FPGA control of wheelchair movement for paralyzed persons using Steady State Visual Evoked Potential signals

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Abstract

A paralyzed person has a restricted mobility, they depends on other human beings. Independent mobility is an important aspect for human life. For these paralyzed persons, FPGA (Field Programmable Gate Array) based Brain Computer Interface (BCI) system provides an enhanced solution. To improve the mobility of paralyzed persons, vision based Steady State Visual Evoked Potential (SSVEP) signals plays important role. Direction of wheelchair depends on the frequency range of the SSVEP signals. The movement of the wheelchair is controlled by variation in the concentration level of the person on the stimulus screen. The proposed system is based on Discrete Wavelet Transform for extracting the features like Mean, Variation of SSVEP signals. Directions for the movement of wheelchair can be detected using Support Vector Machine (SVM) depends on frequency level of the signal.

Keywords: *Brain Computer Interface, SSVEP, Moving Average Filter, DWT, SVM.*

1. Introduction

The human brain is the collection of neurons, interconnected together to communicate with each other resulting different neuron activity corresponding to different emotions and thoughts. Neuron creates and electrical signals which can be measured by placing electrode plates on the scalp, these signals are small in range. Brain Computer Interface is used to measure brain signals. An interfacing device providing a communication between human brain and computer. Paralysis is the loss of muscle function in part of human body. It happens when something goes wrong with the way messages pass between brain and muscles. Loss of ability to move some parts of body is known as Paralysis. Using Canonical Correlation Analysis the vision based Steady State Visual Evoked Potential signals are classified [1].This Method shows less accuracy. Joint short SSVEP signals are the combination of SSVEP signals to form a joint temporal spatial selective attention feature, to classify signals [2] with improved accuracy. The joint short SSVEP signals are the average of the SSVEP signals. A BCI system which controls the wheelchair movement in only for forward direction has developed in [3]. A BCI that controls the wheelchair in three direction (i.e., turn left, turn right, and move forward) has applied in [4], [5].In MUSIC method based SSVEP classification, Eigen value, Eigen Vectors are calculated to improve the direction control of wheelchair. [6]. Discrete Wavelet Transform (DWT) has been widely used to analyze epileptic EEG. Deeper DWT can yield more detailed depiction of signals but it requires substantially more computational time. Mother wavelets used in this work achieve high seizure detection accuracy at high decomposition levels [7]. The Daubechies filters provide excellent spatial and spectral locality. In this algorithm [8] the algebraic integer representation of the wavelet coefficients provides error-free calculations until the final reconstruction step. The architecture is also cascadable for computation of one- or multi-dimensional Daubechies Discrete Wavelet Transforms. The AI-based DAUB4 architecture provides acceptable reconstruction with moderate hardware complexity and cost, and is far better than conventional fixed-point architectures [8].EEG signals are classified by Support Vector Machines to detect whether a subject's planning to perform a task or not. Various different kernels were utilized to find the best kernel function and after that, a feature selection process was realized. To find the most suitable kernel, different Support Vector Machines are trained with original data. [9]. In the existing work the wheelchair movement was based on fixed path grids and controlled using Spartan FPGA 6 kit. [18]

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2. Proposed Methodology

The proposed work is based on non-invasive BCI system which captures EEG signals from the brain and control the movement of wheelchair. These EEG signals (SSVEP) are used as an input to the wheelchair to classify user intension for controlling the functionality of the wheelchair.

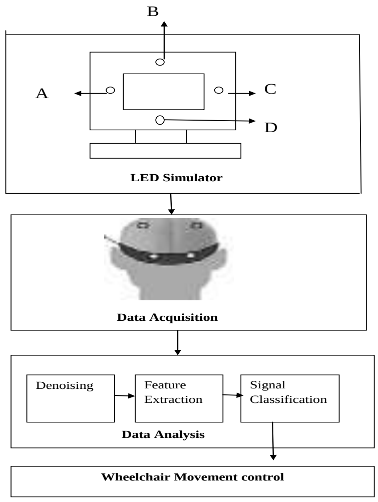

Figure .1 Block Diagram of Proposed Methodology

The proposed methodology includes the data acquisition of EEG signals real time signals are taken for processing. The Mind wave mobile headset is used to record EEG signals for data acquisition. The acquired EEG signals are preprocessed to remove the noise and artifacts in the brain signals using Moving Average Filter and decomposed by DWT, Daubechies Wavelet Transform to extract features. The classification of EEG signal is done using support vector machine. The block diagram of the proposed method is described in Figure .1

