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AREA OPTIMIZED BALANCED MULTIWAVELETS FOR WIRELESS COMMUNICATION

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ABSTRACT

New technologies are emerging to take the challenges in the wireless communication. According to the requirements for the next generation technologies have led to unparalleled insist for high speed architectures for complex signal processing applications. In this paper, we propose a modified DMWT architecture based on CardBal filter. The DMWT coefficients that are fractions are converted to integers and are modified to reduce the number of multiplications and additions. The reduced CardBal filter coefficients are used to process the data, thus reducing the computation complexity and making it suitable for FPGA implementation. The design operates at maximum frequency of 300MHz and consumes less than 1% resources and thus is suitable for real time applications optimizing area, speed and power. The model is tested for its functionality using HDL code and is synthesized using Xilinx ISE targeting FPGA.

Keywords: *Cardinal Multiwavelets, CardBal Filter, Balanced Multiwavelets, DMWT, FPGA*

1. INTRODUCTION

The Discrete Wavelet Transform (DWT) is an efficient and useful tool for signal and image processing. This growing "success" is due to the achievements reached in the field of mathematics, to its multi resolution processing capabilities, and also to the wide range of filters that can be provided. These features allow the DWT to be tailored to suit a wide range of applications [1]. The DWT is a transformation that can be used to analyze the temporal and spectral properties of non-stationary signals [5].The aim of eliminating noise is achieved by inverse transformation, like wavelet transform. Successful exploitation of wavelet transform might lessen the noise effect or even overcome it completely [12Fast Wavelet Transform (FWT) highlights the benefit of a faster compression and faster processing as compared to DWT with higher compression ratios at the same time and reasonably good image quality [17]. Multiwavelets offer the possibility of superior performance for signal processing applications, compared with scalar wavelets. A multiwavelet system can simultaneously provide perfect reconstruction while preserving length, good performance at the boundaries, and a high order of approximation [19]**.** Multiwavelets are extension from scalar wavelets, and have several advantages in comparison with scalar wavelets. The experiment results show that this fusion algorithm, based on multiwavelet transform, is an effective approach in image fusion area. Multiwavelets offer the advantages of combining symmetry, orthogonality, and short support, which cannot be achieved by scalar two-channel wavelet systems at the same time [22]. The performance of multiwavelets in general depends on the image characteristics. For the images with mostly low frequency content, (ordinary still images scalar wavelets generally give better performance. However multiwavelets appear to excel at preserving high frequency content. In particular, multiwavelets better capture the sharp edges and geometric patterns that occur in images [24]. The relatively new field of multiwavelets shows promise in obviating some of the limitations of wavelets. Multiwavelets offer more design options and are able to combine several desirable transform features. The few previously published results of multiwavelet-based image compression have mostly fallen short of the performance enjoyed by the current wavelet algorithms. The multiwavelet transform and quantization methods and introduces multiwavelet packets. Extensive experimental results demonstrate that our techniques exhibit performance equal to, or in several cases superior to, the current wavelet filters. Finally, good results have been presented for

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applying multiwavelets to the denoising of 1-D and 2-D signals. Combined with the success shown here for multiwavelet image compression [27]. Multiwavelet transform can be implemented by tree structured matrix filter bank, which operates on vector sequence input instead of scalar ones. Therefore, unlike in scalar wavelet system, preprocessing is usually required to extract vector sequence input from the input signal for better performance. A technique for applying multiwavelet transform to 2-D signal is proposed. Its simple structure results in 65% reduction in preprocessing computation compared with the recent 1-D technique while maintaining similar energy compaction capability. The reduced computation requirement for preprocessing comparable with scalar wavelet transform in computation intensive application such as video processing [30].

2. PROPERTIES OF MULTIWAVELETS:

The important properties of multiwavelets are orthogonality, admissibility and the regularity conditions and these properties which gave named to their wavelets.

2.1Admissibility

The square integral function Y(t) satisfying the admissibility condition,

$$\int \frac{|\psi(w)|^2}{|w|} \mathrm{dw} < +\infty$$

Can be used to first analyze and then reconstruct the signal without loss of information. In the above equation Y (w) is the Fourier Transform of Y(t) . The admissibility condition implies that the Fourier Transform of Y(t) vanishes at zero frequency, i.e.

$$\int \frac{|\psi(w)|^2}{|w|} \mathrm{dw} < +\infty$$

This means that wavelets must have a band pass like spectrum. A zero at the zero frequency also means that the average value of the wavelet in time domain must be zero.

$$|\psi(w)|^2 = 0;\ |w| = 0$$

Therefore it must be oscillatory. That is Y (t) must be a wave.

