Compression of Brain Waves

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***Abstract* – In recent periods, more stress is given to compression of EEG due to the fact that it carries huge data and requires massive memory and bandwidth for storage and transmission respectively. Powerful EEG signal compression requires vigorous effort. This is due to the data contained in the EEG signal. So it is very difficult to obtain very high and powerful compression. An algorithm for compressing the EEG signal is framed and is applied to EEG dataset. A convenient method to express the exact EEG signal is in the form of an image or matrix. Wavelet transform can be applied to EEG signals which are followed by encoding the compressed dataset. This helps in good storage and transmission. In order to receive back the original EEG signal with minute losses, the difference produced between the original and after performing inverse DWT on already transformed signal, which is taken as the error and it can also encoded.**

***Keywords*– Compression, Electroencephalogram (EEG), run length coding, wavelet transform, dataset.**

I. INTRODUCTION

The term EEG is an imaging approach used in medical fields which records the electrical activities in the brain. Brain neurons are cells that can process and transmit signals. The variations in voltage produced within the neurons are measured by the EEG. It is very small usually in the range of microvolt. The frequency varies from high to low. This recording is only for a small time period which maximum exceeds up to 40 minutes. It is captured from many electrodes which are placed on the scalp of the head. EEG is useful in case of epilepsy, coma stage, brain tumors and death etc. EEG can observe minute details of the neurons at very small time periods with very large resolutions. This is a non-penetrative method.

The EEG data recording is preferably chosen to perform at a low sampling rate of about 250Hz and high sampling rate of about 2000HZ. Nowadays EEG can be measured above 20,000HZ also. Amplitude of the signal has variations from 10μV to 100μV. EEG is measured by placing many electrodes in the human scalp. The diameter of head electrodes used is 10mm but neurons do have a diameter of about 20μm. Hence one electron is able to cover 2, 50,000 neurons. Recordings of brain waves take a lot of time. These measured waves need a storage space. Hence these systems need to work under low power. Due to the difficulty in storing these large amount of data, the EEG signal need to be compressed which can be easily transmitted. Thus it reduces the power consumption drastically. Since the EEG datasets are large, ranging from gigabytes to terabytes, the need for compressing is more demanding.

EEG can be compressed in three ways. Lossless compression, lossy compression and near lossless compression. In lossless compression, the original EEG can be reconstructed from the compressed signal with no loss. Here the compression rate is tolerable. But in medical cases, the exact retrieval of information is more important than the compression rates achieved. Hence lossless compression can be used here. It is a reversible compression technique. In lossy compression, the original EEG cannot be reconstructed from compressed signal. It massively compresses the EEG. The compression rate is also very high. It is a non-reversible compression technique. In near lossless compression, EEG can be compressed effectively with minimum loss of data. Here the reconstructed signal is not changed in magnitude greater than δ compared with the original signal.

International 10/20 configuration is used for collecting the EEG signals from healthy people who were asked to perform motor imagery tasks. The EEG signals are sampled at 250HZ. The array of data contains seven rows and around 2500 columns. The 7 rows correspond to channels occipital lobe 1, central 3, parietal 3, central 4, parietal 4, occipital 2 and Electro-oculography. For 10sec, samples are recorded at 250HZ. First cell looks like subject1 baseline trial 1 as 7*2500. The recording is done for five works which are baseline work, multiplication work, letter work, rotation work and counting work.

II. EEG COMPRESSION

A1 (1) to A1(L) represents the first row of the EEG dataset. A2 (1) to A2 (L) represents the second row that is the second channel of the EEG dataset. AM (1) to AM (L) represents the M^{th} row of the EEG dataset which is the M^{th} channel. Fig 3.1 shows 2D image formation from multichannel EEG. A matrix is being formed when recordings from different channels of EEG are arranged in a particular manner. Columns can give us the timings. The channels of the EEG can be represented by the rows. Scanning is done in a spiral fashion. Adjacent channels of EEG signal are arranged as adjacent rows of the corresponding image. They are correlated. Fig. 1 shows image formation of brain waves.

