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A Hardware Implementation of a qEEG-Based Discriminant Function for Brain Injury Detection

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***Abstract*— This paper presents a feature extraction engine based on using Electroencephalogram (EEG) as a tool for Traumatic-Brain-Injury (TBI) detection. The design focuses on the development of hardware accelerator components integrated onto an FPGA platform. Utilizing a combination of four key quantitative-EEG (qEEG) features, the hardware design can perform a discriminant function (DF) based on 20 variables used for predicting TBI. Since the design is intended to operate in real-time and needs to perform intensive EEG-processing tasks, the emphasis is on the architectural aspects and speed capabilities of the feature extraction work.**

***Index Terms*— TBI, EEG, qEEG, Signal Processing, FFT, Discriminant Function, FPGA, SoC, ZYNQ UltraScale+.**

I. INTRODUCTION

Traumatic-Brain-Injury (TBI) occurs when an external force like a hard blow, a sudden acceleration-deceleration, or a penetration by an object causes internal damage to the brain. The result of the injury can be tearing of brain tissue, bruising, bleeding and in more severe cases hematoma. Every year in the European-Union, 2.5 million people endure a TBI, 1.5 million of whom are admitted to hospitals and a reported 57,000 deaths occur [1]. Also, the economic burden stemming from the consequences of TBI amounts to $400bn worldwide. From a patient's perspective, some common symptoms occurring directly after the impact might be loss of consciousness, ringing in the ears, blurred vision and dizziness. Furthermore, some of these implications help categorize the severity based on their duration. Brain injury types are classified as, mild, moderate, and severe. Neurological changes that are observed for each of these types after a TBI has occurred, form the stages which are described as acute (hours to weeks), subacute (weeks to months) and chronic (more than 6 months) [2].

Although most physical and neurological symptoms repair in the acute and subacute stages, other functional complications last longer, and affect everyday life of people who have experienced brain trauma. The long-lasting implications of a TBI vary from persistent headaches to irreversible cases like permanent disability. In general, the complications can be physical, cognitive, social, emotional and behavioural. Many patients suffer post-injury from sleep disorders, memory and speech problems, motor problems, inability to control their emotions and many others that make their daily life difficult. To conclude, TBI is a major problem and a late or misdiagnosed case can lead to severe consequences. Therefore, early and fast detection of an injury especially in emergency settings will help prognoses and prevent discomfort sequelae.

A tool that looks promising [3] for fast TBI detection is Electroencephalogram (EEG) and specifically quantitative-EEG (qEEG), which is the mathematically processed EEG signal. There is a twofold application for EEG as a tool, one is clinical and the other is Brain-Computer Interfaces (BCI). A temporal depiction of the human brain via electrical waves unveils new diagnostic opportunities and the capabilities spawned from this tool have started to emerge. With advances in Machine Learning (ML) over the last decade, research based on EEG signals has increased dramatically [4]. Furthermore, researchers have easier access to cost-affordable EEG equipment and development tools leading to more areas of investigation. EEG signals for BCI applications represent the highest volume of works, given the spectrum of application areas such as control of prosthetic limbs, smart homes, VR & AR. In contrast, applications in the clinical environment are notably limited as challenges are associated with using EEG as a medical tool.

A particular challenge for EEG is the accepted alternatives used in the field such as Magnetic Resonance Imaging (MRI), functional MRI (fMRI), Positron Emission Tomography (PET) and Computer Tomography (CT). These brain-imaging techniques offer a structural mapping of the brain as opposed to functional, which is carried out by EEG, so trauma can be visually examined and detected by doctors at hospitals with high-quality images in terms of pixel resolution. Despite their advantages over EEG, the large equipment required for a single image makes them prohibitive for use in portable devices. Compared to these techniques, EEG outperforms in temporal resolution (i.e., it captures the ongoing activity taking place in the brain) and has an advantage in terms of cost and equipment size to enable fast and in-field examination. Therefore, EEG is a potential solution for brain examination when an emergency is a priority. In this paper, the utilization of qEEG variables which are combined to form a discriminant function (DF) is investigated and a hardware implementation for the feature extraction engine is described. The remainder of the paper is structured as follows.

