

A Generalized Preprocessing and Feature Extraction Platform for Scalp EEG Signals on FPGA

L.P Wijesinghe*, D.S Wickramasuriya, and Ajith A. Pasqual

Abstract— Brain-computer interfaces (BCIs) require real-time feature extraction for translating input EEG signals recorded from a subject into an output command or decision. Owing to the inherent difficulties in EEG signal processing and neural decoding, many of the feature extraction algorithms are complex and computationally demanding. Presently, software does exist to perform real-time feature extraction and classification of EEG signals. However, the requirement of a personal computer is a major obstacle in bringing these technologies to the home and mobile user affording ease of use. We present the FPGA design and novel architecture of a generalized platform that provides a set of predefined features and preprocessing steps that can be configured by a user for BCI applications. The preprocessing steps include power line noise cancellation and baseline removal while the feature set includes a combination of linear and nonlinear, univariate and bivariate measures commonly utilized in BCIs. We provide a comparison of our results with software and also validate the platform by implementing a seizure detection algorithm on a standard dataset and obtained a classification accuracy of over 96%. A gradual transition of BCI systems to hardware would prove beneficial in terms of compactness, power consumption and much faster response to stimuli.

I. INTRODUCTION

Research into brain-computer interfaces (BCIs) has been carried out over several decades as a means of enabling persons suffering from severe neuromuscular disabilities interact with their environment, have more autonomy and enjoy improved quality of life. BCIs typically consist of a signal acquisition front end, where, for instance, neuroelectric or haemodynamic activity of the brain is recorded, a preprocessing and feature extraction stage followed by a final classification stage connected to an output device. Present day BCIs include brain-controlled wheelchairs, spelling and communication devices, cursor control applications and robotic arm control systems which permit the brain to perform tasks bypassing conventional physiological output pathways. Although initially envisioned for the benefit of patients suffering from “locked-in syndrome” due to spinal cord injury, Amyotrophic Lateral Sclerosis (ALS), brain stem stroke etc., present day BCIs also target people who retain significant neuromuscular capabilities as a novel means of providing gaming and entertainment experience.

Despite the amount of research conducted in this field, many promising systems still remained confined to research

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laboratories with studies investigating their long term use for patients who have most need of them just beginning [1]. One of the reasons for this delay in bringing BCIs to the home user has been the need for a bulky personal computer performing the analysis of brain signals and translation into output commands. Hence, there has been growing interest in developing BCIs on mobile platforms [2]. We present a generalized preprocessing and feature extraction platform for EEG signals on FPGA where features to be computed can be selected by a user. While in a typical BCI system only the initial stages of signal acquisition and amplification would be performed in hardware and the remaining ones (artefact suppression, feature extraction and translation) implemented in software, shifting this hardware-software interface even further would afford lower power consumption, greater compactness and parallel feature computation.

II. LITERATURE REVIEW

Complete BCI implementation on FPGA has been quite a recent concept. In 2010, Shyu *et al.* [3] published their work of a phase-encoded Steady-State Visually Evoked Potential (SSVEP) BCI multimedia control system and claim that, “this BCI system, to the authors’ best knowledge, is the first design of a low-cost FPGA-based BCI.” The design essentially features an analog front end, an SSVEP processing module on FPGA and a wireless link to a multimedia device which also functions as a means to provide immediate feedback to the user. Although 3 electrodes are used to acquire EEG signals, the channels are combined at the pre-amplifier stage and the FPGA module only processes a single EEG signal. Shyu *et al.* [4] developed an SSVEP based BCI enabling a user to control the attitude of a hospital bed. An accuracy of 92.5% was achieved with an architecture very similar to the one used for the multimedia device controller. Both systems were developed using an Altera Cyclone EPC2C20Q FPGA.

Khurana *et al.* [2] developed an FPGA-based real-time P300 spelling device to detect letters and digits on a 6x6 grid utilizing 7 EEG channels corresponding to electrode locations Cz, C3, C4, Pz, P3, P4 and Oz. They obtained a classification accuracy of 65.37% when 2 rounds of data per character was used. The system was designed with 3 MicroBlaze processors using a Spartan 3E FPGA. Lin and Huang [6] implemented a BCI system for controlling an electric wheelchair. They captured 2-channel EEG signals using NeuroSky ASICs which were transmitted to an FPGA-based controller via a Bluetooth link. A winking signal and an α rhythm were processed to determine direction and motion of the

wheelchair. The system was implemented on a Spartan FPGA with a XC3S500E-PQ208 chip.

