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IMPLEMENTATION OF IMAGE RECONSTRUCTION FROM MULTIBAND WAVELET TRANSFORM COEFFICIENTS

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Abstract:

Image compression plays an important role in web applications. Many methods are employed to compress images. Wavelet Transform based methods play an important role in image compression. The wavelet coefficients of certain sub bands carry significant information whereas the wavelet coefficients of other sub bands do not carry significant information. The sub bands that do not carry significant information need not be encoded. This saves significant storage space. However the wavelet transforms and inverse wavelet transforms are complex operations requiring a great deal of hardware. In this work a method to recover original image from the wavelet coefficients without the use of complicated filters is presented. One of the methods to construct the image from the sub bands is to simply add all the sub bands. The drawback in this method is that we need all the sub bands to faithfully reconstruct the image. Suppose we have all the sub bands by some means. Even then the ideal operation of all the filters that produce different sub bands cannot be perceived. To avert all these problems, the proposed reconstruction method aims at interpolating the subband images and then interleaving the low-pass subband image and the high-pass subband image to reconstruct the original image.

Keywords: Image Processing, Multiband Wavelet Transform, Image Compression, Encoding

1. Introduction

Transforms in signal processing convert signals in time domain to signals in frequency domain and vice-versa. When a time domain signal is converted into frequency domain all the time information is lost. Similarly when a signal is converted into time domain from frequency domain all the frequency information is lost. There are applications where both the time domain information and frequency domain information must coexist and are of equal importance. For example in audio signal processing the time of occurrence of a particular note may be important. In such applications the existing transforms have to be applied to a portion of the input signal by selecting it. The process of selecting a portion of the input signal is called windowing. If the window is large the time resolution is poor and the frequency resolution is better and vice versa. To adjust the width of the window, hence the time resolution we use a constant k, and to adjust the frequency resolution we use scale s. The factor s appears in the denominator of the basis function. Increase in factor s compresses the wavelet function and decrease in factor s expands the wavelet function. If the wavelet function is compressed, on transformation it extracts the high frequency components whereas if the wavelet function is expanded, on transformation it extracts the low frequency components. The frequency components that are present in the wavelet function are passed to the output after scaling by a certain factor, whereas all the other frequency components are attenuated.

2. Related Work

[Anand Darji, et al, 2014] present a multiplier less, high speed, low power pipeline architecture with novel dual Z scanning technique, for lifting based 2D Discrete Wavelet Transform. The multipliers are replaced with pipelined adders and shifters to reduce the critical path detected and update operations to one adder delay. The architecture is fully pipelined to improve the operating frequency so as to use it for real time HD video processing. The Z scanning technique is used to reduce latency as well as transposing register array size. [Jiaqui An, 2015] proposed a self adaptive 2D continuous wavelet transform based algorithm for extracting wave information from images. The application of wavelet transform for image processing is assessed, and the effect of the scale on the output yield is determined. [Nasrin M. Makbol., et.al, 2015] discussed about block based discrete wavelet transform using singular value decomposition.

[Huseyin Kusetogullari, 2015] discussed dynamic multiple description wavelet based image coding. The method is proposed for data transmission in dynamically changing network topologies like MANETS(Mobile Ad-Hoc Networks). [Nazeer Muhammed et., al, 2015] described a method for decomposing images based on wavelet transform using singular value decomposition. The scaling factor determines robustness against various image processing operations. The proposed algorithm is highly reliable. Hyper spectral images have high spectral resolution, but suffer from low spatial resolution [Patel R.C et., al, 2015]. In this work a new learning based approach based on super resolution for discrete wavelet transform is proposed. The novelty of the work lies in the design of application specific wavelet co-efficients. An initial review of spatial resolution is done using filter co-efficient and the spectral resolution is made in the wavelet domain.

