. PROPOSED WORK

Fig 1 shows the block diagram of the proposed system. Initially the image is given to the bi-orthogonal wavelet filter, where the image is decomposed based on sub band coding. The coefficients which we got from the bi-orthogonal wavelet filter are quantized using fixed point approximation. Finally the image is reconstructed.

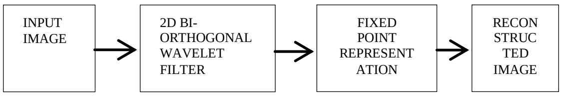

Fig.1 Block diagram of proposed system

SUB-BAND CODING

Generally image is decomposed based on sub-band coding. This sub-band coding is the general form of bi-orthogonal wavelet transform. If the scaling and wavelet functions are separable, the summation can be decomposed into two stages. First step is along the x-axis and then along the y-axis. For each axis, we can apply wavelet transform to increase the speed. The two dimensional signal (usually image) is divided into four bands: LL (left-top), HL (right-top), LH (left bottom) and HH (right-bottom). The HL band indicated the variation along the x-axis while the LH band shows the y-axis variation. The power is more compact in the LL band. Fig.2 shows the single level decomposition and Fig.3 shows the second level decomposition of image along rows and columns.

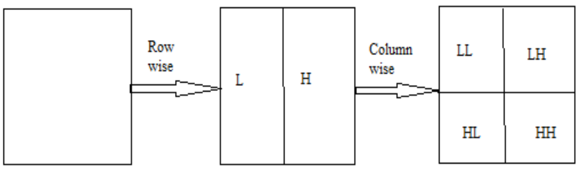

Fig.2 First level of decomposition

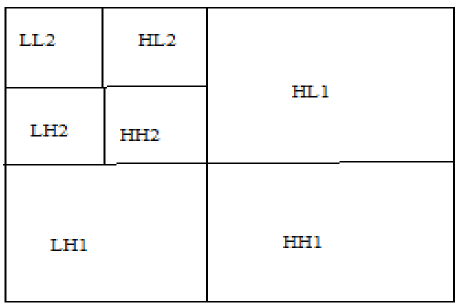

Fig.3 Second level of Decomposition

III. BI-ORTHOGONAL WAVELET TRANSFORM

Already known that bases that span a space do not have to be orthogonal. In order to gain greater flexibility in the construction of wavelet bases, the orthogonality condition is relaxed allowing semi-orthogonal, bi-orthogonal or non-orthogonal wavelet bases. Bi-orthogonal 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 bi-orthogonal case, rather than having one scaling and wavelet function, there are two scaling functions $\varphi, \tilde{\varphi}$ that may generate different multiresolution analysis, and accordingly two different wavelet functions Ψ, $\tilde{\Psi}$ is used in the analysis and is used in the synthesis. In addition, the scaling functions φ, $\tilde{\varphi}$ and the wavelet functions Ψ, $\tilde{\Psi}$ are related by duality in the following equations (1) and (2)

$$\int \psi_{j,k}(x)\tilde{\psi}_{j',k'}(x)dx = 0 \qquad (1)$$

as soon as $j \neq j'$ or $k \neq k'$ and even.

$$\int \varphi_{o,k}(x)\varphi_{0,k'}(x)dx = 0 \qquad (2)$$

as soon as $k = k'$

There are two sequences, g_n and h_n to act as decomposition sequences and two sequences to act as reconstruction sequences. If c_n^1 is a data set, it should be decomposed as which is shown in the equation (3) and (4)

$$c_n^0 = \sum_k h_{2n-k} c_k^1 \qquad (3)$$

$$d_n^0 = \sum_k g_{2n-k} c_k^1 \qquad (4)$$

For reconstruction it is shown as

$$c_l^1 = \sum_n \tilde{h}_{2n-l} c_n^0 + \tilde{g}_{2n-l} d_n^0 \qquad (5)$$

If we want perfect reconstruction, so decomposing and then reconstructing shouldn't change anything. This imposes some conditions shown in equation (6) & (7)

$$g_n = (-1)^{n+1} \tilde{h}_{-n} \quad (6)$$

$$\tilde{g}_n = (-1)^{n+1} h_{-n} l \quad (7)$$

The separation of analysis and synthesis is such that the useful properties for analysis (e.g., oscillations, zero moments) can be concentrated on the $\tilde{\psi}$ function. The interesting property for synthesis (regularity) which is assigned to the Ψ function has proven to be very useful.
The dual scaling and wavelet functions have the following properties:

(a) They are zero outside of a segment.
(b) The calculation algorithms are maintained, and thus very simple.
(c) The associated filters are symmetrical.
(d) The functions used in the calculations are easier to build numerically than those used in the Daubechies wavelets.

IV. FIXED POINT APPROXIMATION

The designs of a wavelet transform processor, to treat the data and filter coefficient values in fixed-point values. Fixed point has the advantages of being easier to implement, requires less silicon area, and makes multiplications faster to perform. Floating point allows a greater range of numbers, though floating point numbers require 32 or 64 bits. Fixed-point numbers can be 8 to 32 bits (or more), possibly saving space in the multiplier.

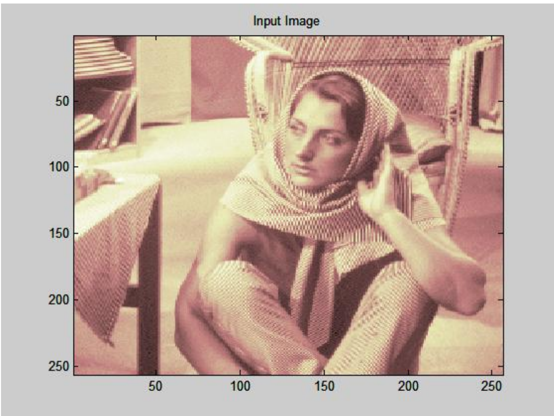

Fig.3 Original image

The wavelet transform has compact support, and the coefficients have small sizes that do not take advantage of the floating-point number's wide range. Also, using fixed-point numbers allows for a simpler design. It can be explained in another way as, the extra hardware that floating point requires is wasted on the DWT. A standard design for integer multiplications high speed Booth multiplier is needed. In the horizontal and vertical filters, decimal numbers including some bits for the fractional part represent the values. When the results leave the filters, the values are truncated to fixed format.

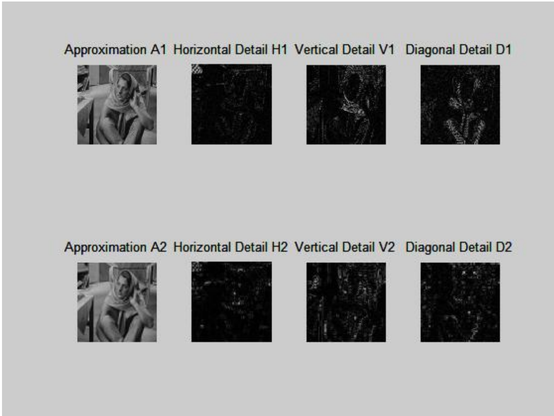

Fig.4 Approximation details of Barbara image

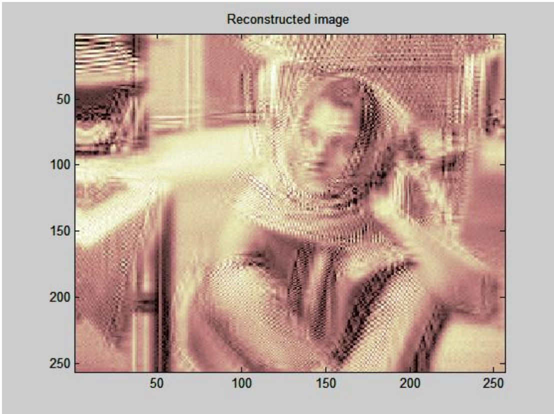

Fig.5 Reconstructed image based on fixed point representation using daubechies wavelet transform