There has also been considerable interest in developing energy efficient biomedical processors and System on Chip (SoC) architectures suitable for long term signal monitoring and alarm triggering. Kwong and Chandrakasan [5] developed a low power biomedical signal processing platform featuring a 16-bit microcontroller, SRAM and accelerators. The SoC is programmable and capable of running different types of algorithms in an energy efficient manner for long term monitoring. Sridhara *et al.* [7] developed an ultralow power embedded processor platform chip for medical signal processing. The processor comprises of an FFT, SRAM and DC-DC converter. They demonstrate the functionality of the SoC by implementing a seizure detection algorithm which utilizes band energies for threshold calculation. Verma *et al.* [8] developed a low-power SoC for continuous EEG monitoring and seizure onset detection. Band energies in 7 frequency bands are computed using a bank of bandpass filters and a user may wear up to 18 channels. Classification was performed on a separate processing platforms.

Most of the existing BCI implementations on FPGA process just a few channels of EEG recordings whereas a typical EEG headcap would have between 14-256 electrode locations. Also, due to inherent complexities in EEG signal processing, several applications that have shown promise require multiple types of features to be computed simultaneously (e.g. [9]). Currently, on-chip implementations of medical signal processors are only capable of extracting a single type of feature at a time. Moreover, each signal requires its own processing module. To overcome some of these drawbacks we present the FPGA implementation of a platform for EEG signal analysis capable of computing multiple types of features in realtime. We exploit the low bandwidth of scalp EEG signals to develop an architecture that reuses each basic feature extraction module through multiplexing. Section III of this paper details the overall architecture of the platform and the preprocessing stage, while Section IV describes the features we provide. Thereafter we provide a comparison of the results we obtained with existing software using recordings from the EMOTIV neuroheadset. We conclude with Section VI noting several possible future directions of work.

III. PLATFORM ARCHITECTURE

We utilize a multirate design in our system and partition the platform into two subsystems with a set of shared memories functioning as the interface between them. The first subsystem comprises of a bank of highpass and notch filters. Each digitized 24-bit EEG signal is filtered and read into n separate shared memories (M_i). The first subsystem runs at the sampling frequency f_s of the signal acquisition device. Once all sample points corresponding to a predefined epoch of EEG have been read in, data is read off from each of the shared memories in turn and fed into the feature extractors (FE) which belong to the second subsystem. This is run at a conventional FPGA clock frequency of 50 MHz. The limited bandwidth of the EEG signals enables us to extract features

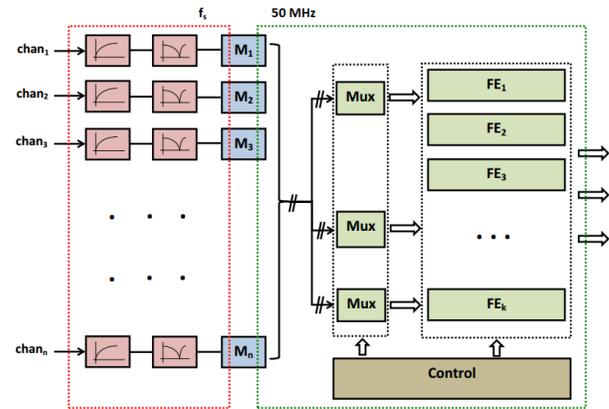


Figure 1: Platform architecture (M_i - Shared Memory, FE - Feature Extractor)

from each of the n epochs serially (reusing an FE) before the next new EEG sample is read into the memory bank after $1/f_s$ s. In this design we utilize three multiplexers to feed in the EEG samples into the FEs. The first one, first allows the EEG epoch recorded from the first electrode, stored in M_1 , to pass through whichever FEs have been enabled. Likewise, this is repeated for all the other $(n - 1)$ single EEG epochs. The other two multiplexers serve to feed in any combination of two single EEG epochs into the bivariate FEs. If the FE modules require a large number of clock cycles for computation or signals from a large number of electrode positions are recorded, a multiple set of FEs could be utilized in parallel. A single set of FEs is sufficient for the set of measures we propose in this system. The architecture of the system is illustrated in Figure 1 and is capable of calculating multiple types of features simultaneously in realtime for non-overlapping epochs as are typically required in asynchronous BCI applications. Typically the entire set of features in the platform would not be required at a time and a user has the ability to select whichever FEs that need to be activated by an enable signal.

