FPGA Implementation of Discrete Wavelet Transform For Electroencephalogram Analysis

Pawar Chander[$], Dr. Y Padmasai[#]
[$]SRES COE,Kopargaon, M.H.
[#] VNR Vignana Jyothi Inst. of Engg and Tech., Hyderabad, AP.

Abstract:
Neurological disorders affect about five percent of the population. Approximately one percent of this group has been found to be epileptic. Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures. These seizures are due to abnormal, excessive, episodic neuronal activity in the brain. Diagnosis of epilepsy calls for long-term video EEG monitoring. This technique is not routinely used because of its high cost and inconvenience to the subject as the subject has to be in the hospital for longer time (typically one week to 10 days). Electroencephalogram (EEG) is an important tool in the diagnosis of certain neurological disorders. The ability of the wavelet transform to capture the signal energy in a few transforms coefficients and provide time and frequency information from the transient signal make it a very attractive tool for signal processing applications in several fields. In other words, The Discrete Wavelet Transform (DWT) has gained the reputation of being a very effective signal analysis tool for many practical applications. However, due to its computation intensive nature, current implementations of the transform fall short of meeting real-time processing requirements of most applications. This paper describes implementation of the Electroencephalogram data using Discrete Wavelet Transform and it's inverse.
Key Words: Electroencephalogram, Epilepsy, Discrete Wavelet Transform, Analysis and Synthesis filters

I. Introduction:

One of the most developing researches in Engineering that utilizes the extensive research in medicine is Biomedical Engineering. This area seeks to help and improve our everyday life by applying engineering and medical knowledge with the growing power of computers. The computers are efficient, straight forward and never get tired or sick, while humans though are smart and creative, become sick, weak and limited. Communication between humans seem usually much simple than the one involves humans and machines. This difficulty increases when a person is disabled. However, especially this kind of people has more to gain by assisting a machine in their everyday life.

The number of nerve cells in the brain has been estimated to be on the order of 10^{11}. Cortical neurons are strongly interconnected. Here the surface of a single neuron may be covered with 1,000-100,000 synapses (Nunez, 1981). The resting voltage is around -70 mV, and the peak of the action potential is positive. The amplitude of the nerve impulse is about 100 mV; it lasts about 1ms.

Electroencephalogram is a valuable diagnostic tool in medicine and useful in the diagnosis of the epilepsy, sleep status, etc. EEG analysis would also support the research an intellihent robot and assisted tools for the disabled. The study has been found to be time consuming, tedious and inefficient. Application of digital processing techniques to the recorded data or real time data results in helping the neurologist in speedy and accurate diagnosis in addition to data compression and ease of transmission for remote diagnosis. These techniques help in reviewing the records quickly, reduce human error making the expert neurologists' services available to a larger populace. A powerful theory was proposed in late 1980's to perform time –scale analysis of signals: the wavelet theory. This theory provides a unified framework for different techniques which have been developed for various applications [5]. The Wavelet Transform (WT) is appropriate for analysis of non-stationary signals and this represents a major advantage over spectral analysis. Hence the WT is well suited to locating transient events such as spikes, which occur during epileptic seizures. The authors in their previous work demonstrated the use of Continuous Wavelet Transforms in Epilepsy detection and its performance [6]. Now in the present analysis DWT is implemented. The aim of this work is to classify normal and epileptic subjects based on Discrete Wavelet Transform (DWT) and to implement this using a digital signal processor (DSP).

1.1 Materials

EEG is the measurement of brain electrical activities using electrodes, which are placed on a patient's scalp following the international 10-20 system.

The first recording of the electric field of the human brain was made by the German psychiatrist

Hans Berger in 1924 in Jena. He gave this recording the name *electroencephalogram (EEG)*. (Berger, 1929).(From 1929 to 1938 he published 20 scientific papers on the EEG under the same title "Über das Elektroenkephalogram des Menschen".). The amplitude of the EEG is about 100 µV when measured on the scalp, and about 1-2 mV when measured on the surface of the brain. The bandwidth of this signal is from under 1 Hz to about 50 Hz.

Different frequency components exist in the measured signals. EEG waves are classified into five frequency bands. Each frequency band is generated by different regions of the brain and indicates certain features in the patient such as his depth of sleep.

The recorded EEG signals are used as input for health care monitoring and diagnosis, such as epileptic seizure detection, emotion monitoring, sleep monitoring, etc. For instance, one of the early signs of epileptic seizure is the presence of characteristic transient waveforms (spikes and sharp waves) in EEG data.

The amount of data contained in electroencephalogram (EEG) recordings is quite massive and this places constraints on bandwidth and storage. The requirement of online transmission of data needs a scheme that allows higher performance with lower computation [16]. Among the most popular are wavelet transform (WT), Fourier transform (FT), autoregressive model and bi-spectral analysis. Since the EEG signals are non-stationary, (discrete) wavelet transform (DWT) is widely used for EEG analysis [1]-[3] and [4]. This is because the DWT maintains both time and frequency resolution, which is essential for non-stationary signals.

