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A Novel Poly-Phase Architecture For High Performance Discrete Wavelet Transform In FPGA

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Abstract:

Wavelet Transforms are used in number of application. They are applied in different fields such as signal processing, speech and image compression, biometrics, and so on. Design of discrete wavelet transforms is complex due to large number of arithmetic operations involved. In this Paper, pipeline VLSI architecture for the computation of the 1-D discrete wavelet transform (DWT) using poly-phase filter bank structure is proposed. The main focus of the scheme is on reducing the number and period of clock cycles and reducing the complexity of hardware resources needed for the computation. For hardware implementation, the choice of filter bank structure determines the efficiency and accuracy of computation of the DWT. here poly-phase filter bank structure is proposed for DWT computation which increases performance of computation as in poly-phase implementation units can operate in parallel, and therefore the filtering operation have less delay and however, pipelining can be used in this scheme to reduce the delay.

Key words: Discrete wavelet transform, poly-phase filter bank structure, VLSI architecture, computation of DWT, poly-phase implementation units, parallel, pipeline

1.Introduction

The wavelet transform becomes an emerging signal processing technique and it is used to decompose and reconstruct nonstationary signals efficiently.

Discrete wavelet transform (DWT) is based on time-scale rather than time-frequency representation. Wavelets are represented by scaling or dilation equations as opposed to difference equations. The discrete wavelet transform provides time-scale representations of discrete-time signals. This multigrid representation is computed using dilation equations rather than traditional difference equations. The DWT decomposes the approximation of the signal at each level of resolution into approximation and detail of the signal at the next level of resolution. Each level can add more detail to the information content.

The discrete wavelet transform uses translated and scaled mother wavelets as a set of basis functions to represent a signal. The translation factor shifts the original signal in the time domain and the scale factor determines the frequency band. As a result, the discrete wavelet transform gives time-frequency joint representations of the original signal. The discrete wavelet transform is a mathematical function that involves multiplication and addition operation to convolve signal of interest with predefined wavelet expansion coefficients.

The DWT consists of banks of low pass filters, high pass filters and down sampling units. Half of the filter convolution results are discarded because of the down sampling at each DWT decomposition stage. Only the approximation part of the DWT wavelet results is kept so that the number of samples is reduced by half. The level of decomposition is limited by the distortion tolerable from the resulting signal.

Several VLSI designs of the discrete wavelet transform have been reported for the discrete wavelet transform implementations. The DSP device is usually a general-purpose, fixed-architecture technology. The DSP processor is not capable of configuring the data path width and it may waste hardware resources. Besides, it needs long development cycle, and it may consume more power. As a low cost fast prototyping tool, FPGA design offers flexibility of re-programmability. The FPGA device allows easy configuration of the design data path, easy modification of the design architecture and also provides high performance at the same time.

The Discrete wavelet transform (DWT) has been developed as an efficient DSP tool for signal analysis and synthesis, speech compression, image compression, and even video compression. Due to its growing number of applications in various areas, it is necessary to explore the hardware implementation options of the Discrete Wavelet Transform (DWT).

The DWT is computationally intensive because of multiple levels of decomposition involved in the computation of the DWT. Design of discrete wavelet transforms is complex due to large number of arithmetic operations involved. It is therefore a

challenging problem to design an efficient VLSI architecture to implement the DWT computation for real-time applications, particularly those requiring processing of high frequency or broadband signals.

The Discrete wavelet transform (DWT) has gained the reputation of being a very effective signal analysis tool for many practical applications. This dissertation presents an approach towards VLSI implementation of the Discrete Wavelet Transform. In Discrete Wavelet Transform, the filter implementation plays the key role. The poly phase structure is proposed for the filter implementation, which uses multiply accumulate technique.

The implementation architecture is characterized by several parameters such as sample speed, system latency, and hardware area and power consumption. This dissertation describes several algorithm-architecture trade-offs associated with the implementation of the DWT.

The main focus of the scheme is on reducing the number and period of clock cycles for the DWT computation with little or no overhead on the hardware resources.

2.Poly-Phase Structure

There are various architectures for implementing a two channel filter bank for DWT. A filter bank basically consists of a low pass filter, a high pass filter, decimators or expanders and delay elements. Commonly used structures for hardware implementations of filter bank architectures are: direct form, polyphase and lattice, lifting. In this dissertation poly-phase structure for filter bank implementation is used.

For hardware implementation, the choice of filter bank structure determines the efficiency and accuracy of computation of the DWT. All structures have some advantages and drawbacks which have to be carefully considered and based on the application, the most suitable implementation can be selected.