A. Data Acquisition:

EEG signals acquisition is mainly done by placing electrodes on the scalp. LED is used as the stimulator in this system, consisting of four different LEDs blinking with different frequency in the subjects control screen, four LED lights representing four moving directions were set to four different flicking frequencies.

- LED A representing left and flicked at 18 Hz,
- LED B representing forward and flicked at 20 Hz,
- LED C representing right and flicked at 22 Hz,
- LED D representing backward and flicked at 24 Hz

B .Pre-Processing:

EEG Signals are recorded from various lobs of the brain. Unwanted noise in the brain signals are known as artifacts. The Pre-processing method is used to remove physical artifacts such as movements like body movement, eye ball movement.

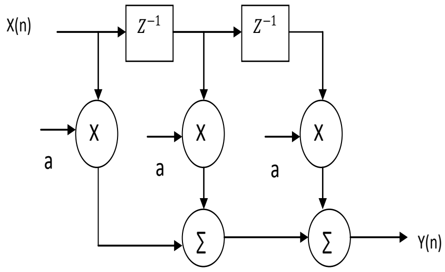

Figure.2 M point Moving Average Filter

Moving Average Filter is involved in preprocessing step. The group delay for this 3 point Moving Average filter is 2. To reduce the number of multiplication BOXCAR Moving Average Filter is used. The input and output values of this filter are defined as the following set of equations.

$$Y[n] = \sum_{k=0}^{N-1} h[k]x[n-k] \qquad (1)$$

Where x[n] - Sequence of input sample
h[k] - Sequence of filter coefficient
y[n] - Output of the filter
N - Number of taps to the filter

The Moving Average filter coefficients are same, and it can be removed from implementation The following Figure.3 shows the implementation of Moving Average Filter without multiplication.

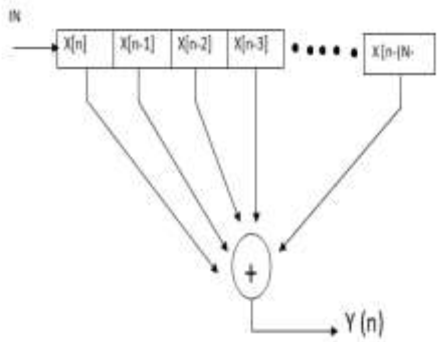

Figure.3 Modified Moving Average Boxcar Filter

Output of this filter design is summation of a set of input values made on every clock signal. Output values for this modified filter is given as, continuous addition and subtraction of adjacent summation output.

$$Y[n] = \sum_{k=0}^{N-1} x[n-k] \qquad (2)$$

C. Feature Extraction:

To reduce dimensionality of data, Feature extraction method involved. The technique utilized here for the degeneration of separated EEG flag is Daubecheis Wavelet Transform. Daubechies wavelet coefficients are calculated by computing wavelet coefficients Cn (where n = 0, 1,2. .. N− 1 and N is the number of coefficients) .The Fixed-Point DAUB4 architecture is used in Figure. 4

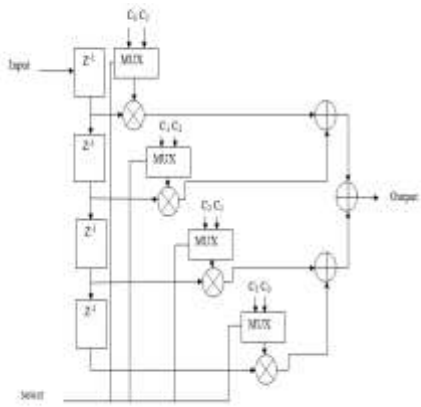

Figure.4 Fixed point DWT Architecture

Architecture of the Daubechies wavelet includes changes with the multipliers mux and with a defer unit. The structure utilizes coefficients C0, C1, C2 and C3 for low pass filters (smoothing channel) and the coefficients C3, −C2, C1 and −C0 for high pass filters (non-smoothing channel). The Signals from the preprocessing output is given as input to feature extraction block. Daubechies Wavelet Transform is used for feature extraction. Mean and variance values are calculated. Mathematically Mean value is defined as