The original EEG data in epileptic and normal situation is provided by Nizam Institute of Medical Sciences (NIMS), Hyderabad.

II. Methods

2.1. Wavelet Transform Algorithm

The problem of an adequate interpretation of epileptic EEG recordings is of great importance in the understanding, recognition and treatment of epilepsy. Wavelet theory provides a unified framework for a number of techniques developed for various signal processing applications like detection of unknown transient signals [7-9]. The Discrete Wavelet Transform (DWT) is simply a sampled version of the Continuous Wavelet Transform (CWT) [10, 11], and the information it provides is highly redundant as far as the reconstruction of the signal is concerned. This redundancy, on the other hand, requires a significant amount of computation time and resources. DWT, on the other hand, provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time.

The DWT means choosing subsets of the scales **a** and position **b** of the mother wavelet ψ (t)

$$\psi (a, b) (t) = 2a/2\ \psi (2\text{-}a/2\ (t\text{-}b)) \quad \rightarrow \text{eq. 1}$$

Choosing scales and positions are based on powers of two, which are called dyadic scales and positions {a j =2-j; b j , k =2-j k } (j and k are integers). Eq. (1) shows that it is possible to build a wavelet for any function by dilating a function ψ (t) with a coefficient 2j , and translating the resulting function on a grid whose interval is proportional to 2-j . Contracted (compressed) versions of the wavelet function match the high-frequency components, while dilated (stretched) versions match the low-frequency components. Then, by correlating the original signal with wavelet functions of different sizes, the details of the signal can be obtained at several scales. These correlations with the different wavelet functions can be arranged in a hierarchical scheme called multi-resolution decomposition. The multi-resolution decomposition algorithm separates the signal into "details" at different scales and a coarser representation of the signal named "approximation" [7-10].

The algorithm of the DWT decomposition and reconstruction can be summarized by following procedure:

Consider an EEG signal x(n) of length n, starting from x(n), the first step produces two sets of coefficients: approximation coefficients ***a*1** and detail coefficients ***d*1**.These vectors are obtained by convolving x(n) with the low-pass filter for approximation and with the high-pass filter for detail, followed by dyadic decimation. This is shown in Fig. 1. The length of each filter is equal to 2N. If n = length (x (n)), the signals F and G are of length n + 2N - 1, and then the coefficients ***a*1** and ***d*1** are of length

$$\text{Floor } ((n\text{-}1)/2) + N \qquad \rightarrow \text{eq. 2}$$

The approximation coefficients are further decomposed into two parts using the same scheme, replacing s by ***a*1** and producing ***a*2** and ***d*2** and so on. So, the wavelet decomposition of the signal s analyzed at level i has the following structure: [***a*i**, ***d*i**... ***d*1**]. Conversely, starting from ***a*i** and ***d*i**, the Inverse Discrete Wavelet Transform (IDWT) reconstructs ***a*i** -1, inverting the decomposition step by inserting zeros and convolving the results with the reconstruction filters, as shown in Fig. 1. Fourier analysis is extremely useful for data analysis, as it breaks down a signal into constituent sinusoids of different frequencies. The Fast Fourier transform (FFT) is an efficient algorithm for computing the DFT of a sequence.

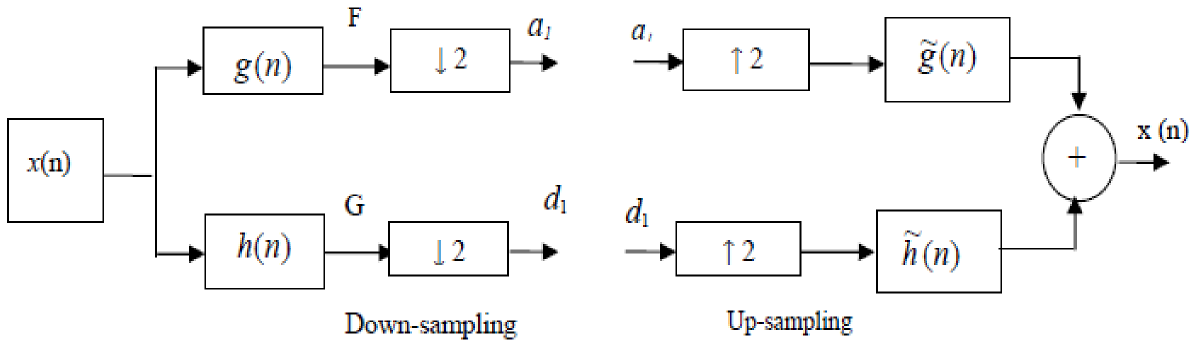

Fig.1: The algorithm of the DWT/IDWT for one level Decomposition

2.2 Field Programmable Gate Arrays

Field programmable gate Arrays (FPGA's) now possess sufficient performance and logic capacity to implement a number of digital signal processing (DSP) algorithms effectively. The DSP algorithms can be implemented in an FPGA with levels of performance unattainable using a traditional single-chip processor [12]. The specific system simulator used in this investigation is Simulink [13], which runs within the MATLAB programming environment [14].The design parameters relating to the DWT are entered in the Simulink block and passed to the HDL generic map and port map in the elaboration process. In this flow a parameterized DWT HDL design has been completed and only needs to be instantiated by the elaborator. In a similar flow the IDWT design process can take place.

