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A Novel Architecture Based DWT with Folded and Pipelined Schemes for Infrasound Signal Classification

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Abstract:

Infrasound is a low frequency acoustic phenomenon that typically ranges from 0.01 to 20 Hz. The data collected from infrasound microphones are presented online by the infrasound monitoring system operating in Northern Europe. Processing the continuous flow of data to extract optimal feature information is important for real-time signal classification. Performing wavelet decomposition on the real-time signals is an alternative. In this paper, we propose a novel, efficient VLSI architecture for the implementation of one-dimension, lifting-based discrete wavelet transform (DWT). Both of the folded and the pipelined schemes are applied in the proposed architecture; the former scheme supports higher hardware utilization and the latter scheme speed up the clock rate of the DWT. Our approach uses only two FIR filters, a high-pass and a low-pass filter. A compact implementation was realized with pipelining techniques and multiple uses of generalized building blocks. The design was described in VHDL and the FPGA implementation and simulation were performed on the Xilinx ISE

Keywords: DWT, Lifting, Pipeline.

1. Introduction

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time-frequency representation of the signal. It was developed to overcome the short coming of the Short Time Fourier Transform (STFT), which can also be used to analyze non-stationary signals. While STFT gives a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions.

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy.

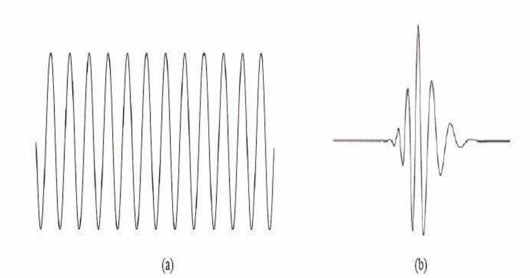

FIG 1.Demonstraction of (a) Wave and (b) Wavelet

The wavelet analysis is done similar to the STFT analysis. The signal to be analyzed is multiplied with a wavelet function just as it is multiplied with a window function in STFT, and then the transform is computed for each segment generated. However, unlike STFT, in Wavelet Transform, the width of the wavelet function changes with each spectral component. The Wavelet Transform, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies; the Wavelet Transform gives good frequency resolution and poor time resolution.

Discrete wavelet transform

Discrete wavelet transform (DWT) has been widely used in many different fields of audio and video signal processing. Recently, DWT is being increasingly used as effective solutions to the problem of image compression. One well- known example is that DWT has been adopted by the JPEG2000, one of the several popular image compression standards defined by the Joint Picture Expert Group (JPEG), due to the efficient decomposition of a signal into several components (sub-bands) with DWT. In general, DWT can be implemented by direct convolution and several DWT architectures implemented by filter convolution have been proposed. However, such an implementation suffers the need of a large number of computations and a large storage resource. Discrete wavelet transformation (DWT) transforms discrete signal from time domain into time-frequency domain. The transformation product is set of coefficients organized in the way that enables not only spectrum analyses of the signal, but also spectral behavior of the signal in time. This is achieved by decomposing signal, breaking it into two components, each caring information about source signal. Filters from the filter bank used for decomposition come in pairs: low pass and high pass. The filtering is succeeded by down sampling (obtained filtering result is "re-sampled" so that every second coefficient is kept). Low pass filtered signal contains information about slow changing component of the signal, looking very similar to the original signal, only two times shorter in term of number of samples. High pass filtered signal contains information about fast changing component of the signal. In most cases high pass component is not so rich with data offering good property for compression. In some cases, such as audio or video signal, it is possible to discard some of the samples of the high pass component without noticing any significant changes in signal. Filters from the filter bank are called "wavelets". Mathematical model of this process and the way to synthesize filter banks can be found in. Mallat shows that the DWT can be viewed as a multi-stage signal decomposition process using the basic filter bank structure shown in Fig 1. In this implementation the input signal is decomposed into its coarse approximation coefficients from the low-pass filter (G0) channel and its detail coefficients from the high-pass filter (H0) channel. Down sampling is applied after filtering the signal through the analysis filter bank to remove the redundancy introduced when a single length input is converted to a double length output. The filter bank operates recursively on the low-pass filtered data to generate coarser decompositions of the input signal and its corresponding details. Enhanced signal information and a better understanding of the signal behavior can be gained by observing the output of the signal at different levels of decomposition. Three stages of decomposition are usually considered sufficient for many applications