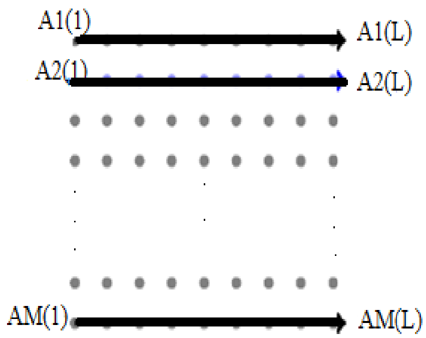

Fig.1 Image Formation

Multichannel EEG dataset is converted into a matrix form. The corresponding matrix formed is represented by I. Image of size 256*256 is formed from the matrix formed above. This image is taken to test this algorithm. Then discrete wavelet transform using sub band coding scheme is used to get the transformed image. This compressed image is applied to a run length coder. Run length encoding yields compact information which is suitable for both storage and transport of signal. Fig. 2 gives the encoding part.

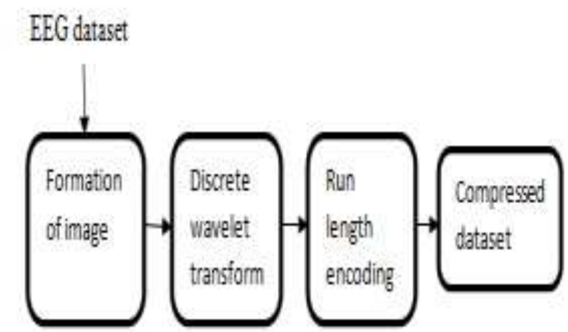

Fig. 2 Encoding for brain waves

Then decoding algorithm using run length is applied to the encoded data, which is in the form of a vector. Then this is followed by applying the inverse discrete wavelet transform which results in the reconstructed image. Fig. 3 gives the decoding part diagram.

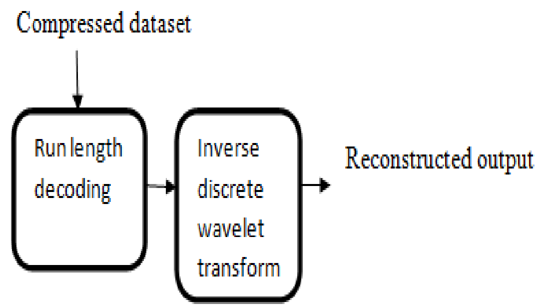

Fig. 3 Decoding for brain waves

Here, brain waves are converted to matrix type. The matrix form is represented by I. At the encoding side, compression of matrix is done by a discrete wavelet transform which results in a compressed dataset. Here the wavelet transform employs lifting scheme. Inverse discrete wavelet transform is applied to the transformed data to give lossy approximation of the original EEG matrix. The error formed is encoded along with the inverse discrete wavelet transform to give the compressed data. The compressed data is in the form of a vector. The reduced information is decoded to yield the original brain wave. Fig. 4 gives the new encoding diagram.

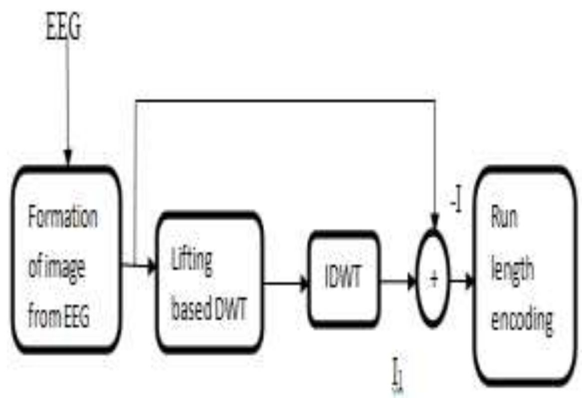

Fig. 4 Enhanced Encoding part

At the output of the decoder, EEG data signal is reconstructed. Applying the discrete wavelet transform to the original image results in a compressed data. For the purpose of storage and transmission, the compressed data is encoded. Decoder reconstructs the EEG data with some loss. Fig. 5 gives the diagram for new decoding part.