$$\mu = \frac{1}{N}\sum_{i=0}^{N-1} x_i \qquad (3)$$

Mathematically Variance value defined as,

$$\mathrm{Var} = \frac{1}{N-1}\sum_{i=0}^{N-1} (x_i - \mu)^2 \qquad (4)$$

D. Signal Classifier:

An efficient classification technique is used to distinguish EEG segments. Classification and data analysis has been performed using Support Vector Machine to classify the signal based on direction control of the wheelchair. The architecture for SVM classifier is shown in Figure .5

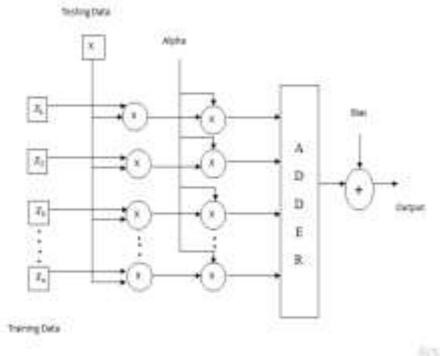

Figure.5 Architecture of SVM classifier

The extracted features are taken and they are trained and then tested with different set of values. Based on the training and testing set the signal classified to control the wheelchair movement in different direction .The training set should more than that of the testing set.

3. Results and Discussion

Using Modelsim 6.4a the Verilog coding for simulation of pre-processing, feature extraction and signal classification is performed. The implementation part of the process utilizes the FPGA hardware platform.Virtex5 FPGA serves the purpose of implementation of the design.

1. Simulation Results:

Preprocessing is done using a simplified Moving Average Boxcar filter. The filter used here is three tap filter design. Preprocessed output is shown as “out” point in the output waveform of Moving Average filter shown in figure 6.

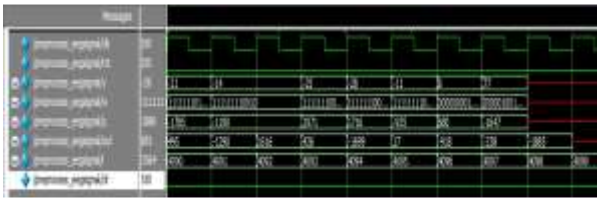

Figure .6 Moving Average Filter Output

The preprocessed output is given as wavelet block and using the output wavelet features are extracted from preprocessed data. Daubechies Wavelet Transform is used to extract the features. From Figure.7 the point "out wave" indicates the output of wavelet and, "mean1" indicates mean value,"variance1" indicates variance value.

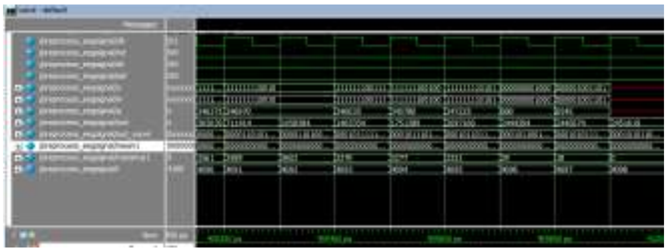

Figure.7 DWT Output

Using the Extracted Feature values the signals are classified using SVM classifier based on the frequency level of the signals. The output is indicated as "00" , "01", "10" and "11".If the output is "00" then the direction of wheelchair is 'Right', and if the output is "01" then the wheelchair movement is in "Left" direction. For upward movement the output will be "10".Downward movement of wheelchair is indicated as "11".