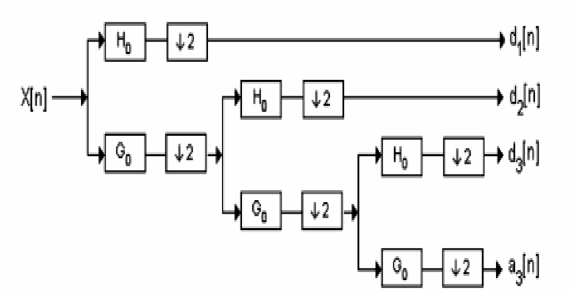

Fig 2. Three-level analysis DWT

3. Lifting Scheme Wavelet Transform

The lifting scheme is a new algorithm proposed for the implementation of the wavelet transform. It can reduce the computational complexity of DWT involved with the convolution implementation. Furthermore, the extra memory required to store the results of the convolution can also be reduced by in place computation of the wavelet coefficient with the lifting scheme. The lifting scheme consists of the following three steps to decompose the samples, namely, splitting, predicting, and updating. Figure 3 illustrates the three steps associated with the lifting scheme based DWT for the one- dimensional signal:(1) Split step: The input samples l are split into even samples and odd samples ;(2) Predict step (P): The even samples are multiplied by the predict factor and then the results are added to the odd samples to generate the detailed coefficients;(3) Update step (U): The detailed coefficients computed by the predict step are multiplied by the update factors and then the results are added to the even samples to get the coarse coefficients. The equations of the lifting scheme for the (5,3) discrete wavelet transform is shown as follows, The equations of the lifting scheme for the (5,3) discrete wavelet transform is shown as follows,

$$h_{j,i} = l_{j-1,2i+1} + \alpha l_{j-1,2i} + \alpha l_{j-1,2i+2}; ---(1)$$

$$l_{j,i} = l_{j-1,2i-2} + \beta h_{j,i} + \beta h_{j,i-1}; -----(2)$$

where (1) h and l are the detailed and the coarse coefficients, respectively; (2) α and β are the predict factor and the update factor of the (5,3) filter, respectively; and (3) i and j represent the input sample index and the decomposition level, respectively.

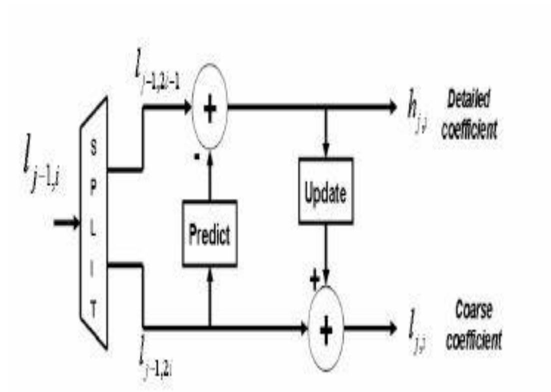

Fig 3 Lifting Scheme

Predict Module

The predict module is shown in Figure 4. As mentioned in Section , the predict module is used to compute the detailed coefficients. Initially, the even sequence comes from MUX_A, then it is multiplied by the predict filter coefficient α, and the result is stored in Register D1. When the corresponding odd sequence comes from MUX_B, it will be added to the data from register D1 and the result will be stored in the register D2 temporarily for two clock unit. Finally, the data stored in D2 will pass through MUX_C and is added to the data from register D1 to generate the detailed coefficient.

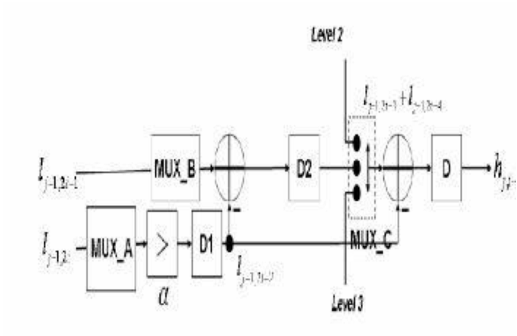

Fig 4 Predict Module

Update Module

The update module is shown in Figure 5. As mentioned in Section 2, the update module is used to compute the coarse coefficients. The detailed coefficient coming from the predict module is firstly multiplied by the update filter coefficient β. The result of the previous step is then added to the corresponding even sequence and the sum is temporarily stored in the register D3 for two clock unit. Then the data stored in D3 will pass through the MUX_E and is added to the delayed detailed coefficient multiplied by β to get the coarse coefficient.