EEG signal processing frequently involves the calculation of multivariate features, hence we provide 2 bivariate measures in our design. Overall, the proposed system makes more efficient use of hardware by reusing resources instead of using a set of FEs for each channel. The set of features we provide include,

- Discrete Wavelet Transform coefficients (Haar, Daubechies 4 and 6)
- Power spectral density
- Band energies
- Correlation
- Zero crossing histogram
- Autoregressive coefficients
- Phase synchronization

In this paper we have implemented the platform for 14 channels and 7 different feature vectors. This makes the variable $n = 14$ and $k = 7$ according to the architecture diagram in Figure 1.

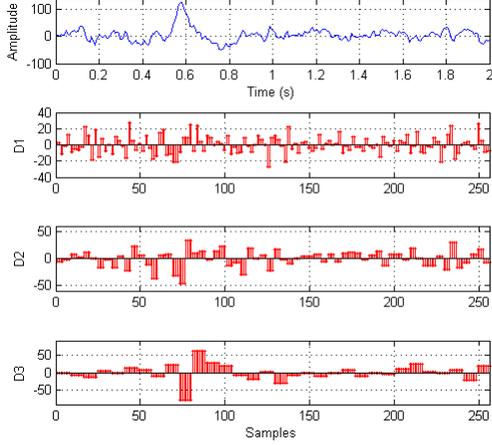


Figure 2 : Decomposition of 2s EEG epoch with Harr wavelet

A. Preprocessing Stage

Scalp EEG recordings in the microvolt range are susceptible to a number of internal and external sources of contamination. These include muscle noise, ocular artefacts, power line noise, baseline wander and motion artefacts. In our design, we utilize a set of 0.5 Hz highpass and 50 Hz notch Finite Impulse Response (FIR) filters to eliminate baseline drift and power line interference. Each of the n channels of EEG pass through two separate 64-tap FIRs having 16-bit coefficients with quantization selected to maximize dynamic range. A window-based method was used to design both filters.

IV. FEATURE EXTRACTION

A. Discrete Wavelet Transform (DWT)

Joint time-frequency analysis has been an invaluable tool in the study of non-stationary EEG signals. Temporal and spatial resolution in conventional spectrum analysis techniques are highly dependent on EEG segment length, model order and other parameters. Wavelet decomposition provides a time-frequency representation of EEG signals as a solution. The DWT has been used in applications such as the detection of seizures [10] and feature extraction based on Event Related Potentials [11].

We apply the DWT on each of the non-overlapping epochs of EEG data and perform 4-level decomposition into 5 frequency sub-bands. Haar and Daubechies (db4 and db6) mother wavelets are used with a lifting-based structure. Classically, the WT is performed using a bank of highpass and lowpass filters. The lifting scheme provides an alternate, more efficient implementation of extracting DWT coefficients. Lifting steps for the three wavelets are indicated below.

Let $x = \{x_l \mid l \in Z\}$ be the EEG segment. The lowpass filter output is the sequence $s = \{s_l \mid l \in Z\}$ while the highpass filter output is $d = \{d_l \mid l \in Z\}$. The intermediate sequences computed during lifting are indicated by $s^{(i)}$ and $d^{(i)}$.

1) Harr

$$s_l^{(0)} = x_{2l} \quad (1.1)$$

$$d_l^{(0)} = x_{2l+1} \quad (1.2)$$

$$d_l = d_l^{(0)} - s_l^{(0)} \quad (1.3)$$

$$s_l = s_l^{(0)} - (1/2) d_l \quad (1.4)$$

2) Daubechies 4

$$d_l^{(1)} = x_{2l+1} - \sqrt{3}x_{2l} \quad (2.1)$$

$$s_l^{(1)} = x_{2l} + \left(\frac{\sqrt{3}}{4}\right)d_l^{(1)} + \left(\frac{\sqrt{3}-2}{4}\right)d_{l+1}^{(1)} \quad (2.2)$$