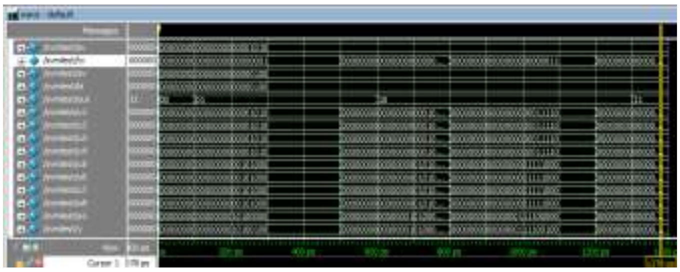

Figure 8 SVM classifier output

2. Implementation using FPGA and RTL Schematic View:

FPGA Implementation of every process is done by Xilinx ISE 14.6 and implemented in VIRTEX 5 with a speed grading of -1. The Moving Average Filter is implemented and the RTL view of the Moving Average Filter involves the 12 bit input it is given to the delay unit and then it is sent to the M point moving average point and then to the adder unit. Single 12 bit output is received at "out" point. The RTL view is shown in the Figure.9

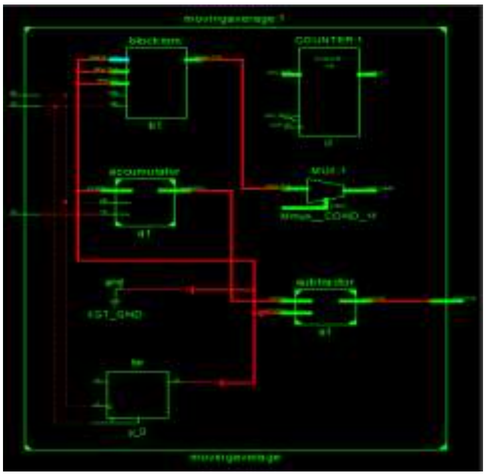

Figure .9 RTL view of Moving Average Filter

The Fixed point Daubechies wavelet transforms are performed and implemented in the VIRTEX 5 FPGA. Daubechies wavelet transform is done with the input of 12 bits and output of 24 bits is received. Then the RTL view of Daubechies wavelet shown in Figure 10.

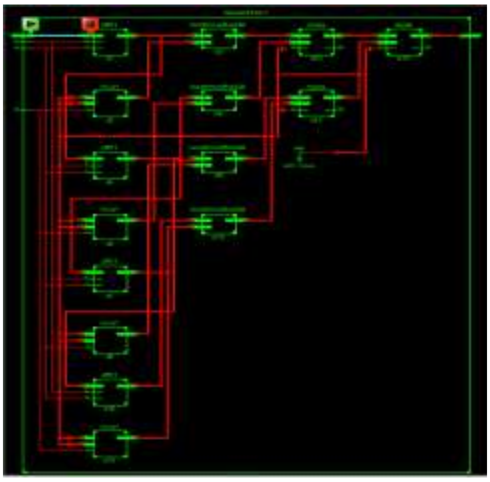

Figure .10 RTL view of DWT

From the output of DWT the features Mean and Variance are calculated and implemented. The RTL view of Mean is shown in Figure.11

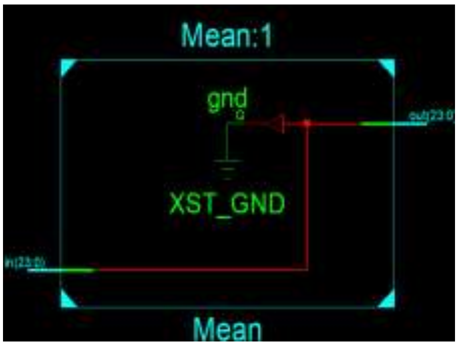

Figure .11 RTL view of Mean calculation

The RTL view of variance calculation is shown in Figure 12.