It is observed that the direct form is a very inefficient method for DWT implementation. This method is almost never used for DWT computation. The polyphase structure appears to be an efficient method for DWT computation. But the lattice and lifting implementations require fewer computations than the polyphase implementation and therefore are more efficient in terms of number of computations. However, the polyphase implementation can be made more efficient than the lattice and lifting schemes in case of long filters by incorporating techniques like MAC Arithmetic.

In the case of the lattice and lifting schemes, the filtering units cannot operate in parallel as each filtering unit depends on results from the previous filtering unit. In the case of convolutional polyphase implementation, the units can operate in parallel, and therefore the filtering operations have less delay. However, pipelining can be used in the other schemes to reduce the delay. The nonpolyphase structure is inefficient: in analysis, downsampling discards half the samples just computed by the filters; in synthesis, upsampling before filtering means that half of the filter multiplication operations are multiplying by zero.

In short, half of all mathematical computations are wasted. In contrast, a polyphase structure does not perform the wasted operations: downsampling precedes filtering and upsampling follows filtering. The polyphase filter structure is computationally equivalent to the original structure, but much more efficient. The result is a theoretical doubling in throughput compared to the nonpolyphase structure.

$$\begin{bmatrix} G_{0even}G_{0odd} \\ H_{0even}H_{0odd} \end{bmatrix} \times \begin{bmatrix} X_{even} \\ Z^{-1}X_{odd} \end{bmatrix} = \begin{bmatrix} Y_0 \\ Y_1 \end{bmatrix}$$

The input signal is split into odd and even samples, similarly, the filter coefficients are also split into even and odd components so that convolves with of the filter &

Convolve with of the filter. The two phases are added together in the end to produce the low pass output. Similar to the high pass filter where the high pass filter is split into even and odd phases H0even and H0odd.



Figure 1: Block Diagram Of The Poly-Phase Structure

3.Choice Of Pipeline Structure For Dwt Computation

In a pipeline structure for the DWT computation, multiple stages are used to carry out the computations of the various decomposition levels of the transform. Thus, the computation corresponding to each decomposition level needs to be mapped to a stage or stages of the pipeline. In order to maximize the hardware utilization of a pipeline, the hardware resource of a stage should be proportional to the amount of the computation assigned to the stage.

In this two-stage structure, stage 2 performs by operating on the data produced by stage 1 and on those produced by it, and therefore, the operations of the two stages need to be synchronized in a best possible manner.



Figure 2: Pipeline Structure With Two-Stage[21]

4. Architecture Design

In the stage-equalized architectures, the two stages together perform the DWT computation, with the amount and type of computations of the individual stages being the same, each of the two stages can use identical processing units. However, the control units to be employed by the stages have to be different.



Figure 3: Block Diagram Of The Two-Stage Architecture [21]

5.Processing Unit For Filtering Computation

In each stage, the processing unit by employing an - MAC cell network performs an -tap filtering operation and, at each clock cycle, generates a total



Figure 4: Block Diagram Of The Processing Unit For Filtering Computation[21]

6. Buffer Unit

All the output data must be synchronized. This synchronization process is facilitated by introducing in stage 2 a buffer, which stores output data from the two stages and provides input data to stage 2.



Figure 5: Structure Of The Buffer [21]

7.Mac (Multiply-Accumulate) Unit

It is crucial to aim at achieving the shortest critical data path when designing an -MAC-cell network for this architecture.



Figure 6: Structure Of The -Mac-Cell Network [21]

8.Mac Logic Imlementation

The goal of this project was to design and VLSI implementation of pipelined MAC for high-speed DSP applications. For designing the MAC, various architectures of multipliers and one bit full adders are considered. The static and dynamic one bit full adder was implemented as the basic block. The total process is coded with VHDL to describe the hardware. Finally, the whole process is implemented on VERTEX 7 Board.

MAC is composed of an adder, multiplier and an accumulator. Usually adders implemented are Carry-Select or Carry-Save adders, as speed is of utmost importance in DSP. One implementation of the multiplier could be as a parallel array multiplier. The inputs for the MAC are to be fetched from memory location and fed to the multiplier block of the MAC, which will perform multiplication and give the result to adder which will accumulate the result and then will store the result into a memory location. This entire process is to be achieved in a single clock cycle is the architecture of the MAC unit.