2.2 Regularity

From the equation below,

$$x_{cwt}(s,\tau) = \int x(t)\psi_{z,\tau}(t)dt$$

The wavelet transform of a one-dimensional function is two-dimensional. The time-bandwidth product of the wavelet transform is the square of the input signal and for most practical applications this is not a desirable property. Therefore one imposes some additional conditions on the wavelet functions in order to make the wavelet transform decrease quickly with decreasing scales. These are the regularity conditions and they state that the wavelet function should have some smoothness and concentration in both time and frequency domains. Regularity is a quite complex concept and try to explain it a little using the concept of vanishing moments (approximation order).

2.3 Vanishing moments

If we expand the wavelet transform into the Taylor series at t=0 until order n τ=0 for simplicity) we get,

$$X(s,0) = \frac{1}{\sqrt{z}} \sum_{p=0}^{N} x^{(p)}(0) \frac{t^p}{p!} \psi\left(\frac{t}{s}\right) dt + R(n+1)$$

Here x (p) stands for the pth derivative of x and R (n +1) means the rest of the expression. Now if we define the moments of the wavelet by

$$N_{p=} \int t^p\, \psi(t) dt$$

From the admissibility condition we already have that the 0^{th} moment NO= 0 so that the first term in the right hand side of above equation is zero. If we now manage to make the other moments up zero, then the wavelet transform coefficients x (s,t) will decay as fast as s n+2 for a smooth signal x (t). This is known in as the vanishing moments or approximation order. If a wavelet has N vanishing moments, then the approximation order of the wavelet transform is also N. With increasing number of vanishing moments the wavelet becomes smoother or more regular. Summarizing, the admissibility condition gave us the wave, regularity and vanishing moments gave us the fast decay or the let, and put together they give us the wavelet.

3. TYPES OF MULTIWAVELETS:

The first construction for polynomial multiwavelet was given by Alpert, who used them as a basis for there presentation of certain operators. Later, Geronimo, Hardin and Massopust constructed a multi-scaling function with 2 components using fractal interpolation.

3.1 GHM Multiwavelets

This multiwavelet was introduced by Geronimo, Hardin, and Massopust. Both scaling functions are symmetric and multiwavelet functions

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are symmetric-antisymmetric. It has approximation order2 of two.For notational convenience, the set of scaling functions can be written using the vector notation $\Phi(t)=[\phi_1(t)\quad \phi_2(t)\quad \cdots\quad \phi_r(t)]^T$, where $\Phi(t)$ is called the multiscaling function. Likewise, the multiwavelet function is defined from the set of wavelet functions as $\Psi(t)=[\psi_1(t)\quad \psi_2(t)\quad \cdots\quad \psi_r(t)]^T$.

When r = 1, $\Psi(t)$ is called a scalar wavelet, or simply wavelet. While in principle, r can be arbitrarily large, the multiwavelets studied to date are primarily for r = 2.

$$\Psi(2^j t) = \sum_k G_{j+1}(k)\Phi(2^{j+1}t-k)$$

$$\Phi(2^j t) = \sum_k H_{j+1}(k)\Phi(2^{j+1}t-k)$$

However, that H_k and G_k are matrix filters, i.e. H_k and G_k are rxr matrices for each integer k. The matrix elements in these filters provide more degrees of freedom than a traditional scalar wavelet.The two-scale equations (1) and (2) can be realized as a matrix filter bank operating on r input data streams and filtering them into $2r$ output data streams, each of which is down-sampled by a factor of two. Signals get decomposed into coarse approximation and fine detail at a several resolution multiple wavelet basis uses translation and dilation of scaling and mother wavelet function. Require input data to be preprocessed to obtain more economical decomposition. Preprocessing method depends on length, degree and Orthogonality Differences between multiwavelet and scalar wavelet bases, these differences become apparent when one implements discrete multiwavelet transform.

The lowpass filter H and highpass filter G in the multiwavelet filter bank are 2×2 matrices. Thus, they need to be convolved with two rows of data. However, for 1-D signals, we have only one row of data; so we have to pre-process the 1-D signal to obtain two rows of data. We note that, the pre-processing should not destroy orthogonality and/or symmetry of the bases. One solution to this problem is simply to repeat the input. But this solution is equivalent to oversampling and results in an expansive technique that is not suitable for compression. Besides, it increases the computational complexity of the transform.