3. Image reconstruction from Wavelet Transform

Image reconstruction is done using interpolation followed by filtering. The interpolation process creates a periodic spectrum of the basic image. The unwanted frequency components need to be filtered out. The filtering of image is done using two dimensional filters. The filters are created for one dimensional filtering. The one dimensional filters are recursively called to do two dimensional filtering. The input compressed image is interpolated row wise first. After interpolation the size of the row is increased by a factor of two. This creates additional periodic images in the spectrum. Next the input compressed image is interpolated column wise. This also creates additional images in the spectrum. The images need to be filtered out to get the original image back. For this the one dimensional filter is first applied along the row. A part of the subset of periodic images in the spectrum is removed after one dimensional filtering. Then the same one dimensional filter is applied column wise to get rid of the remaining periodic images in the spectrum. The compressed images are is of two types. The pixels in the image are called wavelet co-efficients. The compressed image consists of detail and average coefficients. The similar areas of image contain average coefficients, and hence for the corresponding pixels the differential coefficients are zero. So these coefficients need not be encoded at all or if the coefficients are very small it will require least number of bits for encoding. This forms the basis of image compression using wavelet transform. The method including forward wavelet transform is shown in Figure 1.

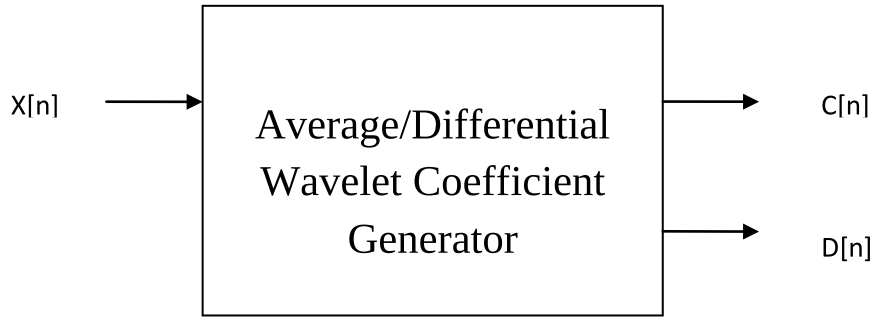

Figure 1 Generation of Wavelet Coefficients both average and detail

In the above diagram X[n] represents the input samples and C[n] is the average coefficients of the input samples. The D[n] represents the detailed coefficients. The equation for C[n] and D[n] as a function of the input sample is given in Equation 1 and Equation 2.

$$c[n] = 0.5x[2n] + 0.5x[2n+1] \qquad (1)$$

$$d[n] = 0.5x[2n] - 0.5x[2n+1] \qquad (2)$$

The average coefficients and the detail coefficients can be used to reconstruct the original image using Equation 3 and Equation 4.

$$x[2n] = c[n] + d[n] \quad (3)$$

$$x[2n+1] = c[n] - d[n] \quad (4)$$

The block diagram for reconstruction is shown in Figure 2.

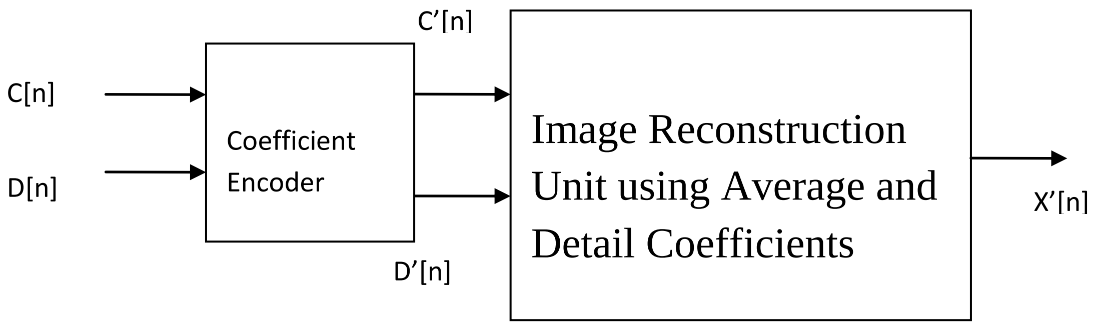

Figure 2 Reconstruction of Sparse Image from Wavelet Coefficients

It is clear from the above block diagram, as the number of decomposition levels increase, the decomposition units or filters also increase logarithmically. The wavelet transform units also occupy a significant chip area. The complexity involved is illustrated in Table 1.