Figure 7: Structure Of The Mac-Cell Network [21]

9.Simulation Results

Na	ime	Vali	0 ns	200 ns	400 ns	600 ns	800 ns
	🔚 speech_length	1000			1000		
	🇓 speech_read	1					
	15 n	1000			1000		
M	🏹 speech[1:8]	[104	[104.000000,1	5.000000,103.000000	,104.000000,46.00000	9,119.000000,97.00000	0,118.000000]
1.1	-	' I					
		/readsp	beech/speech[1:8]				

Figure 8: Reading Audio File Consisting Of 8 Samples

N	ame		Val	 999,996 ps	999,997 ps	999,998 ps	999,999 ps	1,0
	16	clk	0					
	16	reset	0					
	16	clk_enab	0					
►	3	in_rsvd[7	[11	[118,	97,119,46,104,103,1	.05,104]		
	10	ce_out	0					
►	3	even[3:0]	[97		[97,46,103,104]			
►	6	odd[3:0]	[11		[118,119,104,105]		
	16	clk_perio	100		10000 ps			
	16	clk_enab	100		10000 ps			

Figure 9: Separating Samples In Even And Odd Component

								70.000 ns		
Value	0 ns	10 ns	20 rs	30 ns	40 ns	50 ns	60 ns	70 ns	80 ns	90 г
110110	010110	101010	111110				110110			
101100	010110	110010	110011				101100			
011	01	1	001				011			
001		011					001			
0011001110	0010000100	0100010100	0011010111				0011001110			
0011001110	0010000100	0100010100	0011010111				0011001110			
25.750000	16.500000	34.500000	26.875000				25.750000			
	Value 110110 101100 011 0011001110 0011001110 25.750000	Value Dins 110110 010110 101100 010110 011 01 001 001000100 0011001110 0010000100 0011001110 0010000100 0011001100 0010000100 25. 750000 16.500000	Value 0 ns 10 ns 110110 010110 10100 101100 010110 110010 011 011 011 001 0110 010100 001 011 011 001 010000100 0100010100 0011001110 0010000100 0100010100 25. 750000 16.500000 34.500000	Value 0 ns 10 ns 20 ns 110110 010110 101010 111110 10110 010110 110010 111110 011 011 011 001 001 011 011 001 001 011 011 001 001 011000100 01000100 0010010111 001000100 01000100 0101010111 25.750000 25.750000 16.500000 34.500000 26.875000	Value 0 ns 10 ns 20 ns 30 ns 110110 010110 101010 111110 10110 010110 110010 111110 011 011 001 001 001 011 001 001 001001100 00100000 00000100 0011010111 0011001110 00100000 010001000 0011010111 25. 750000 16.500000 34.500000 26.875000	Value 0 ns 10 ns 20 ns 30 ns 40 ns 110110 010110 101010 111110 10000000 10000000 011 011 001 001 0000000 0000000 00000000 00110001000 0100001000 0010001010 0011010111 10000000 00000000 00110001100 0010001000 0010010100 0011010111 10000000 00000000 25. 7500000 34.500000 26.875000 16.500000 34.500000 26.875000 10000000	Value 0 ns 10 ns 20 ns 30 ns 40 ns 50 ns 110110 010110 110100 111110	Value 0 ns 10 ns 20 ns 30 ns 40 ns 50 ns 60 ns 110110 010110 101010 111110 110110 110110 0110 010100 110010 110011 011 011 001 011 001 011 001 011 001 011 001 001 001 001 001000100 01000100 00110111 001100110 001100110 001000100 01000100 0011010111 001100110 001100110 011001100 011010111 0011001100 021100110 021100110 011001100 011010111 0011001100 021100110 021100110 011001100 011010111 0011001100 025.750000 25.750000 25.750000	Value 0 ns 10 ns 20 ns 30 ns 40 ns 50 ns 60 ns 70 ns 11010 01010 10100 11110 11010 10110 10110 0110 01010 110010 110011 011 011 011 001 011 001 001 001 001 001 001 011 001 001 001 001 001 001000100 01000100 00110111 001001100 001100110 00100110 001000100 01000100 0011010111 001100110 001100110 00100110 25. 750000 34.50000 26.875000 25.750000 25.750000 25.750000	Value 0 ns 10 ns 20 ns 30 ns 40 ns 50 ns 60 ns 70 ns 80 ns 11010 01010 10100 11110 110110 110110 10

Figure 10: Result Of Mac Logic (Ieven = 5.5,10.5,15.5,13.5, Iodd = 5.5,12.5,12.75,11, Heven = 1.5,1.5,0.5,1.5, Hodd = 1.5,1.5,1.5,0.5)