$$d_l^{(2)} = d_l^{(1)} + s_{l-1}^{(1)} \quad (2.3)$$

$$s_l = (\sqrt{3} + 1)/\sqrt{2}s_l^{(1)} \quad (2.4)$$

$$d_l = (\sqrt{3} - 1)/\sqrt{2}d_l^{(2)} \quad (2.5)$$

3) Daubechies 6

$$s_l^{(0)} = x_{2l} \quad (3.1)$$

$$d_l^{(0)} = x_{2l+1} \quad (3.2)$$

$$d_l^{(1)} = d_l^{(0)} + \alpha(s_l^{(0)} + s_{l+1}^{(0)}) \quad (3.3)$$

$$s_l^{(1)} = s_l^{(0)} + \beta(d_l^{(1)} + d_{l-1}^{(1)}) \quad (3.4)$$

$$d_l^{(2)} = d_l^{(1)} + \gamma(s_l^{(1)} + s_{l+1}^{(1)}) \quad (3.5)$$

$$s_l^{(2)} = s_l^{(1)} + \delta(d_l^{(2)} + d_{l-1}^{(2)}) \quad (3.6)$$

$$s_l = \zeta s_l^{(2)} \quad (3.7)$$

$$d_l = d_l^{(2)}/\zeta \quad (3.8)$$

Here, $\alpha = -1.586134342$ $\beta = -0.05298011854$ $\gamma = 0.8829110762$ $\delta = 0.4435068522$ $\zeta = 1.149604398$. The lifting scheme is implemented on FPGA as one of the feature extraction blocks and it will be capable of performing Discrete Wavelet Transform. Figure 2 illustrates the first three detail components of a four level decomposition using Harr wavelet.

B. Power Spectral Density (PSD)

Power spectral density of EEG signals has been utilized in the detection of seizures [12], diagnosis of depression [13], motor imagery based BCIs [14] and several other applications. The Welch method [15] is a non-parametric approach to estimate PSD of a time series using modified periodograms. In this design, we split each epoch of EEG samples into smaller sized fixed windows $x_i[n]$ with 50% overlap and a final circular overlap as proposed in [16]. Each segment is multiplied with a Hamming window $w[n]$ and its FFT is computed to yield the i^{th} modified periodogram,

$$\tilde{P}_{XX}^i = \frac{1}{MU} \left| \sum_{n=0}^{M-1} x_i[n]w[n]e^{-j2\pi fn} \right|^2 \quad (4)$$

Here,

$$U = \frac{1}{M} \sum_{n=0}^{M-1} w^2[n] \quad (5)$$

The final PSD is obtained by averaging,

$$P_{XX}^W(f) = \frac{1}{L} \sum_{i=0}^{L-1} \tilde{P}_{XX}^i(f) \quad (6)$$

EEG samples are read from a shared memory and are multiplied by the coefficients of the Hamming window which are stored in a ROM. A separate address generator module is

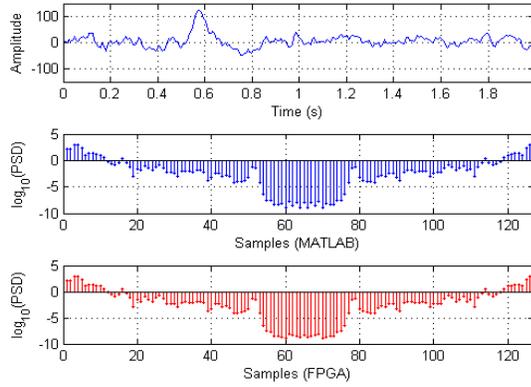


Figure 3 : MATLAB and FPGA estimates of PSD for a 2s EEG epoch

used to generate the correct indices of each of the windows. The modified EEG window samples are then scaled and fed to an FFT module and their outputs are stored in separate memories. While the FFT output of the final modified window is valid, the values of all other stored periodograms are read off from memory, added and multiplied by a scaling term to yield the final PSD estimate. FPGA and MATLAB estimates of an epoch of EEG are depicted in Figure 3 (log values have been plotted for convenience).

C. Band Energies

An EEG signal can typically be decomposed into 5 separate frequency bands: δ (0.5-4 Hz), θ (4-8 Hz), α (8-12 Hz), β (12-30 Hz) and γ (30-60 Hz). EEG band energies have been studied in numerous applications ranging from seizure detection and motor imagery identification to on-screen primitive shape classification [17].

Energy values of the 5 frequency bands are calculated by first computing the FFT of each EEG epoch and then summing the squares of the spectral components in each of the bands using separate accumulators. Energy of the γ band is calculated for the frequency range 30-45 Hz.

D. Correlation

Correlation measures the similarity between two EEG epochs. Cross-correlation refers to the correlation between two completely different EEG signals and the accompanying plot is known as a “correlogram”. Siuly and Li [18] used statistical features based on cross-correlation for motor imagery classification using a Least Square Support Vector Machine (LSSVM) and achieved an accuracy of 95.72%.