Section II provides further discussion on TBI and EEG related research outcomes that have the potential for enabling device applications. Section III discusses the methodology that forms the feature extraction signal-processing steps and the key variables for analysing the spectral content of EEG signals helping to diagnose a TBI event. This content helps with defining the signal processing requirements. In Section IV of this paper, the architecture and design implementation towards a real-time system is explored. The design focuses on the development of hardware accelerators that calculate each of the key discriminant function (DF) variables integrated onto a System-on-Chip (SoC) Field-Programmable-Gate-Array (FPGA) platform. Results are provided in Section V that compares the operation in terms of hardware vs. software capabilities. Finally, a conclusion and future work is presented in Section VI.

II. RELATED WORK

Up until now, one of the most common clinical indexes for TBI assessment is the Glasgow-Coma-Scale (GCS) [5]. GCS is a calibration scale for the severity of the head injury. It provides a level of consciousness by measuring the response of a patient to the eye, verbal and motor stimuli. Each category eye, verbal and motor are labelled with a number from 1 to 4, 1 to 5, and 1 to 6 correspondingly. The aggregation of them indicates the level of the severity of the injury. Loss of consciousness and post-traumatic amnesia are measurements of the duration of unconsciousness and amnesia respectively after TBI. A study by Thatcher et al [6] has shown a strong correlation between qEEG parameters and these indices. Since these indices are TBI predictors and categorize the severity, a conclusion from this work is the potential use of qEEG for TBI classification. The high percentages reported in this work for accuracy 96.39%, and specificity 97.44%, constitutes a milestone in a series of studies that support the use of qEEG-based discriminant functions for TBI detection [3].

The majority of studies in literature concentrate on mild traumatic brain injury also known as concussion in medical parlance. The reason for that is that mild TBI is the most frequent of the three cases which are classified as mild, moderate, and severe. The work in [7] highlights the potential of qEEG as a TBI detection tool where the authors examined 608 mild head-injured patients and contrasted them to 108 healthy participants. Although the discriminant function developed in each study [6, 7] is completely different, both works provide compelling evidence of the high validity of discriminant functions as detection and classification tools. The large sample of patients, the test-retest reliability and the similarly high percentages of accuracy (94.8%), and specificity (93.2%) made the discriminant function in [7] the selection for the hardware implementation in the context of this paper.

Generally, there are not many studies about portable devices for TBI available. Nevertheless, the work in [8] demonstrates the development of a multi-sensor helmet for military personnel. Since the purpose of this helmet is for extreme conditions; emphasis is on the structure of the helmet. Particularly, this helmet seeks to track EEG, blast pressure, head acceleration, oxygen saturation, and heart rate parameters. The challenges associated with this equipment are the placement of the sensors for each of these modalities, the response time and the triggering conditions for data acquisition, including wireless communication of the helmet with emergency personnel.

The work in [9] also stands out because it includes Automatic Wavelet Independent Component Analysis (AWICA) in its methods. This technique is resourceful as it provides an automated routine for artefact rejection. Figure 1 shows a typical pipeline for EEG processing tasks, which includes the artefact rejection step. Artefacts are considered noise that contaminate the EEG signal, which is induced by any source other than the brain. Two of the most common EEG contaminants are power line noise and ocular artefacts. In real-life settings, experts typically inspect the EEG signals visually, to exclude whole segments of non-clean data where the noise is dominant. Also, the artefact rejection step must be repeated several times for a better signal-to-noise ratio, and all of this requires human-involvement. However, human intervention can be avoided by using an algorithm like AWICA. This indicates that a system device can be implemented completely in hardware operating software-independently. This paper focuses on the qEEG feature extraction step and a hardware design aligned with the aim of developing a real-time device for TBI analysis.