Where the input length 2 vectors are formed from the original signal as

$$v_{o,k} = \begin{bmatrix} v^0_{0,k} \\ v^1_{0,k} \end{bmatrix} = \begin{bmatrix} X_k \\ \alpha\, X_k \end{bmatrix}$$

$$k = 0,1,\cdots,N-1$$

3.2 Cardinal multiwavelets

Cardinal multiwavelets were introduced to avoid the prefiltering step in multiwavelet computations Multiwavelet bases, for which the zero moment properties carry over to the discrete-time filter bank, are called balanced . CardBal2 is a cardinal balanced multiwavelet with length 6 and approximation order of two. CardBal3 is a Cardinal balanced multiwavelet with length 8 and approximation order of three. CardBal4 is a Cardinal balanced multiwavelet with length 12 and approximation order of four.

To obtain cardinal orthogonal multiscaling functions, it is useful to characterize them in terms of the scaling filters and For to generate orthogonal scaling functions , it is necessary that and be orthogonal to their shifts by 4.Specifically.

$$\sum H_i(n)H_j(n+4k) = \delta(i-j).\delta(k).$$

This is the condition that characterizes the orthogonality of four-channel filter banks. It arises here because the two channel multiwavelet filter bank can be drawn as a four channel *scalar* filter bank with interleaving of subband signals.

3.3 C L Multiwavelets

This multiwavelet was introduced by Chui and Lian and has approximation order of two. According to the definition of Daubechies wavelet, the multiwavelet in the interval [0, 3] can be known as CL4 multi-wavelet, whose filter length is 4. CL multi-wavelet with smoothness, compact support, symmetry and orthogonality together has two scale functions and two wavelet functions.

The properties of CL Multiwavelets are described below

1. They have short support in the interval [0, 2].
2. All integer translate of scaling functions are orthogonal.
3. The system has second order of approximation (constant and linear functions can be represented exactly by a linear combination of translates Φ1 (t – k), Φ2 (t – k), k Є Z). The shape of the CL Multiwavelet is in such a way that it is well suited

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to the real time speech processing applications. Thus the CL Multiwavelet is selected for signal denoising with soft threshold.

4. BER PERFORMANCE OF DMWT IN AWGN CHANNEL:

In this section, the result of the simulation for the DMWT-OFDM system is calculated and shown in figure (3), which gives the BER performance of DMWT-OFDM in AWGN channel. when compared to the two previous system FFT-OFDM and DWT-OFDM, it is shown that the DMWT-OFDM is much better. This is a indication to the fact that the orthogonal bases of the multiwavelets is much important than the orthogonal bases used in FFT-OFDM and DWT-OFDM.

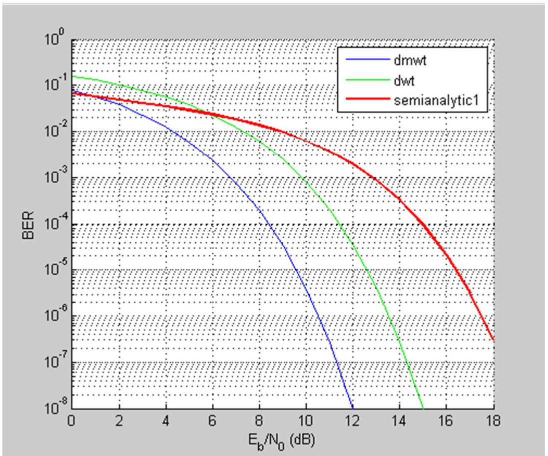

Figure1: BER performance of DMWT-OFDM in AWGN channel model.

5. CARDINAL MULTIWAVELETS:

Cardinal multiwavelets are called balanced multiwavelets, were introduced to avoid the prefiltering step in multiwavelet computations Multiwavelet bases, for which the zero moment properties carry over to the discrete-time filter bank. We were obtained a four-balanced cardinal orthogonal multiwavelet system with filters of length 23. The cardbal4 filter co-efficient of cardinal multiwavelet is,

$$\mathrm{H0} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \quad \mathrm{H1} = \begin{bmatrix} 0.173 & 1/\sqrt{2} \\ 0.662 & 0 \end{bmatrix}$$

