Seizure Prediction using Hilbert Huang Transform on Field Programmable Gate Array

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***Abstract*—The Hilbert Huang Transform (HHT) has been used extensively in the time-frequency analysis of electroencephalography (EEG) signals and Brain-Computer Interfaces. Most studies utilizing the HHT for extracting features in seizure prediction have used intracranial EEG recordings. Invasive implants in the cortex have unknown long term consequences and pose the risk of complications during surgery. This added risk dimension makes them unsuitable for continuous monitoring as would be the requirement in a Body Area Network. We present an HHT-based system on Field Programmable Gate Array (FPGA) for predicting epileptic seizures using scalp EEG. We use bandwidth features of Intrinsic Mode Functions and obtain a classification accuracy of close to 100% using patient-specific classifiers in software. Details of FPGA implementation are also given.**

***Keywords*—Hilbert Huang Transform, FPGA, scalp EEG, seizure prediction.**

I. Introduction

Epilepsy is a common neurological disorder characterized by the abnormal firing of neuronal populations in the brain which manifests itself in the form of recurrent seizures. Approximately 50 million people suffer from epilepsy worldwide, about 25% of whom do not respond positively to medication or surgery [1]. One of the most debilitating aspects of epilepsy has been the unpredictability of seizures giving patients a feeling of helplessness. Spontaneous unprovoked seizures often place patients in a vulnerable position with increased susceptibility to injury including falls, motor accidents, submersion injuries and burns [2]. The ability to forewarn patients of an impending seizure event would prove beneficial in improving their quality of life.

Typically, electroencephalography (EEG) signal activity during a seizure exhibits higher amplitude, more rhythmicity and less irregularity when compared to that of normal periods (see Fig. 1). Research has demonstrated that the change from normal to the seizure state is gradual and accompanied by quantifiable changes in EEG patterns and dynamics [3]. Consequently, many studies have sought to distinguish the preictal (period preceding seizure onset) stage from the interictal (between seizures) stage using machine learning algorithms.

Despite many promising Brain-Computer Interfaces (BCIs) being proposed in the literature, most have been implemented in software and remain confined to research laboratories - the necessity of a bulky computer being one of the primary drawbacks in bringing them to the everyday user. Hardware implementation would help bring these technologies closer to the people who need them the most. Here, we present the Field Programmable Gate Array (FPGA) implementation of an EEG-based seizure prediction system using the Hilbert Huang Transform (HHT).

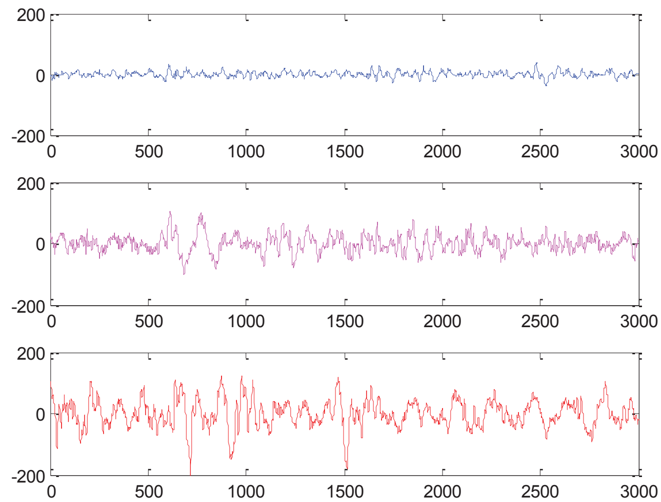

Fig. 1: Single channel EEG from the normal (top), preictal (middle) and ictal periods (bottom)

II. Literature Review

Presently, the *detection* of seizures using binary classifiers to distinguish between different EEG-based features in the ictal and interictal periods may be considered a largely solved problem. However, a clinically acceptable seizure *prediction* algorithm with suitable sensitivity and specificity requires further research effort [4]. The HHT has been a popular tool used in the study of EEG with its ability to analyze both nonlinear and non-stationary biomedical signals by decomposing them into data-dependent basis functions. It has been utilized both in detecting and predicting seizures. Here, we briefly review the existing literature where the HHT has been utilized for feature extraction in seizure prediction.

Zhu *et al.* [5] decomposed single-channel EEG signals recorded from patients into 7 Intrinsic Mode Functions (IMFs) and extracted complexity based features from each of them.

These features were used to train a Neural Network classifier and they obtained an overall accuracy of 74.38% in predicting seizures. Ozdemir and Yildirim [6] used the HHT to decompose intracranial EEG (iEEG) into 6 IMFs which were used for feature extraction with Neural Network based classification and obtained a sensitivity of 93.1%. Ozdemir and Yildrim [7] extracted statistical properties such as maxima, minima, mean, standard deviation and the ratios of band powers in the δ, θ, α, β and γ EEG bands from IMFs which were used to train a Support Vector Machine (SVM) classifier. They obtained a sensitivity of 89.66% with a False Positive Rate of 0.49 h^{-1} using patient specific classifiers. Ozdemir and Yildrim [8] decomposed iEEG into IMFs and calculated groupiness factor values and standard deviation of different energy bands. Patient-specific Bayesian Networks were trained and a prediction sensitivity of 96.55% along with a 0.21 h^{-1} False Positive Rate were obtained. In a very recent study, Parvez *et al.* [9] used the Discrete Cosine Transform to extract features based on temporal correlations of IMFs. The IMFs were generated from artefact suppressed iEEG using Independent Component Analysis at an earlier stage of the seizure prediction pipeline. They used an SVM and obtained a 100% prediction accuracy employing the first IMF.