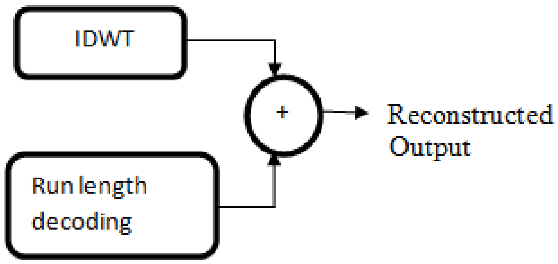

Fig. 5 Enhanced decoding part

In wavelet transformation using discrete signals, filter and decompose techniques are employed for wave decomposition. An image is decomposed in to low-high, high-low, low-low, high-high frequency bands. An image of size N*N can be sub-sampled by a factor of two. Resulting frequency band contains N/2*N/2samples. The original signal or image is produced when these four bands are integrated.

One of the efficient DWT implementation is lifting based scheme. In order to decrease the total number of bits needed to represent an image, encoding can be used. Data having the probability of re occurrence is reduced by run length encoding. It has two possibilities only. Run length pair means those which have runs of same intensity. Variable length encoding can also be applied to run lengths.

The efficiency for brain wave compression can be evaluated by compression ratio which is the reduction in size. The compression ratio results in the decrease of the number of bits at the output of the encoding part. The reduction in the output file thus enables the data to be stored or transmitted effectively. Peak signal to noise ratio is the ratio of the signal to the noise. For calculating peak signal to noise ratio maximum absolute error must be known. MAE depends on the EEG sample having largest. The distortion measure called as peak-signal-to-noise measures the peak signal to noise ratio.

III. RESULTS

This section includes the MATLAB results. A text file containing the EEG information is written in double format. Input image is created from MATLAB. EEG dataset used for compression is the motor imagery dataset.

A. Simulation Results

This section includes the simulation results designed using VHDL and implemented in Xilinx and simulated using ModelSim. The simulation result of simple discrete wavelet transform is shown in Fig. 6.

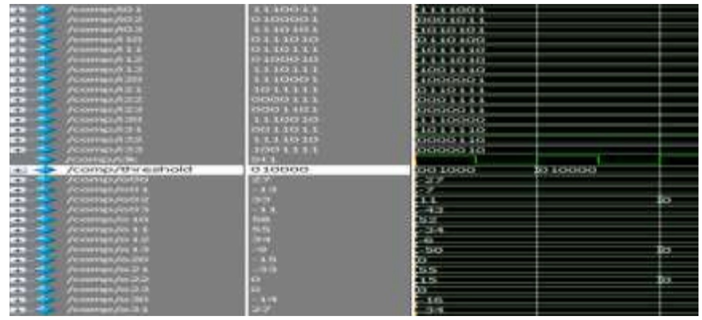

Fig. 6 Simulation result of Compression

The inverse of the discrete wavelet transform is performed and it is subtracted from the original input to get the error call. The simulation report of IDWT is shown in Fig. 7

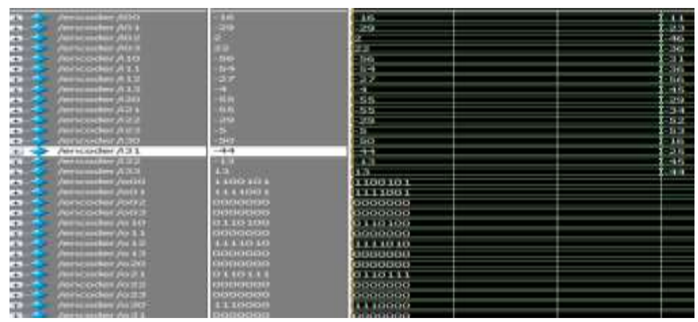

Fig. 7 Simulation result of IDWT

The error call obtained from the subtraction of the inverse discrete wavelet transform from the original input. This result is to be encoded. Simulation report of error call is shown in Fig. 8