III. Methodology

As shown in Fig. 1, a typical EEG processing pipeline consists of three steps,

1. Pre-processing - filtering and artefact rejection,
2. Feature extraction and selection,
3. Classification.

This work focuses on step 2 and the calculation of features that are most suitable for TBI detection. The feature selection step is the method of selecting the optimal combination of features available that best describe a target application. For TBI detection, the authors in [7] have completed this process where multiple statistical tests were conducted to end up with the most suitable ensemble of qEEG variables (or features). One of the statistical tests conducted is multivariate analysis of variance, which can perform even better than genetic algorithms [10]. From Fig. 1, independent variables are associated with the 16 EEG channels or electrodes positions that follow the rules of the 10-20 system defined in [11]. For example, Relative Power (RP) for channel P3 is a single variable, while the Coherence (CO) measurement for dual channels Fp1-F7 is another separate variable.

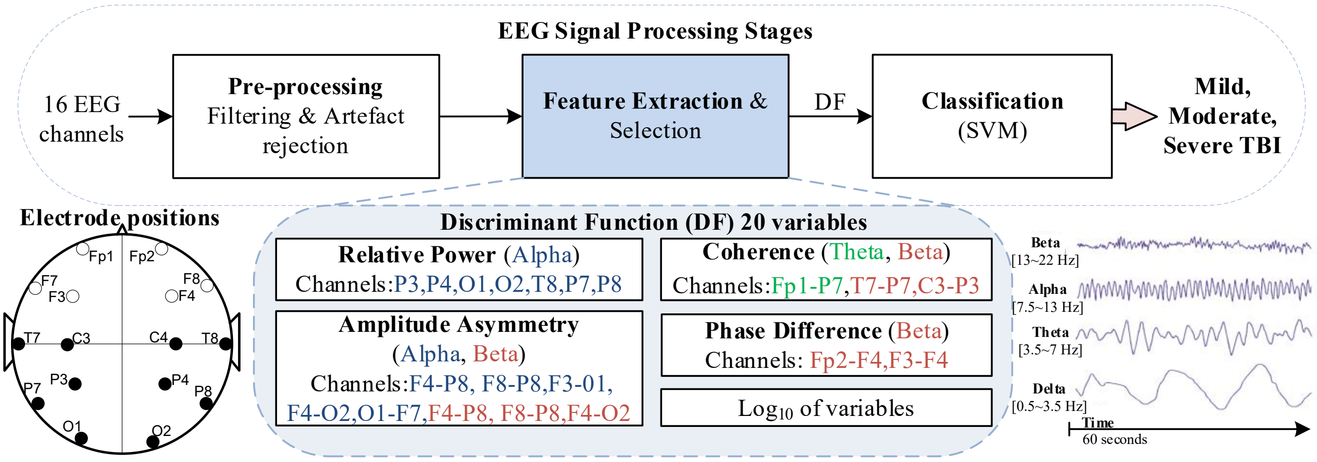

Fig. 1. TBI detection EEG processing pipeline.

qEEG refers to data processing and mathematical interpretation of EEG signals describing brain activity. These interpretations are attributed to a change or alteration in the current state of the brain such as the phase of signals. These signal properties cannot be visually detected by the human eye but can be detected using qEEG parameters. Therefore, these parameters help in investigating signals and to catch patterns that would otherwise be impossible to detect. In [7], the authors conclude that after a brain injury, the brain switches to a state of reduced processing ability and neurophysiological complexity. It is known that after an injury, the brain takes over by recruiting non-harmed parts of the brain to maintain proper functionality, which stems from neuroplasticity. Although a transition to a new state after an injury occurrence has not been strongly supported so far, the case is that brain states are associated with certain patterns of brain waves.

The brain wavebands are delta (0.5~3.5 Hz), theta (3.5~7 Hz), alpha (7.5~13 Hz), beta (13~22 Hz) and gamma (above 30 Hz). For example, during sleep, the brain is at the lowest level of engagement and delta waves are prominent. Then during arousal states, if a person is in meditation alpha waves are observed in the EEG signals or when the person is actively thinking, beta waves are prominent. Perhaps in the future, scientists will be able to describe the post-injury functionality of the brain with a new state and associate it with certain patterns of brain waves. However, since the qEEG-based interpretation of TBI is a nascent field, there is insufficient evidence to back up these claims right now. However, some general findings show relative consistency amongst studies whereby increased delta theta beta power and reduced alpha power [3] are useful parameters.