$$\mathrm{H2} = \begin{bmatrix} 0.937 & 0 \\ -0.24 & 1 \end{bmatrix} \quad \mathrm{H3} = \begin{bmatrix} 0.242 & 0 \\ 0.031 & 0 \end{bmatrix} \qquad (3)$$

$$\mathrm{H4} = \begin{bmatrix} 0.031 & 0 \\ -0.24 & 0 \end{bmatrix} \quad \mathrm{H5} = \begin{bmatrix} 1 & 0 \\ 0.022 & 0 \end{bmatrix}$$

$$\mathrm{G0} = \begin{bmatrix} -0.02 & 0 \\ 1 & 0 \end{bmatrix} \quad \mathrm{G1} = \begin{bmatrix} -0.17 & 1/\sqrt{2} \\ -0.66 & 0 \end{bmatrix}$$

$$\mathrm{G2} = \begin{bmatrix} -0.93 & 0 \\ 0.242 & 1 \end{bmatrix} \quad \mathrm{G3} = \begin{bmatrix} -0.24 & 0 \\ -0.03 & 0 \end{bmatrix} \qquad (4)$$

$$\mathrm{G4} = \begin{bmatrix} -0.03 & 0 \\ 0.246 & 0 \end{bmatrix} \quad \mathrm{G5} = \begin{bmatrix} -1 & 0 \\ -0.02 & 0 \end{bmatrix}$$

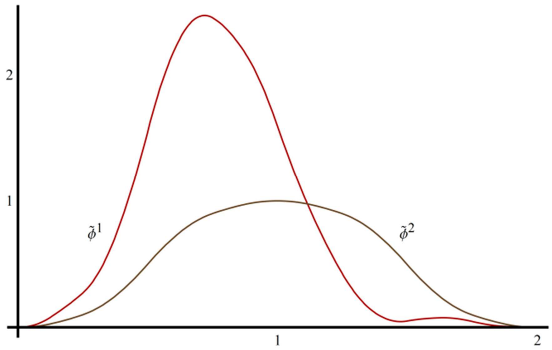

Figure2: Cardinal Multiwavelet

A. Smoothness

It is disappointing that as the balance order is increased, the cardinal multiscaling functions do not become significantly smoother. Apparently, the interpolation property, taken together with orthogonality and compact support, is quite restrictive. We suppose that by increasing the multiplicity of the multiwavelet basis (the number of scaling and wavelet functions) to, smoother solutions might be available.

B. Scaling Function Similarity

The two-channel multiwavelet filter bank can be drawn as a four-channel *scalar* filter bank with interleaving of subband signals. If the filters are too different, then the interleaving becomes a problem when the filter bank is iterated on one of its subband signals. Either a prefilter is required, or the filters must be appropriately designed. Certainly, when one scaling filter is simply the shift of the other (or nearly so), then the interleaving of subband signals presents no problem. For the multiscaling functions considered in this paper, balancing conditions appear to make them similar to one another, with higher balancing leading to greater similarity. A similar phenomenon occurs for the multiscaling functions as the balance order increases, the two scaling functions resemble each other more.

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C. Prefiltering

The use of cardinal wavelet bases also simplifies the initialization step of the discrete wavelet transform, that is, the estimation of the the fine scale scaling coefficients. However, with cardinal (or interpolating) scaling functions, no such initialization step is needed. The samples are themselves the values sought.

6. DMWT/IDMWTARCHITECTURE:

The transformation matrix based on cardbal filters for DMWT is chosen to be of size 12 x 12. The input is taken into group of 4 samples, and is repeated with scaled values. The input matrix which is of size 4 x 1 is resized to 12 x 1 after extension and scaling as shown in equation 4. The input matrix is transformed to output using the cardibal filter. After matrix multiplication we get equations for computing the output matrix of size 12 x 1. From the equations, there are redundant factors between samples y0 andy11, in order to eliminate redundancies and reduce computation time; the equations are regrouped by reducing the common factors. The simplified constants are scaled by 128 to convert the fractions to nearest integers. Due to rounding effect the loss is restricted to less than 2%. The simplified expression for cardibal filters are rewritten in matrix form, from the two matrices it is found that the input samples are of size 4x1 and are used simultaneously to compute the output samples y0 to y11. Here it is scaled with scaling factor 128. The table below shows co-efficient before and after scaling.