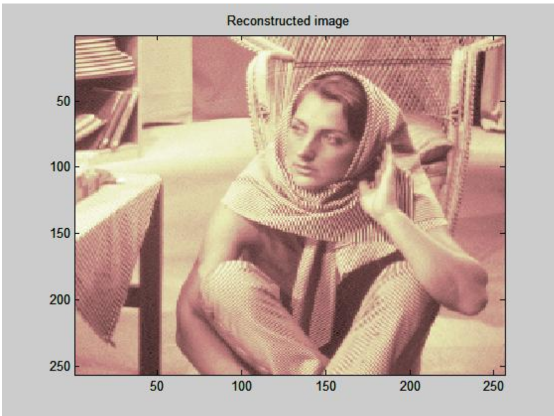

Fig.6 Reconstructed image based on fixed point representation using bior wavelet transform

For multiresolution, the DWT coefficient's range will grow. The increase is upper-bounded by approximately 2. An extra bit of precision for each transform octave or dimension will be needed. For a 1-D architecture, also notes that 12 bits of precision are enough. It is also noted that wavelet transformed data is naturally floating point, but it itself round it to the nearest integer values, to minimize data loss. The chip has 16x16 size in multipliers, but keep 16 bits of the result, which is chosen by software. Therefore, fixed-point numbers with an assumed radix is used to work for computing the DWT.

For the computation of a 2-D DWT or IDWT, we need to recover the integer part of the result and the most significant bit of the fractional part, to allow correct rounding. To produce output results in a conventional number system, we make a final substitution of the representation of z in the polynomial representation of the output data. Since z is irrational, we will not find an error-free finite representation within a conventional weighted system (e.g. binary) therefore, we have to use an approximation, and the error relating to that approximation dictates the quality of the output result.

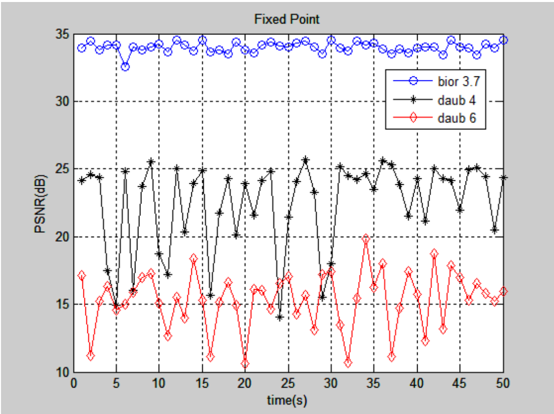

Fig.7 PSNR graph for Barbara image

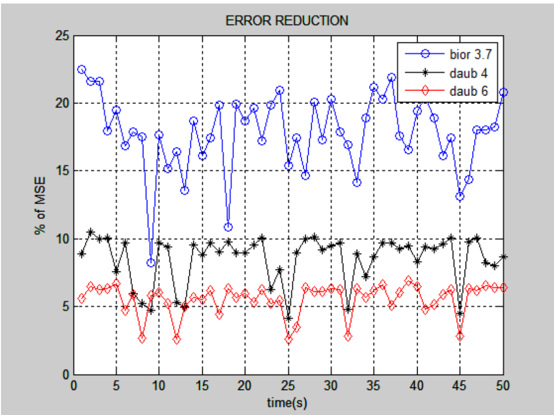

Fig.8 Percentage of error reduction graph for Barbara image

The proposed structure is a lattice design for the bi-orthogonal 7/3 filter bank using lattice structures. The design is verified using matlab programming. They also gives the objective results of the matlab representation for this design in terms of the PSNR values when using some of the standard gray scale images. In addition, the results of the input gray scale images are compared with the resulting images of the proposed structure are also shown using cascade analysis-synthesis.