III. Results and Discussions

The EEG off-line data of both normal and epileptic subjects are used in this analysis. In the current analysis 16 samples of the EEG data are considered and its DWT coefficients are computed for all 4 channels. These four channels are considered because it is concluded in the paper [15], that only 4 electrode positions are sufficient for classifying the subject.

In this case, a two-level multi-resolution decomposition using db8 wavelet is implemented. The original signal $x(n)$ can be reconstructed by the process of IDWT. The input samples are being processed using discrete wavelet transform with the help of MODELSIM software environment. Selection of filter coefficients is being done using Matlab wavelet toolbox.

3.1 Decomposition of EEG data

The analysis procedure using EEG samples & filter coefficients are shown below

The Shifted EEG Samples are:

X={12,1B,18,12,12,1A,25,25,1B,19,1F,2A,2B,25,1F ,24}

The Shifted scaling coefficients are:

h0=FF h1=04 h2=03 h3=E9 h4=FD h5=50 h5=5B h7=1D

The Shifted wavelet coefficients are:

g0=1D g1=A5 g2=50 g3=03 g4=E9 g5=FD g5=04 g7= 01

The input data is fed and convolution is performed between the above coefficients and the input data. The results are displayed in the command window Fig.2.

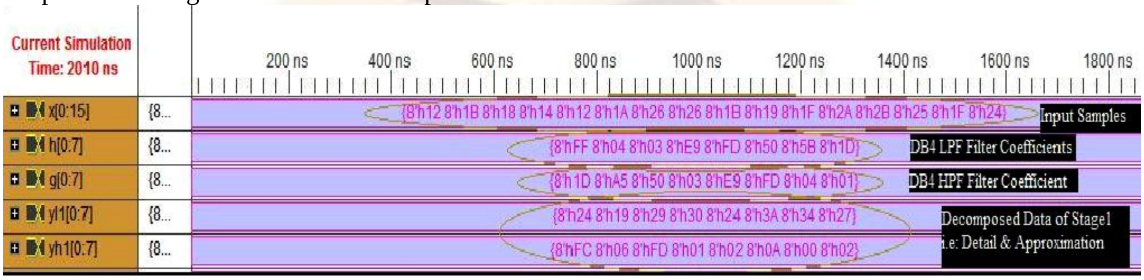

Fig.2: Synthesis waveform for I stage decomposition

The decomposed data is as follows:

- LPF Decomposed outputs are:

yl1 = {24, 17, 29, 30, 24, 3A, 34, 27}

- HPF Decomposed outputs are:

yh1 = {FC,05,FD,01,02,0A,FF,01}

3.2 Reconstruction of EEG data:

During reconstruction, the decomposed data is being taken as input and the reverse process is done using the same filter coefficients as selected earlier. The synthesis waveform for the first stage reconstruction generated is shown in Fig.3.

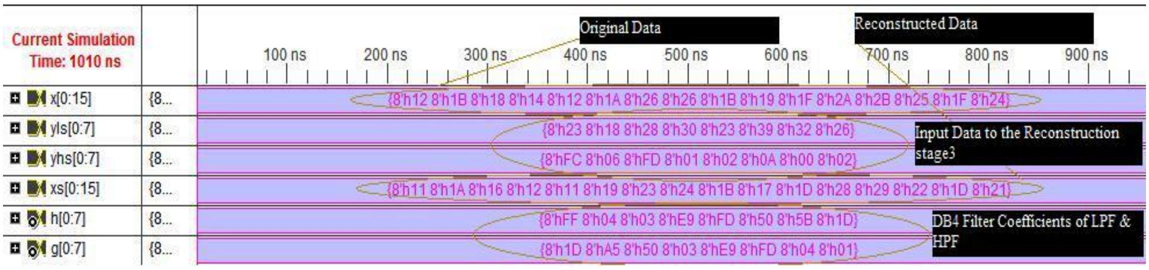

Fig.3: Synthesis waveform for last stage reconstruction

The results of reconstruction are given below which are same as that of VHDL generated outputs for the first stage.

The Reconstruction outputs are:

Xs = {10, 19, 15, 10, 10, 17, 22, 23, 19, 17, 1B, 27, 28, 21, 1C, 21}

Hence, the values of first stage results have been verified and the values are cumulated.

IV. Conclusions

The EEG data compression is necessary to speed up the process so that we can recognize the disabilities of the patient as soon as possible. This method has been implemented useful for compressing the data and to increase the accuracy compared with the other languages. By increasing the precision the accuracy of data after reconstruction can be obtained. This analysis serves as a handy tool in streams of engineering and medical sciences to know the behavior of a subject (human brain).

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