Table1: Scaled and Un scaled co-efficient

Before scaling	After scaling
0.171	21
0.195	25
0.707	90
1.644	210
1.022	130
0.488	62
0.242	30
0.153	19
-0.226	-28
0.7382	94
-1.43	-184
0.997	125
0.675	86
-1.63	-213

$$Y0 = 21*x0+25*x2+90*x3+210*x4 \quad (12)$$

$$Y1 = 130*x0+62*x2-28*x4+128*x5 \quad (13)$$

$$Y2 = 210*x0+30*x2+19*x4+90*x5 \quad (14)$$

$$Y3 = -28*x0+128*x1+94*x3+28*x4 \quad (15)$$

$$Y4 = 30*x0 +19*x2+64*x3+212*x4 \quad (16)$$

$$Y5 = 94*x0+28*x2-19*x4+ 90*x5 \quad (17)$$

$$Y6 = 24*x0-25*x2+90*x3-184*x4 \quad (18)$$

$$Y7 = 125*x0-62*x2+28*x4+128*x5 \quad (19)$$

$$Y8 = -210*x0-32*x2-19*x4+212*x4 \quad (20)$$

$$Y9 = 28*x0+128*x1+86*x2-28*x4 \quad (21)$$

$$Y10 = -19*x0+64*x1-213*x2-24*x4 \quad (22)$$

$$Y11= -28*x0+19*x2+90*x3+125*x4 \quad (23)$$

The filter coefficients are obtained from the simplified equations. Reducing the above equations into matrix form. The simplified equations derived from above matrix are used in design of multiwavelet architecture. The optimized architecture consists of a FIFO of size 4, that stores the input samples, and the FIFO are accessed to compute the output samples as per the simplified equations. The optimized architecture is modelled using HDL and is simulated using ModelSim. In this work a cardbal based DMWT and IDMWT is implemented on FPGA optimizing area, power and speed performances.

7. RESULTS AND DISCUSSION:

In this section, we proposed a cardibal filter for cardinal multiwavelets and the VLSI implementation of Discrete Multiwavelet transform and inverse discrete multiwavelet transform is presented. The DMWT coefficients that are fractions are converted to integers and are modified to reduce the number of multiplications and additions. The modeled HDL is simulated and tested for its functionality; the functionally verified HDL code is synthesized using Xilinx ISE targeting Virtex-5 FPGA. The design consists of 110 million gates and has 1136 I/Os. The synthesized net list and synthesis report are analyzed for the performance of designed DMWT architecture. The

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results obtained are compared and discussed in this section.

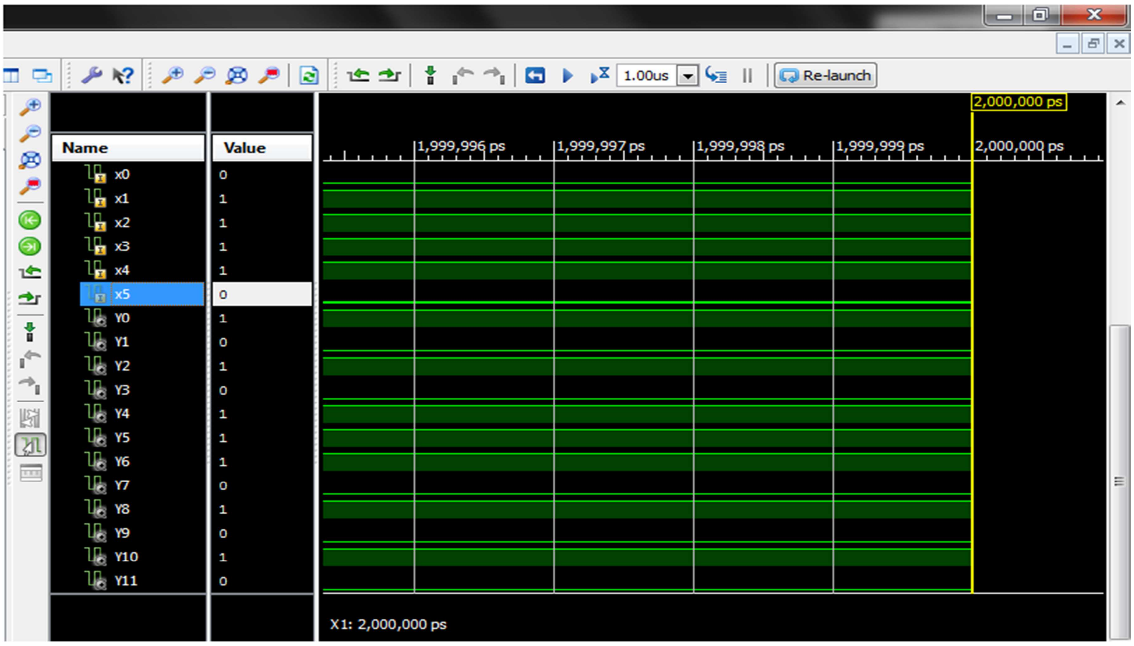

Figure3: post and place simulation

Target Device: xa9536xl-15-vq44
Minimum input arrival time before clock: 8.362ns
Maximum output required time after clock: 3.293ns
Total memory usage is 144660 kilobytes