There are two methods for TBI examination using frequency-based qEEG features. These are termed ***Spectral analysis*** and ***Functional connectivity***. Spectral analysis refers to the investigation of individual signal spectra whereas functional connectivity involves the investigation of the cross-power spectrum between the shared activity of two signals. Two qEEG features for TBI detection are derived from the power spectrum, these are Relative Power (RP) and Amplitude Asymmetry (AA). The cross-power spectrum-derived features are specifically Coherence (CO) and Phase Difference (PD). Although it is possible to have a study based on a single qEEG feature, the best way is to combine one or more of these features into a discriminant model. The conclusion of the systematic review in [3] suggests that single qEEG features cannot stand-alone effectively as detections tools; rather the joint usage of qEEG variables is a powerful tool, termed the discriminant function that is used for the detection and classification of TBI. For the discriminant function reported in [7], 20 variables based on the qEEG features need to be combined as shown in Fig. 1. The equations for each of these four qEEG features from [7] are explained.

A. Relative power (RP): RP is calculated as

$$RP(f_1, f_2) = \frac{P(f_1, f_2)}{P(0.5,22)} * 100\%, \tag{1}$$

where RP is the percentage of power in a specific frequency band f_1 to f_2 across the whole frequency range from 0.5 to 22 Hz. RP is a measure of how brain activity is distributed.

B. Amplitude asymmetry (AA): AA is represented as

$$AA(f_i) = \frac{A(f_i) - B(f_i)}{A(f_i) + B(f_i)}, \tag{2}$$

where A indicates the amplitude value at a specific frequency location, whereas B is the amplitude value at the same frequency but a different channel site. Alpha band AA is associated with cognitive tasks and task difficulty.

C. Coherence (CO): CO is given by

$$C_{xy}(f) = \frac{|G_{xy}(f)|^2}{G_{xx}(f) * G_{yy}(f)}, \tag{3}$$

where $C_{xy}(f)$ is the CO value for signal channels x and y at frequency f, G_{xy} indicates the cross-spectral density between x and y, G_{xx} is the spectral density for x, and G_{yy} is the spectral density for y. CO measurements indicate the functional relationship across brain region and coordination of brain activity.

D. Phase difference (PD): PD is stated as

$$P(f) = \frac{\tan^{-1}\left(\frac{q_{xy}(f)}{c_{xy}(f)}\right)}{SC}, \tag{4}$$

where $P(f)$ is the value of phase shift between signals x and y, $q_{xy}(f)$ is the imaginary part of the cross-spectrum density value at frequency f. $C_{xy}(f)$ is the real part of the cross-spectrum density number at frequency f and SC is the center-frequency of the examined frequency band. PD reflects the transmission of information between brain regions.

To apply the above equations, there is a need to compute the power and cross-power spectral density values. Equations (5) and (6) show the difference between power and cross-power terms.

$$P_x = FT_x * conj\{FT_x\}, \tag{5}$$

$$P_{xy} = FT_x * conj\{FT_y\}. \tag{6}$$

In (5), the formula for the power spectrum of a signal x is based on the multiplication of the Fourier-Transform (FT) of the signal x with the complex conjugate of itself, whereas in (6), the formula for the cross-power spectrum between two signals x and y is based on the multiplication of the FT of signal x with signal's y complex-conjugate FT.