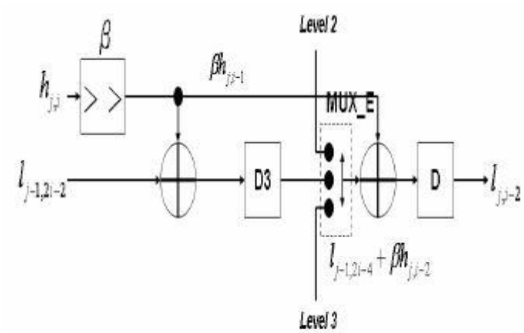

Fig 5 Update Module

Register Module

The register module contains four sets of units denoted as register set A, register set B, register set C, and register set D. The main function of these register is to temporarily keep the data to meet the timing plan. Register set A is used to keep the input samples for the computation of the coarse coefficients. Register set B and Register set C are used to temporarily store the data for computing the final detailed coefficients and coarse coefficients, respectively. Register s e t D is used to store the coarse coefficients generated by the predict module for the computation of the detailed coefficients of the next decomposition level.

THE 1 D DWT ARCHITECTURE

The 1D DWT levels 2 to 9 can be used as components of a feature vector. This implies that the implementation of nine levels is necessary. In our experiment, only three levels of a 16-coefficients Daubechies orthogonal 1D DWT filter have been implemented. It should be noted that our implementation is scalable for different filter lengths and additional levels. For the polyphone structure, the filter coefficients are divided into even and odd parts. We represent the filter coefficients using the 2's complement, fixed point notation by incrementing the word length during the calculation to 18 bits so as to maintain a good SNR at the output. When compared with the architectures and the proposed architecture requires the same number of adders and multipliers (shifters) shown figure 6.

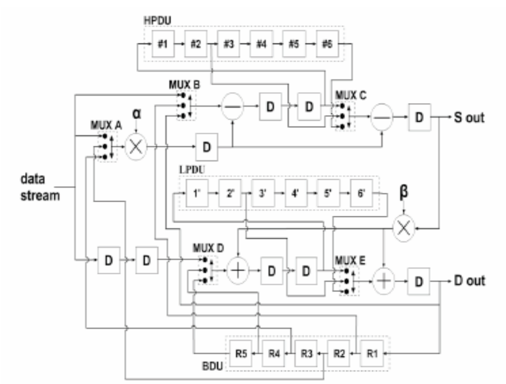

Fig 4. 1 D DWT ARCHITECTURE

4. Simulation Results

In order to quantify the performance of the implemented architecture, we conducted several tests using different sets of input data. The decomposition capability has been demonstrated for three different wavelets (db2, db4 and db8). Input data word lengths of 8 bit fixed point format have been used in the simulations. shows the corresponding waveforms of the approximations and details computed using the proposed 1D DWT architecture. the paper requiring the delay up to 2*Ta+Tco+Tsu, the architecture proposed in this article can shorten the delay of the critical path to a Ta due to the usage of the pipelined scheme, where Ta is the delay of an adder, Tco is the delay of a register, and Tsu is the setup time of a register. The proposed architecture was successfully synthesized using virtex device family from Xilinx Corp. Table 2 shows the simulation results of the synthesis report generated by Xilinx ISE.

Device Utilization for v50ecs144

Resource	Used	Avail	Utilization
IOs	44	94	46.81%
Function Generators	737	1536	47.98%
CLB Slices	369	768	48.05%
Dffs or Latches	353	1818	19.42%

5. Conclusion

This paper presents a design framework for the implementation of one-dimension, lifting-based discrete wavelet transform (DWT) an FPGA using a polyphase structure. The proposed architecture extracts enhanced signal information from infrasonic data in real-time using only two FIR filters, a high-pass and a low-pass filter. The energies of the 1D wavelet levels 2 to 9 can be used along with the skewness and kurtosis as inputs to the infrasound classifiers. In this paper, an efficient1 D DWT architecture utilizing folded and pipelined method has been proposed. The architecture has been verified successfully and realized with the FPGA device of Virtex family from Xilinx Corp.

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