Figure3 below shows the RTL schematic diagram of the cardibal filter design with interconnects between the various blocks. It is a technology independent schematic. From the optimized architecture the number of multipliers and adders are minimized. Apart from reduction in multipliers and adders, the throughput and latency of the optimized design is also improved.

Table2: Comparison Of Post Layout Synthesis Result Of The Existing Structures And Proposed Structure

Structures	Block-Size(P)	Multipliers	Adders	Registers	Power (Mw)	I/O Pins
Cheng et al [6]	2	12	16	24	8.93	66
Lai et al [7]	2	10	16	44	13.416	84
Tian et al [8]	4	6P	8P	10P	11.645	83
Proposed	6	8P	6P	12P	9.35	163

The arithmetic unit designed works on fixed point number system and thus introduces loss when compared with floating point number system. The DMWT architecture operates at a maximum frequency of 340MHz and consumes power less than 25mW. The power consumption is reduced by adopting various low power techniques as recommended for FPGA implementation.

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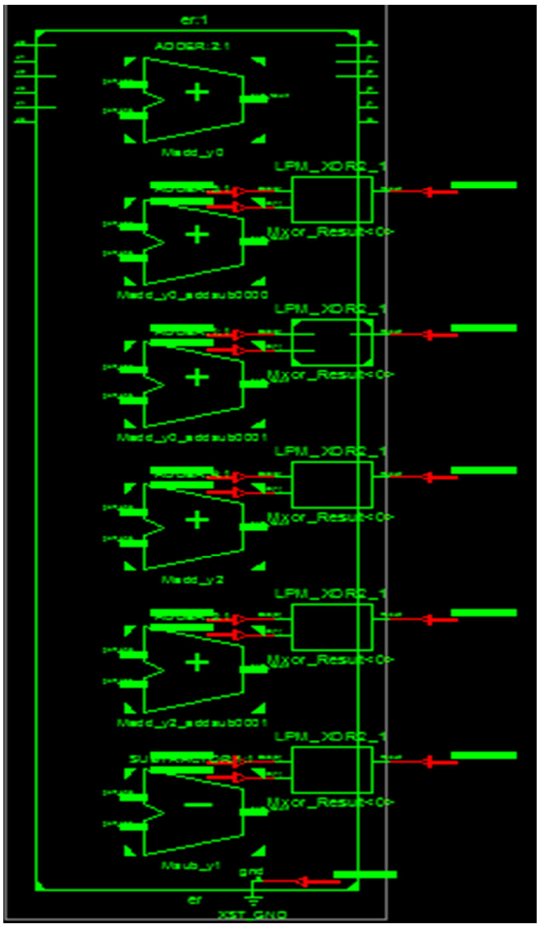

Figure4: RTL Schematic

8. CONCLUSION:

In this work, we propose a modified DMWT architecture based on cardBal filter. The DMWT coefficients that are fractions are converted to integers and are modified to reduce the number of multiplications and additions. The reduced cardBal filter coefficients are used to process the data, thus reducing the computation complexity and making it suitable for FPGA implementation. The modified equations are modeled using HDL and implemented on FPGA. The design operates at maximum frequency of 300MHz and consumes less than 1% resources and thus is suitable for real time applications.

9. CONCLUSION AND FUTURE WORK

In this work, we propose a modified DMWT architecture based on cardbal filter. The DMWT coefficients that are fractions are converted to integers and are modified to reduce the number of multiplications and additions. The reduced cardbal filter coefficients are used to process the data, thus reducing the computation complexity and making it suitable for FPGA implementation. The modified equations are modeled using HDL and implemented on FPGA. The design operates at maximum frequency of 300MHz and consumes less than 1% resources and thus is suitable for real time applications. In future, the carbal filter co-efficients can be reduced and reducing the power less than the proposed system.

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