Table 1 Comparison of Filters Required Stage wise for Reconstruction

Stage Number	Multiresolution Wavelet Analysis Reconstruction	Multiband Wavelet Analysis Reconstruction	Reduction in Number of Filters
1	2	D	2-D
2	4	D	4-D
3	8	D	14-D
4	16	D	30-D
5	32	D	62-D

4. Image Reconstruction using Proposed Technique

It is inferred that the conventional reconstruction method has large hardware complexity. It requires large memory for storing the intermediate values. The latency is high and the throughput is low. In order to overcome the problem Image Reconstruction using Multiband Wavelet Coefficients proposed in this paper. In the existing method of Multi Resolution Wavelet Analysis the intermediate values have least significance, but large number of intermediate values is generated.

For example the outputs of low pass filtering not required at each and every stage. The frequency component of Multi Band Wavelet Analysis does not overlap with each other. Hence instead of using complicated filters the image encoded using Multiband Wavelet Transform Coefficients can be easily reconstructed using summation filters. The summation filters can be implemented using parallel or sequential methods. The hardware required to implement the summation filters in parallel and sequential is shown in Table 2 and Table 3 respectively.

Table 2 Summing Filters required for Parallel Reconstruction for a Down Sampling Factor D

Stage Number	Multiresolution Wavelet Analysis Reconstruction	Multiband Wavelet Analysis Reconstruction	Reduction in Number of Filters
1	2	D-1	3-D
2	4	D-1	5-D
3	8	D-1	15-D
4	16	D-1	31-D
5	32	D-1	63-D

It is clear from Table 2 that whatever may be the image resolution the number of summing filters required is always one less than the number of bands or the down sampling factor. If the same hardware is implemented sequentially, only one summing filter is required always.

Table 3 Summing Filters required for Sequential Reconstruction for any Down Sampling Factor

Stage Number	Multiresolution Wavelet Analysis Reconstruction	Multiband Wavelet Analysis Reconstruction	Reduction in Number of Filters
1	2	1	1
2	4	1	5
3	8	1	13
4	16	1	29
5	32	1	61

5. Simulation Results

The simulation result for existing method is shown in the Figure 3. The input “data_in” is the common input to all the multiband filters. The frequency bands are separated and obtained at the output as data_out1, data_out2 and so on. The information present in one frequency band is not present in the other frequency band. Each frequency band is the complement to sum of remaining frequency bands with respect to the original image.

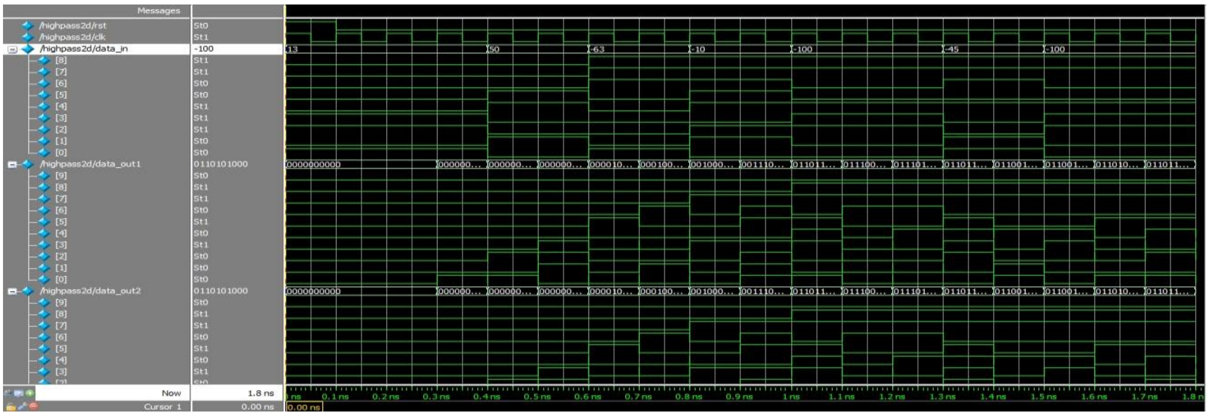

Figure 3 The Different Frequency Bands Generated by the Filters.

The proposed method has two ways of implementation. The parallel method needs more silicon area. Therefore it is preferable to use the sequential method. The simulation result for sequential method is shown in the Figure 4 and Figure 5 respectively.