Let $x[n]$ and $y[n]$ be the 2 EEG epochs, each having N samples. The m^{th} coefficient (m^{th} lag) of the cross-correlation is given by,

$$R[m] = \sum_{i=0}^{N-|m|-1} x[i]y[i-m] \quad (7)$$

$$m = -(N-1), -(N-2), \dots, 0, 1, 2, \dots, (N-2), (N-1)$$

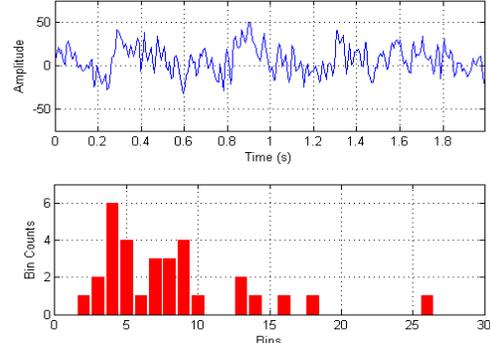


Figure 4 : A 2s EEG epoch and its positive zero crossing histogram

In feature extractor block implementation 20 correlation coefficients are calculated for two different EEG epochs. The architecture is designed in a way that it can be extended easily. Each correlation coefficient is computed in parallel. Architecture is similar to a set of parallel FIR filters, while samples of $x[n]$ are used as filter coefficients and $y[n]$ being the signal that is filtered.

E. Zero Crossing Histogram

Zero crossing intervals of scalp EEG signals have been analyzed in the past and has been demonstrated to yield good results in detecting probable Alzheimer's disease and Vascular dementia [19], predicting seizures [20] and characterizing sleep spindles [21]. The zero crossing histogram is more robust in the presence of contaminating artefacts and is a convenient means of extracting dynamical information about the brain. Here, we provide a single-sample bin positive zero crossing histogram (i.e. number of samples between two successive points during which the signal crosses from negative to positive). A user may concatenate adjacent bins to create larger bins or variable bin sizes at a latter stage as may be required.

The module utilizes simple logic to detect a positive zero crossing by comparing each sample and its predecessor to zero. If a positive sample is detected along with a preceding negative one, a counter is incremented until the next zero crossing occurs, at which point the counter is reset. At this instant, the last value held by the counter is utilized to increment the corresponding bin of the histogram which is stored in memory. After detecting all crossing in the EEG epoch, the values are read out and the memory is reset to contain all zeros. An example histogram for a 2s epoch of recorded EEG is shown in Figure 4.

F. Autoregressive (AR) Coefficients

Autoregressive modelling is an alternative to conventional Fourier-based methods for representing frequency information of a signal. In AR modelling the signal being modelled is considered as the output of an Infinite Impulse Response (IIR) filter when the input to this filter is white noise. In most of the applications the IIR filter coefficients are used as feature vectors. Anderson *et al.* [22] used multivariate AR models to discriminate between mental tasks of a human

subject. Pfurtscheller *et al.* [23] distinguished right and left motor imagery EEG using adaptive AR parameters to control an on-screen cursor.

We compute AR coefficients for each EEG epoch. The order of an AR model should be increased proportional to the sampling frequency [24]. In our approach, Burg's algorithm proposed in [25] is used to estimate AR coefficients for a model of order 6. Each iteration of the Burg's algorithm is implemented as a separate module and cascaded to compute 6 AR coefficients.

According to the Burg's algorithm $f_m(n)$ and $b_m(n)$ are the forward and backward errors of order m related to an EEG epoch $x(n)$. Let the AR coefficients are indicated by the symbols $a_{1,1}, a_{2,2}, \dots, a_{m,m}$. For an intermediate stage r of the algorithm, the inputs are the forward and backward errors of the previous stage ($f_{r-1}(n)$ and $b_{r-1}(n)$). The outputs of the r^{th} stage are the new set of forward and backward errors $f_r(n)$, $b_r(n)$ and $a_{1,1}, a_{2,2}, \dots, a_{r,r}$ coefficients. The nature of the algorithm makes the current stage depend on the previous stage outputs. Hence a cascaded system is suggested for the implementation.

G. Phase Synchronization

Extensive research has been pursued over the past several years into the analysis of EEG signals (both intracranial and scalp EEG) for developing algorithms to automatically detect and predict epileptic seizures. Algorithms that use bivariate or multivariate measures have been investigated in this particular field as they have shown to yield superior performance to univariate measures which lack spatial specificity. Phase synchronization has been one such measure that has yielded promising classification results [26], [27].