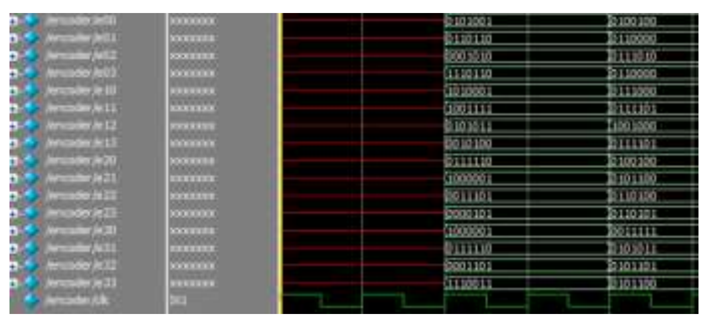

Fig. 8 Simulation result of Error call

For the perfect reconstruction after encoding, the error is to be subtracted from the inverse discrete wavelet transform which is shown in Fig. 9

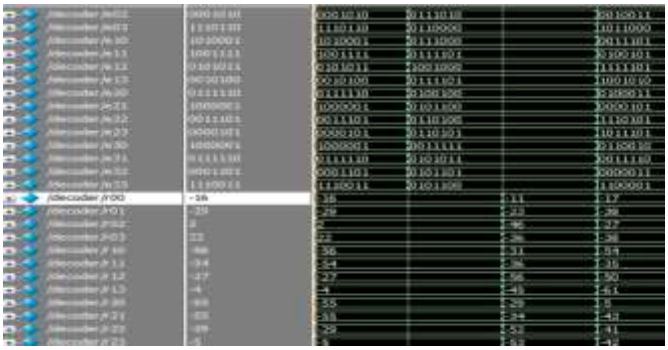

Fig. 9 Simulation result of Reconstruction

For the encoder, high pass filter output and the low pass filter output are calculated. These are given as input and the corresponding high-low filter output, high-high filter output, low- high filter output and low -low filter output is simulated.

These outputs are taken and 1D discrete wavelet transform is applied to it to obtain the corresponding high and low filter outputs. The high-high, high-low, low-high and low-low coefficients are shown in Fig. 10.

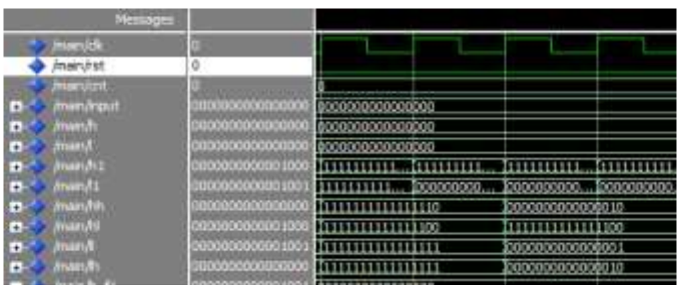

Fig. 10 Simulation result for 2D DWT

The IDW transform is then performed to get the reconstructed EEG image. Fig 4.10 shows the simulation result of the Inverse DW transform is shown in Fig. 11

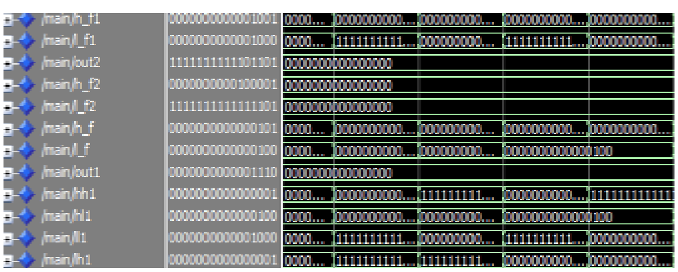

Fig. 11 Simulation result of IDWT

The inverse discrete wavelet transformed image is subtracted from the original image and the error is also encoded. The simulation result of encoder is shown in Fig. 12