Welch's method [12] also called the averaged periodogram is used for power spectral density estimation as part of the discriminant function (DF) design. This technique averages multiple shorter FFTs or modified periodograms. A description of the technique is illustrated in Fig 2. The time signal is divided into multiple segments with an optional overlap between them. For each segment, the procedure involves multiplication of input EEG channel data with a window function followed by a Fourier Transformation and averaging of all segment transforms. Since a window function is applied to each data segment, then the overlap is necessary given that the data sections are suppressed by windowing. This method results in a smoother spectrum as the averaging of the segments reduces

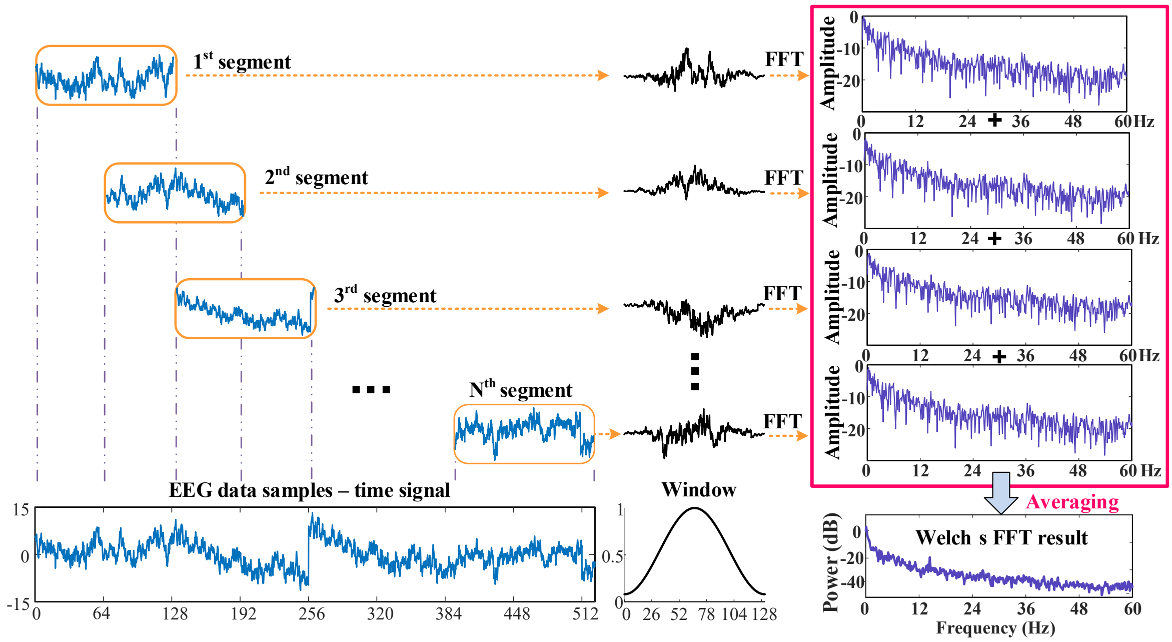

Fig. 2. Representation of Welch's method [13].

variance. For the DF computations, the segment length and number of FFT points is selected to 128. With a sampling-frequency of Fs=125 Hz, an approximate 1 Hz/bin frequency resolution is achieved. The DF variables are calculated over a 60-second epoch and so 8192 samples result in 127 overalapping segments ($N = 2 * (8192/128) - 1$). In total, 16 EEG channels are used in the feature extraction step to score the discriminant function (DF) over the epoch interval. A log-based transform improves the Gaussianity (or normality) of these features before application to a classification stage.

IV. Design Implementation

The important hardware design building blocks are defined by the composition of the DF as shown in Fig. 1 and governed by the spectral density calculations (1) ~ (4). These blocks consist of hardware accelerator units for each of the key qEEG parameters that perform the computations for power spectrum (5), cross-power spectrum (6) and then application of (1) ~ (4). Since there are four key qEEG features to extract, the initial design approach is to implement four separate hardware accelerators according to the list of DF variables. Three out of four accelerators, i.e. AA, CO and PD receive data from a pair of EEG channels, while the RP accelerator unit obtains data from a single EEG channel. In total, the DF feature extraction engine design must make twenty calculations, seven for the RP, eight for the AA, three for the CO and two for the PD. That means twenty transactions between the memory where the channel data is stored and these hardware accelerators. Each accelerator unit is coded in C-code as part of a modern High-Level Synthesis (HLS) design process and follows the general flow chart as shown in Fig. 3. A significant part of the HLS code design for these accelerators is the FFT operation and the baseline algorithm described in [14] was used for the FFT processing. The first approach used a CORDIC design for angle computations, however the final implementation of sine and cosine functions was realized using lookup tables with small, precomputed array values supporting 128-FFT points. Without using Welch's method, the larger size FFT would require significant resources to compute the angle locations. Using small arrays with pre-stored values gives better execution performance in terms of speed and was a priority given the significant processing required to compute all the variables making up the DF design.