Name		V		400 ns		500 ns		, le	600 ns			700 n	s i i l		. 18	300 ns		
10	clk	0	JUUU		MM		uuuu	U	ЛЛЛ	Ш	M		UЛ	M	U		ЛЛ	JU
10	reset	0																
16	clk_enab	0	лллл			Inn	սոու	υļ		ՄՈ		່າກກ	UЛ	תחח	U			ய
► 5 8	input[0:7]	[1		[104.	000000,1	p5.0000	00,103.00	000	00,104.	0000	00,46.0	00000),119	.00000	0,9	7.00000	0,118	.00
► ¶8	coeff[0:1]	[0							[0.7	0710	0,0.707	100]						
10	ce_out	0	JUUU	Innn	MM	INN	սուս	υÜ	JUUU	տ	M	່າກ	ՄՈ	M	U		ЛЛ	ய
10	a11	14								147.	783900	1						
10	a12	14								146.	369700							
16	a13	11								116.	671500							
10	a14	15								152.	026500							
10	d11	-0								-0.7	707100							
10	d12	-0								-0.7	707100							
10	d13	-5								-51.	618300	1						
10	d14	-1								-14.	849100	1						_
L.	a21	20								207.	996011							
10	a22	18								189.	996356							
10	d21	ο.								0.9	99981							
L.	d22	-2								-24.	999521							
16	clk_perio	10								100	000 ps							

Figure 11: DWT Computation Of Samples Using Haar Wavelet

Name	M		20 ns	40 ns	60 ns	180 ns	100 ns		120 ns
Ug clk	1								
▶ 🎆 xin[7:0]	0	0	-3 / -1	1 4	05	-2 6		0	
▶ 崎 yout[15:0]	7	UX O			6 X -17 X -	7 X -2 X -	ĒX	7 X 1	_X-1
🔓 clk_perioc	10				10000 ps				

Figure 12: Direct Form Fir Filter In DWT Computation

N	ame	V		20 ns	40 ns	60 ns	80 ns	100 ns	
	Ug clkx	1							
۲	📲 xeven[7:	0)	-3 X 1	<u> </u>		0		
►	📲 xodd[7:0	0)	-1 X 4	<u>x -5 x 6</u>)		0		
►	📲 yeven(15	0	υχο	X 6 X	1 X -10 X -1	5 X 6 X -			0
►	📲 yodd[15:	0	υχο	X 2 X	-7 X 3 X 1	X -5 X -	2 X 24 X		0
►	📲 youtx[15:	0	U) X (U	0 X	8 X -6 X -	7 X -4 X 1	X -8 X 1		0
	🕼 clkx_peri	10				10000 ps			

Figure 13: Poly-Phase Form Fir Filter In DWT Computation

10.Performance Evaluation

(Selected Device: 7vx330tffg1157-3)

Metrics	Direct Form DWT (1 Level)	Poly-phase Form DWT (1 Level)
Total REAL time to Xst completion	14.00 secs	11.00 secs
Total CPU time to Xst completion	13.08 secs	11.78 secs
9-bit adder	4	8
10-bit subtractor	4	4
8-bit 2-to-1 multiplexer	32	42
8x8-bit multiplier	8	9

 Table 1: Comparison Between Direct & Poly-Phase Form For 1st Level DWT

Metrics	Direct Form DWT (2 Level)	Poly-phase Form DWT (2 Level)
Total REAL time to Xst completion	14.00 secs	15.00 secs
Total CPU time to Xst completion	13.81 secs	14.83 secs
17-bit adder	6	12
17-bit subtractor	6	5
16-bit 2-to-1 multiplexer	48	62
16x16-bit multiplier	12	14

Table 2: Comparison Between Direct & Poly-Phase Form For 2nd Level DWT

Metrics	Direct form DWT	Poly-phase form DWT
Sample Rate	Same as clock Rate	Increases by 2
Number of Clock Cycles	8	4
16-bitadder	14	14
16-bit Registers	16	18
8x8-bit multiplier	2	4

Table 3: Performance Comparison With Selected Device

11.Conclusion

This architecture is better than the existing architecture in terms of computation time and efficient use of available resources. In order to assess the effectiveness of the proposed scheme, the design is simulated using XILINX and MATLAB.Poly-phase architecture is proposed to increase performance of DWT Design is targeted on FPGA with combined Pipeline and Parallel architecture to reduce Hardware Resources.

12.Future Scope

Synthesis filter banks to compute the inverse DWT can be implemented. The architectures of the filter banks can be further improved and the proposed architecture can also be extended to 2-D DWT computation

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