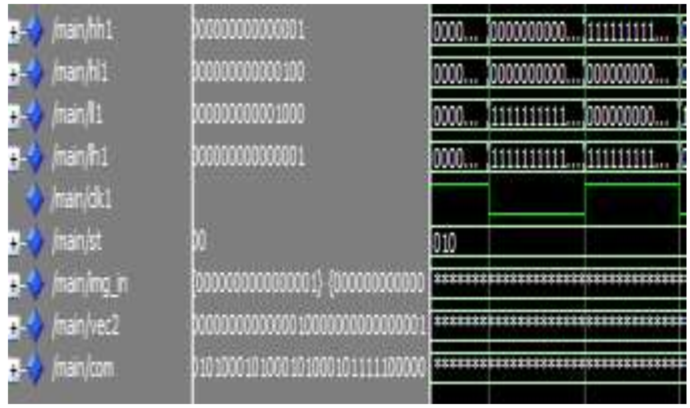

Fig. 12 Simulation result of encoder

The encoded data is then decoded and inverse discrete wavelet transform is applied to the above to get the reconstructed data. Fig. 13 shows simulation result of the decoded data.

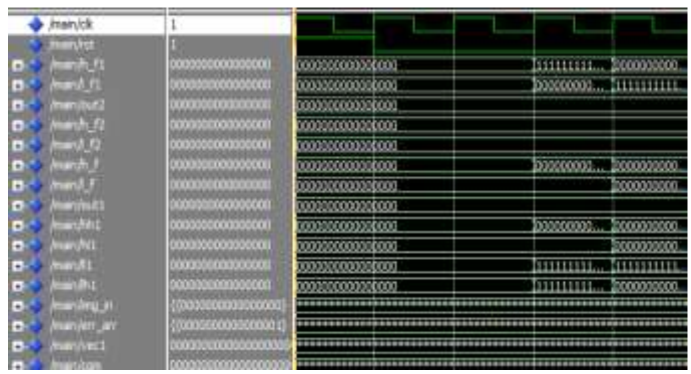

Fig. 13 Simulation result of decoded data

The compression ratio which is the number of input bits to the number of output bits is 1.16. The compression ratio, the peak signal to noise ratio, maximum absolute error is given Table 1

TABLE 1
1 CR, PSNR, MAE

EEG Dataset	Compression Ratio	PSNR	MAE
Motor imagery	1.16	25.16	6.12
Motor imagery	2.99	35.88	4.12

B. Synthesis Results

The synthesis results for discrete wavelet transform are shown in Table 2.

TABLE 2
SYNTHESIS REPORT FOR DWT

Technique	Sub band coding	Lifting
No. of slices	128	86
No of 4 input LUTs	224	113
No of bonded IOBs	225	50
IOB flip flops	112	81

Synthesis results for Inverse DW transform are given in Table 3. The comparison of both techniques is done here.

TABLE 3
SYNTHESIS REPORT FOR IDWT

Technique	Sub band coding	Lifting
No. of slices	128	58
No of 4 input LUTs	224	111
No of bonded IOBs	80	32
IOB flip flops	225	66

Table 4 shows the maximum frequency and minimum period for discrete wavelet using two schemes.

TABLE 4
MINIMUM PERIOD AND MAXIMUM FREQUENCY OF DWT

Parameter	Lifting scheme DWT	Lifting scheme IDWT
Minimum Period	5.474ns	5.484ns
Maximum Frequency	182.673MHZ	182.335MHZ
Delay	11.376ns	11.284ns

IV. CONCLUSION

The multichannel EEG dataset is compressed using Lifting based discrete wavelet transform filters. The lifting based transform filters give attractive results compared to other transform based filters and methods. The algorithm is implemented on FPGA platform using VHDL programming language in Xilinx. In terms of hardware complexity the number of LUTs used is reduced to 50% when compared with sub band coding using simple discrete wavelet transform. The error resulted after comparing the inverse discrete wavelet transform and the original input is also encoded to give better reconstruction of the original signal. The compression ratio improved from 1.16 in sub band coding to 2.99 using lifting based technique. Single channel EEG compression is gives a less compression ratio while the multichannel EEG image often gives higher compression ratios. This can effectively store and transmit the EEG data. Hence the modified algorithm can achieve high speed with lower hardware complexity and smaller storage size. For much better results various algorithms can also be in cooperated with this compression scheme.

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