For the feature extraction engine design, a XILINX Zynq UltraScale+ FPGA SoC ZCU104 board [15] was used with the EEG channel data stored in the DRAM memory section of the Processing System (PS) as shown in Fig. 4. Since this DF engine is part of a planned SoC system that will operate in real-time, a streaming interface between the memory in the PS and the accelerators in the Programmable-Logic (PL), namely the AXI4-Stream interface was applied. Programmable SoCs, such as the ZCU104 FPGA platform, integrate the PL onto the same die as with the PS, which is a complete processing system with Central Processing Unit

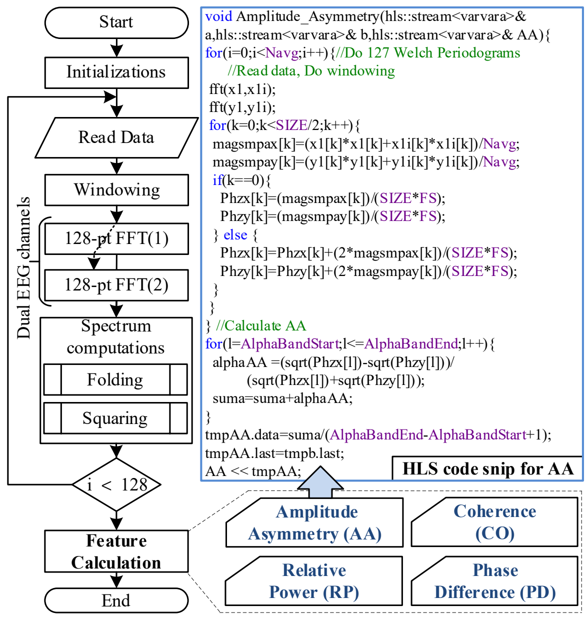

Fig. 3. General flowchart for the HLS accelerator algorithms.