Phase synchronization is calculated to quantify the instantaneous phase lock between 2 EEG channels separated in space. The phase locking between 2 EEG signals V_0 and V_1 is estimated by first applying the Hilbert Transform to the signals to compute their real and imaginary components. The Hilbert Transform is approximated by a 64-tap FIR filter. The instantaneous phases of the 2 channels are then computed to yield ϕ_k ,

$$\phi_k = \arctan \frac{\text{Im}\{V_k\}}{\text{Re}\{V_k\}}; k = 0,1 \quad (8)$$

The phase difference is then obtained as $\Delta\phi = \phi_1 - \phi_0$. The phase locking value (PLV) between the 2 channels is then calculated as,

$$PLV = \frac{1}{N} \sqrt{[\sum_{i=0}^{N-1} \sin(\Delta\phi_i)]^2 + [\sum_{i=0}^{N-1} \cos(\Delta\phi_i)]^2} \quad (9)$$

The module makes use of 4 CORDIC blocks to calculate 4-quadrant arctan, sine, cosine and square roots of the incoming data points to obtain PLV for each EEG epoch in real time. The sine and cosine values of the phase differences are summed using 2 separate accumulators whose final output corresponding to all samples in the epoch is fed into the square root CORDIC block.

V. RESULTS

The platform was implemented on a Virtex 7 FPGA. We utilized the 14-channel EMOTIV neuroheadset with a sampling frequency of 128 Hz for testing. For testing out each individual FE block, we used a 1 hour long single channel recording. This signal was then split into 1800 epochs of 2s (256 samples) duration. For each feature vector \hat{x} calculated in hardware, we compute the corresponding vector x in MATLAB. The mean absolute error between the two estimates which occurs due to the fixed point arithmetic on FPGA is calculated as follows,

$$\text{error} = \frac{\sum_i |\hat{x}_i - x_i|}{\sum_i |x_i|} \times 100\% \quad (10)$$

Table 1 : Comparison of Computed Features with Software

| Feature | Error | Clock Cycles |
|---|---------------------------|--------------|
| DWT Coefficients (Haar) | $2.9808 \times 10^{-6}\%$ | 288 |
| DWT Coefficients (db-4) | 0.0043% | 608 |
| DWT Coefficients (db-6) | 0.002957% | 768 |
| Power Spectral Density | 0.2286% | 1130 |
| Autoregressive Coefficients | 0.0568% | 2839 |
| Zero-crossing Histogram | 0% | 515 |
| Band Energies ($\delta, \theta, \alpha, \beta, \gamma$) | 0.0727% | 874 |
| Correlation | 0.000351% | 270 |
| Phase Synchronization | 17.058% | 423 |

The error per feature vector of each epoch is obtained by averaging and the comparison of results is shown in Table 1 along with the number of clock cycles (at 50 MHz clock frequency) taken for computation of each feature. The functionality of the complete multirate system was tested separately for all EEG channels and after computing features for the n epochs (requiring $n \times$ cycles per feature), over 300000 spare clock cycles remain for any further application prior to receiving the next sample.

Secondly, we validate our platform by implementing the seizure detection algorithm in [28]. db-4 and db-6 wavelet coefficients are extracted for the EEG epochs using hardware co-simulation for a dataset publicly available from University of Bonn (a detailed description about the dataset can be found in [29]). The best features for discriminating between the 2 classes were selected using the Mann-Whitney test at a significance of 1%. We utilize 60% of the data for training and use the remainder for testing on an LSSVM classifier. We achieved an overall accuracy of 96.93% with a sensitivity of 88.43% and a specificity of 99.06% on the test dataset.

VI. CONCLUSION

The need for a bulky PC has been one of the primary drawbacks in bringing BCIs to the home user. Consequently, there has been a recent interest in complete hardware implementation of these systems. However, many of the existing FPGA based BCIs process just a limited number of EEG channels and extract only a single type of feature. We present the FPGA design of a generalized preprocessing and feature extraction platform that is capable of computing multiple features in parallel as required by a user. We evaluate our platform twofold. Firstly, we use data recorded from the

EMOTIV neuroheadset and obtain results comparable with software. Secondly, we utilize our platform to extract features for a seizure detection algorithm and obtain good classification accuracy. Future work would include pushing the hardware interface of BCIs even further to include a set of classification algorithms. Extending the platform to include features commonly utilized in other biomedical signal processing applications (e.g. R-R intervals and area of QRS complexes in electrocardiograms) would also be another useful contribution.

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