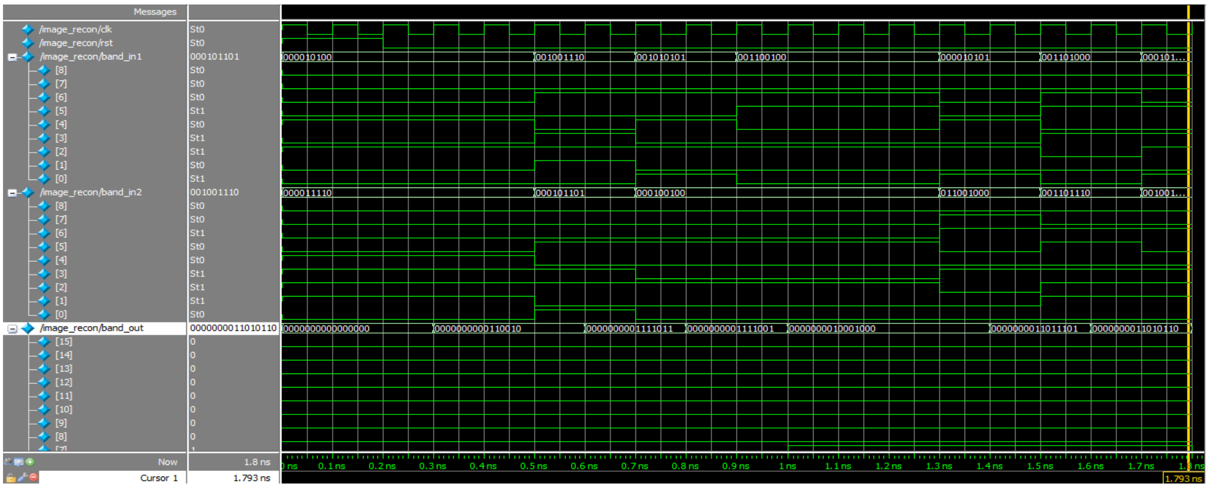

Figure 4 The Input band of Frequencies in the Multiband Wavelet Analysis Method.

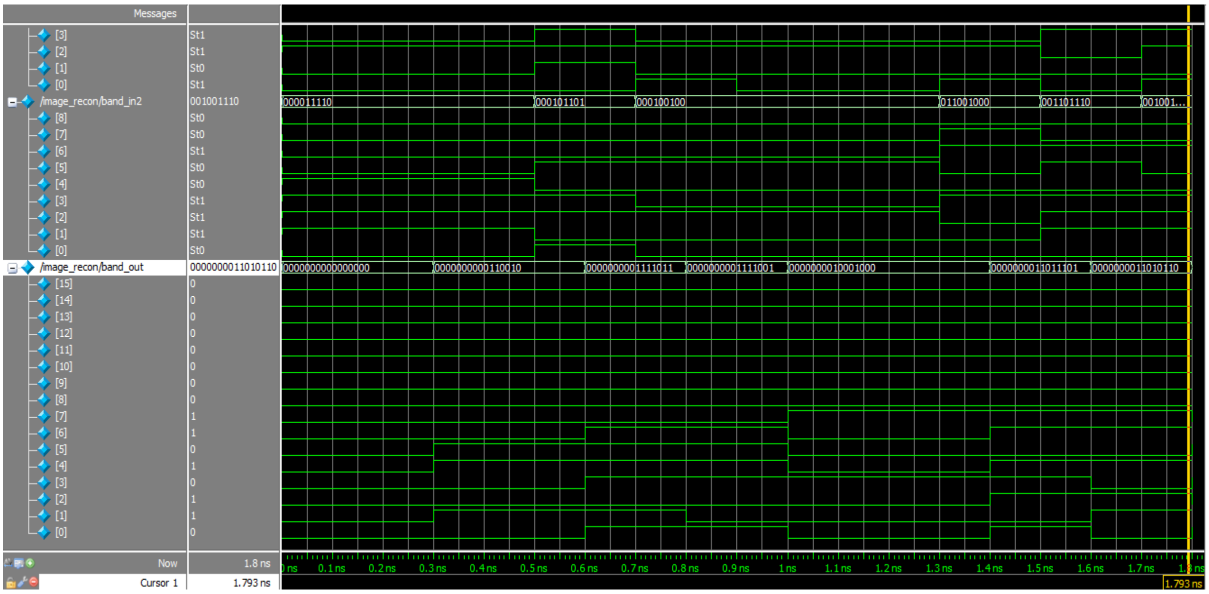

Figure 5 The Output band of Frequencies in the Multiband Wavelet Analysis Method.