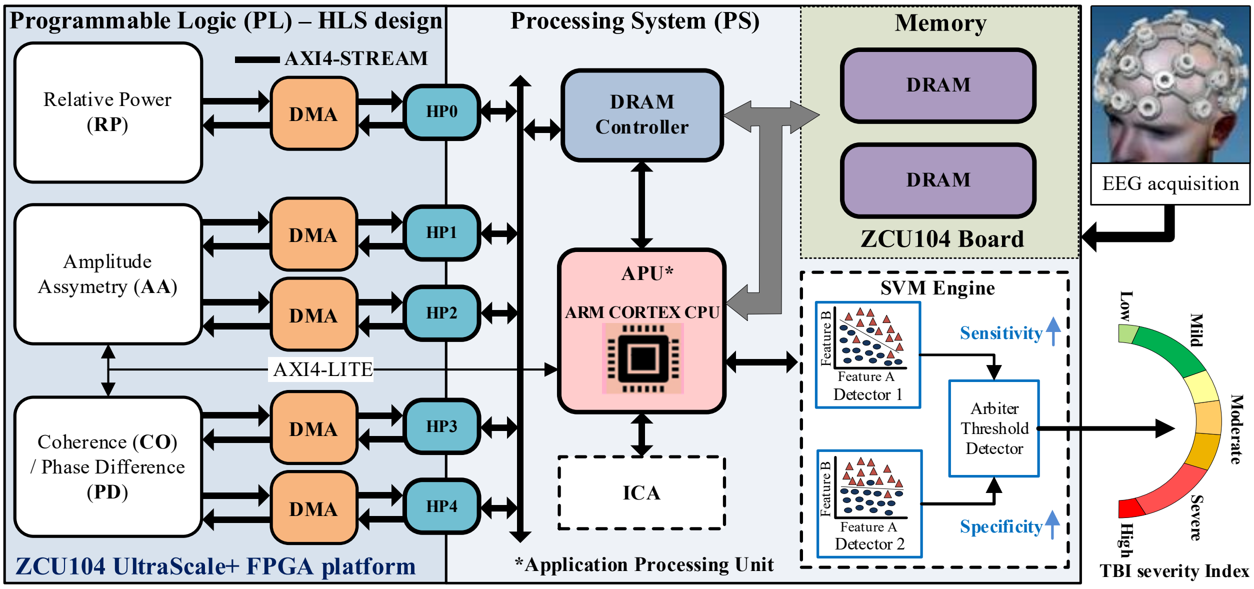

Fig. 4. A block diagram of the proposed TBI detector system. The PL side shows the accelerators formation, PS side contains the ARM CPU and DRAM controller, with DRAM external to FPGA. Future work includes ICA unit for EEG denoising and SVE Engine to classify TBI injury based on DF scores.

(CPU) cores and associated peripherals. In this system, the hardware design for the discriminant function logic is hosted within the PL section as can be seen from the left-hand side of Fig. 4. The PS side of the board is responsible for receiving the digital data from the external world (e.g. an EEG headset) and for streaming the data to the accelerators. For this reason, a streaming interface like the AXI4-Stream utilizes Direct-Memory-Access (DMA). DMAs are used to "detour" the CPU for data transactions to and from the main memory of the system without having to interrupt the CPU throughout the operation.

For real-time system operation, the data is sent in a streaming manner, which is fast and low-cost in terms of resource consumption. Therefore, the first design step was to apply the AXI4-Stream interface to the accelerators using XILINX's HLS tools, which converts C/C++, to RTL code. Additionally, the HLS tool allow developers to apply directives to the design where they are used for the interface definition and performance improvements. Here, the AXI4-Stream interface is a directive applied to the input and output of the HLS accelerator components.

Due to a limitation with the number of DMA interfaces supported by the FPGA platform, it was necessary to modify the design architecture approach and to rebuild the discriminant function overcoming this limitation. To support four accelerators, seven DMA engines are required to transfer the data to and from the DRAM. However, the maximum number of High-Performance (HP0 ~ HP4) ports for accessing DRAM memory from the ZCU104 PS is limited to six. This limitation imposes architectural constraints for the DF logic and consequently the accelerator designs. To address this limitation and reduce the number of DMA instances, two accelerators were merged as shown on the left side of Fig. 4. Using three accelerators compared to the initial four reduces the number of DMA requirements to five. Based on optimizing speed of operation, the RP and the AA computations are performed as separate accelerators, while CO and PD calculations are merged into a single accelerator design. As part of a future investigation, it is possible that the accelerators could be merged even more; for example, the AA and CO_PD accelerators could be combined, however, this has not been investigated fully at this time.

To separate the tasks of the CO_PD accelerator, an extra parameter is used as a "mode" selection. This parameter is set from the PS system, specifically the ARM CPU via the AXI4-Lite interface, which is a single transaction interface. The AXI4-Lite interface is also applied to the AA accelerator to help reduce the number of transactions. As indicated in Fig. 1 there is a need to calculate AA for eight pairs of channels, where three of these are the same EEG channel locations but different frequency bands. Therefore, for these channel pairs, the AA accelerator processes the same input data, and a dedicated mode helps to reduce the number of transactions from 8 to 5, while overall transactions are decreased from 20 to 17. In one mode of operation, the accelerator produces two values at the output, while in the other mode, only a single value is output as is the case for the other accelerator components.

Since the focus of this work is on the feature extraction engine, an assumption is made that filtered noise-free data is input to the system. Since TBI datasets are not commonly available, EEG recordings based on meditative OpenBCI datasets [16] were used for validating the architecture and performing an analysis.