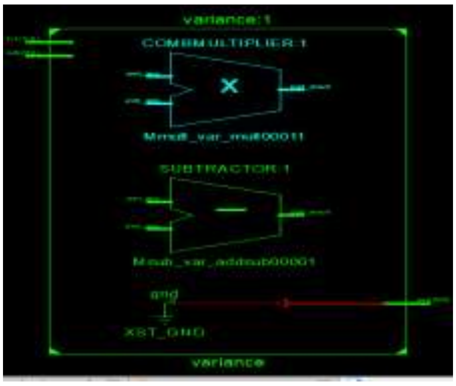

Figure. 12 RTL view of variance calculation

Based on the feature values, the Support Vector Machine signal classification is performed and implemented. The RTL view of SVM classifier is shown in Figure.13

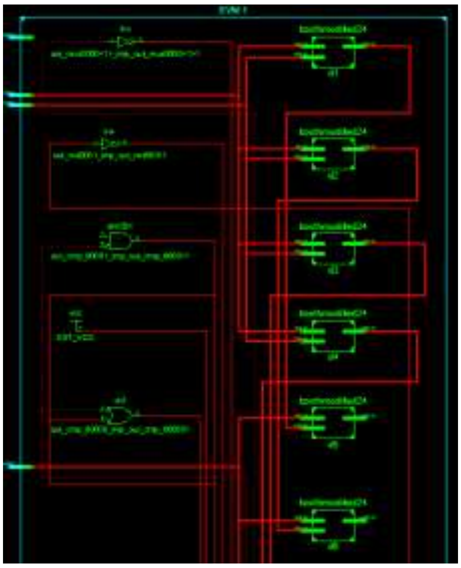

Figure .13 RTL view of SVM classifier

The hardware implementation results for preprocessing, Feature extraction and classification are shown in below table.

I. Implementation Results

Device Utilization Summary			
Slice Logic Utilization	Used	Available	Utilization
Number of Slice LUTs	137	28,800	1%
Number used as logic	137	28,800	1%
Number using O6 output only	127		
Number using O5 and O6	10		
Number of occupied Slices	61	7,200	1%
Number of LUT Flip Flop pairs used	137		
Number with an unused Flip Flop	137	137	100%
Number with an unused LUT	0	137	0%
Number of fully used LUT-FF pairs	0	137	0%
Number of slice register sites lost to control set restrictions	0	28,800	0%
Number of bonded IOBs	48	480	10%

The tables shows the device utilization summary, total memory usage and delay of logics used in Moving Average Filter in Preprocessing , Daubechies Wavelet Transform in Feature Extraction and Support Vector Machine in Signal Classification. The Table.1 shows Device Utilization Summary and Table.2 shows Delay and Memory usage The Table. 2shows the result of Memory usage and the Delay occupied by Moving Average Filter, DWT, and SVM classifier.

II. Delay and Memory usage

Constraints	Moving Average Filter	DWT	SVM classifier
Memory Usage	264760 Kb	297080 Kb	346744 Kb
Delay	1.159ns	1.866ns	3.259ns

In the Existing work [18] the wheelchair movement control was based on fixed path grids. Using Spartan 6 FPGA kit the wheelchair movement was controlled.

DEVICE UTILIZATION SUMMORY (ESTIMATED VALUES)			
Logic utilization	Used	Available	Utilization
Number of slice registers	393	54576	0%
Number of slice LUTs	994	27288	3%
Number of fully used LUT-FF pairs	331	1056	31%
Number of bonded IOBs	21	218	9%
Number of blockRAM/FIFO	1	116	0%
Number of BUFG/ BUFG CTRL	1	16	6%

The proposed methodology was implemented in Virtex 5 FPGA kit, the minimum number of slice registers and Flip flops were used. The total delay in the proposed work was 13.127 ns for the speed grade of -1. The performance complexity and delay was reduced. The wheelchair movement was directed in four direction without fixed path.

4. Conclusion

In the field of Neuroscience and Brain Computer Interface various EEG signal analysis methods are used. FPGA based wheelchair movement control using SSVEP brain signals for paralyzed persons is done. The delay and the memory used by the Moving Average Filter were 1.159ns and 264760 Kb. The delay produced by the Moving Average Filter was very less delay and more efficient The Daubechies Wavelet produced 1.866nsand297080 Kb. The Support Vector Machine produces the delay and memory used was3.259nsand 346744 Kb. The signals are classified based on the frequency level.

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