The synthesis results of the existing and proposed method is shown in Figure 6 and Figure 7 respectively.

lowpass2d Project Status (09/01/2016 - 15:12:05)			
Project File:	hdl.xise	**Parser Errors:**	No Errors
Module Name:	lowpass2d	**Implementation State:**	Placed and Routed
Target Device:	xc3s1000-4fg320	**•Errors:**	No Errors
Product Version:	ISE 12.4	**•Warnings:**	117 Warnings (0 new)
Design Goal:	Balanced	**•Routing Results:**	All Signals Completely Routed
Design Strategy:	Xilinx Default (unlocked)	**•Timing Constraints:**	All Constraints Met
Environment:	System Settings	**•Final Timing Score:**	0 (Timing Report)

Device Utilization Summary				[-]
Logic Utilization	**Used**	**Available**	**Utilization**	**Note(s)**
Number of Slice Flip Flops	29	15,360	1%	
Number of 4 input LUTs	26	15,360	1%	
Number of occupied Slices	30	7,680	1%	
Number of Slices containing only related logic	30	30	100%	
Number of Slices containing unrelated logic	0	30	0%	
Total Number of 4 input LUTs	26	15,360	1%	
Number used as logic	25			
Number used as Shift registers	1			
Number of bonded IOBs	153	221	69%	
Number of BUFGMUXs	1	8	12%	

Figure 6 The Design Summary of the Multi resolution Wavelet Analysis reported by the ISE tool.

image_recon Project Status (09/01/2016 - 12:06:23)			
Project File:	image_recon.xise	**Parser Errors:**	No Errors
Module Name:	image_recon	**Implementation State:**	Placed and Routed
Target Device:	xc3s1000-4fg320	**•Errors:**	No Errors
Product Version:	ISE 12.4	**•Warnings:**	No Warnings
Design Goal:	Balanced	**•Routing Results:**	All Signals Completely Routed
Design Strategy:	Xilinx Default (unlocked)	**•Timing Constraints:**	All Constraints Met
Environment:	System Settings	**•Final Timing Score:**	0 (Timing Report)

Device Utilization Summary				[-]
Logic Utilization	**Used**	**Available**	**Utilization**	**Note(s)**
Number of 4 input LUTs	10	15,360	1%	
Number of occupied Slices	5	7,680	1%	
Number of Slices containing only related logic	5	5	100%	
Number of Slices containing unrelated logic	0	5	0%	
Total Number of 4 input LUTs	10	15,360	1%	
Number of bonded IOBs	36	221	16%	
IOB Flip Flops	16			
Number of BUFGMUXs	1	8	12%	

Figure 7 The Design Summary of the Multiband Wavelet Analysis reported by the ISE tool.

Table 1 compares the Slices and LUTs utilized by the of the Multiresolution Wavelet Analysis method with those utilized by Multiband Wavelet Analysis.

Table 1 Slices and LUTs Utilized.

Index	Method	Slices	LUTs
1	Multi Resolution Wavelet Analysis	30	26
2	Multiband Wavelet Analysis	5	10
3	Percentage Reduction	83.33%	61.54%

6. Conclusion

The inference from the work is that Multiband Wavelet Analysis decomposes the input image into non overlapping frequency bands. Since the frequency bands are non- overlapping the reconstruction procedure becomes fairly simple. Multiband analysis eliminates the necessity to design complex filters. Phase noise, phase distortion due to the frequency overlap is greatly avoided. The avoidance of frequency overlap automatically makes the output band's sampling rate satisfy Nyquist Criteria. Hence throughout the re-construction process there is no need for interpolation filters. The reconstruction process can be done using simple summing filters. The simulation results show that the

Multiband Wavelet analysis method offers 83.33% reduction in number of slices and 61.54% reduction in number of LUTs utilized. Hence the Multiband Wavelet Analysis can be utilized as an alternative tool to Multi Resolution Wavelet Analysis for faster analysis. The hardware required is also very simple.

7. References

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