V. Design Results

Using a combined accelerator for the CO/PD feature, the FPGA resources were reduced with the breakdown for the complete DF logic design shown in Table I. The design operates at 100 MHz, but this could be reduced significantly to lower power consumption depending on the real-time requirements of a complete TBI detection system.

TABLE I. ZYNQ ULTRASCALE+ FPGA RESOURCE BREAKDOWN

Resource	CLB	CLB LUTs	CLB Reg's	F7 MUX'S	F8 MUX'S	LUT - Logic	LUT – Mem.	Block RAM
Available	28800	230400	460800	115200	57600	240400	101760	312
Utilized	6236	35331	27509	31	3	34535	787	70
% Used	21.65	15.33	5.97	0.027	0.0052	14.37	0.77	22.44

As part of the evaluation procedure, a detailed MATLAB model for all the 20 DF variable computations was used to verify the hardware results. Table II shows a selected set of features that highlight the high accuracy of the accelerator units on the FPGA platform. The DF scores each of the variables in the range 0.0~1.0 with '1.0' indicating a high coherence or amplitude symmetry between the two channel locations and a '0.0' indicating low symmetry. Only minor result differences occur as MATLAB uses type double for the PC calculations, whereas the IP accelerators operate with floating-point format.

TABLE II. DISCRIMINANT FUNCTION - FPGA VS. MATLAB RESULTS.

Design	**Feature variable comparison**			
	RP** (alpha)* ***T8	***AA** (alpha)* ***F3-O1***	***CO** (theta)* ***FP1-F3***	***PD** (beta)* ***F3-F4***
Hardware	2.92317e-3	2.73750e-1	8.92454e-01	4.64750e-3
MATLAB	2.92317e-3	2.73719e-1	8.92465e-01	4.66443e-3

To further the evaluation, a second design for the DF was fully executed from the Cortex ARM CPU in a software-only C-code implementation. The software contains all the operations to execute the feature extraction step, these include the FFT computations and power spectral calculations for the qEEG variables that make up the DF. The C-code is compiled to operate on the Cortex ARM CPU without the use of hardware accelerators. From these setups, timing experiments were conducted to compare hardware vs. software implementations and to evaluate the hardware design yielding the results as shown in Table III. The input to each accelerator for these tests consisted of 8192 floating-point values for each EEG channel. The benefits of a hardware implementation are not obvious when comparing the designs individually, but execution times are apparent when running the system as a complete design. For stand-alone parameter testing, the software outperforms hardware in the case of RP, but in terms of the complete comparison, the hardware system is approximately ~2x faster. The benefits of a hardware streaming application are observed, particularly in the case of performing multiple transactions.

TABLE III. INDIVIDUAL ACCELERATORS AND DISCRIMINANT FUNCTION EXECUTION TIME COMPARISON - SOFTWARE VS HARDWARE.

Implementation	**Timing comparison (millisecond)**				
	RP	***AA***	***CO***	***PD***	***Full DF***
Software	15.390	30.564	33.036	31.673	514.957
Hardware	16.416	17.896	21.672	19.174	285.706

VI. CONCLUSION-FUTURE WORK

Here, the first step towards the goal of a real-time system device is presented that runs exclusively on hardware and utilizes EEG signals for detecting TBI events. A design methodology based on dedicated accelerator units can carry out intensive signal processing tasks to compute each of the qEEG variables that make up the DF for detecting a TBI event. The design used XILINX Vivado HLS tools to generate the hardware units and then integrated them into the programmable logic section interfaced to memory and the CPU processing system on a ZCU104 UltraScale+ FPGA board. The hardware design is very accurate and when compared to a stand-alone software Cortex CPU design, it is shown to be ~2x faster. This demonstrates the potential for developing a real-time, in-field TBI detection device combining artefact rejection and ML technique functionality. The results have established that it is possible to compute a DF using computationally efficient FPGA technology. For future work, the plan is to combine this hardware system with a technique [17] using Support Vector Machines for improved sensitivity and specificity, and to assess the efficiency of this complete system tested with real data and as part of a clinical study.

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