V. RESULTS

Matlab simulation is done for the given biorthogonal 7/3 and daubechies 4 and 6 wavelet structure. Fig.3 is an input image taken for decomposition and reconstruction based on fixed point representation. Fig 7 and 8 shows the comparison of PSNR values and percentage of error reduction at different times for both daub4, daub8 and bior 7/3 structures.

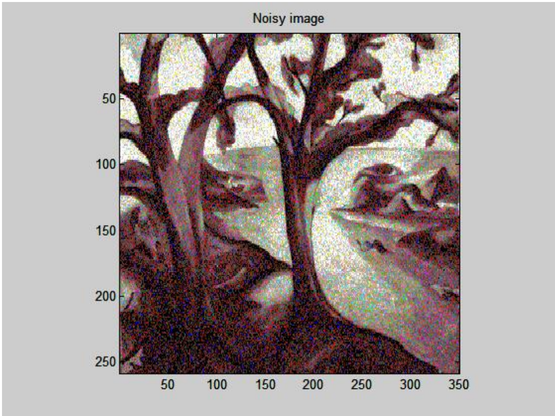

Fig.9 Noisy Image

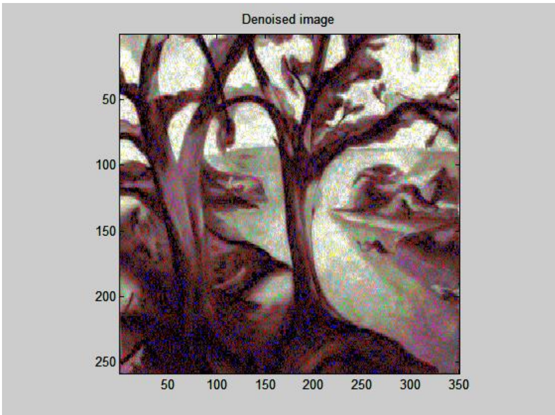

Fig.10 Denoised Image using daubechies wavelet

Parameters	daub 4	bior 7/3
PSNR(dB)	+15.55250	+311.47517
MSE	1.8249e+003	4.6662e-027

Table.1 Comparison between daubechies and Bi-orthogonal Wavelet

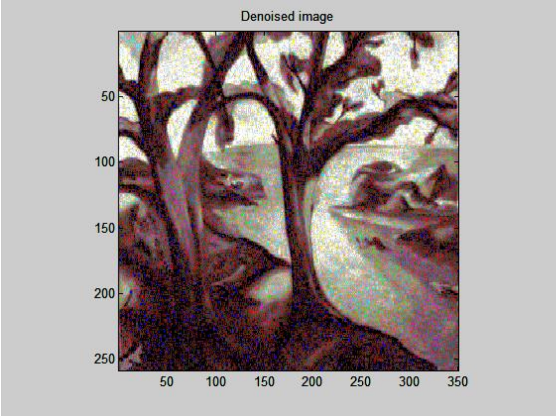

Fig.11 Denoised Image using bior wavelet

Noisy image also denoised by using bior and daubechies wavelet transform. This is shown in fig 10 and 11. Table.1 shows the comparison between daubechies 4 and bi-orthogonal 7/3 wavelet. PSNR and MSE value shows that bi-orthogonal wavelet transform provides increased performance when compared to daubechies wavelet transform.

VI. CONCLUSION

The existing daubechies 4 and 6 wavelet is compared with bi-orthogonal wavelet by finding the PSNR and MSE values of an image. The coefficients of both the wavelets are represented in fixed point. PSNR values and MSE values for each coefficients are found at different times. The results are simulated using MATLAB. The results shown that PSNR values are increased for bi-orthogonal wavelet when compared to the daubechies 4 and 6 wavelet. Rounding off the approximation coefficients may introduce some errors. This can be recovered using different encoding techniques.

VII. ACKNOWLEDGEMENT

I would like to thank my guide Mrs. M.Vidya, Assistant professor, who guided me to complete this project and also thank everyone those who supported me to achieve my target.

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