Bajaj and Pachori [10] proposed using amplitude and frequency modulated (AM and FM) bandwidths of IMFs for detecting seizures. They evaluated different SVM kernels and obtained an accuracy of 100% when using the second IMF with a Morlet kernel. The authors in [9] applied the features proposed in [10] for seizure prediction and claim that its performance "was below the expected result using [a] large dataset" as the "the distributions of AM and FM bandwidths significantly overlapped in [a] large dataset."

Most methods utilizing the HHT for seizure prediction have used the Freiburg iEEG dataset [11] where signals were recorded from patients undergoing pre-surgical invasive epilepsy monitoring. Despite better spatial resolution, superior Signal to Noise Ratio (SNR) and larger bandwidth of invasive recordings, the long term stability of invasive implants with electrodes placed on the cortex for continuous monitoring and warning generation, as would be the requirement in a Body Area Network (BAN), remains open to question [12]. Surgical procedures pose risks in the form of additional complications such as infection and haemorrhaging. Scar tissue can develop around the implanted device over time detracting the quality of the electrical potentials being recorded and may ultimately render it ineffective. The consequences of such an implant over several years, treated as a foreign body in the brain, remains unknown. In contrast, utilizing scalp EEG for continuous monitoring poses none of these risks.

We propose using scalp EEG due to less associated complications and better suitability for a BAN. Furthermore we use the AM and FM bandwidth features used in [10] and show that a good classification accuracy can be obtained by using *patient-specific* classifiers instead of a single global decision threshold. The remainder of this paper is organized as follows. Sections III and IV focus on two separate aspects of this paper. We first attempt to justify the suitability of the selected features and classification algorithms in predicting seizures by implementing them in software. Secondly,we develop the system on FPGA. Section III describes the dataset, features and classifiers we used. Details of hardware implementation are also given. Section IV summarizes the results obtained and we conclude with Section V noting possible improvements and directions for future research.

III. Methodology

A. EEG Database

The proposed system was developed using the CHB-MIT scalp EEG database [13][14]. The data was recorded using scalp electrodes at a sampling frequency of 256 Hz from 22 subjects. Each recording consists of 23 EEG channels acquired using the international 10-20 system (a few recordings comprise of 24 or 26 channels) and the entire dataset contains 198 seizure events.

B. Feature Extraction

Microvolt-range scalp EEG signals captured by electrodes have undergone attenuation due to the skull and can be contaminated with muscle noise, eye blink artefacts and powerline interference. A bandpass FIR filter with cutoffs set to 0.5 Hz and 100 Hz and a 60 Hz notch filter were used at the preprocessing stage to remove baseline wander and suppress powerline noise.

Subsequent to decomposing a signal $x(t)$ using Empirical Mode Decomposition (EMD), $x(t)$ can be expressed as a summation in (1) where c_i is the i^{th} IMF component and $r(t)$ is the residue.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r(t) \tag{1}$$

As suggested in [15], the Hilbert Transform is then applied to all extracted IMFs. Next, it is possible to define the analytic signal $z(t)$ for any real $c(t)$ as shown below.

$$z(t) = c(t) + j\left[c(t) * \frac{1}{\pi t}\right] \tag{2}$$

$$z(t) = A(t)e^{j\phi(t)} \tag{3}$$

Taking $c_H(t) = c(t) * \frac{1}{\pi t}$, it is possible to define terms in equation (3) as shown in (4) and (5).

$$A(t) = \sqrt{c^2(t) + c_H^2(t)} \tag{4}$$

$$\phi(t) = \arctan\left[\frac{c_H(t)}{c(t)}\right] \tag{5}$$

The center frequency $\langle\omega\rangle$ of $z(t)$ is defined as in (6), where E is the energy of the signal and $Z(w)$ is the Fourier transform of $z(t)$.

$$\langle\omega\rangle = \frac{1}{E}\int \frac{d\phi(t)}{dt} A^2(t)dt \tag{6}$$

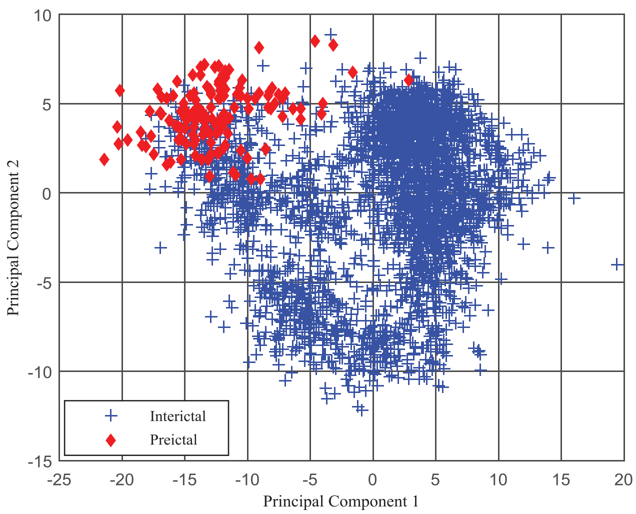

Fig. 2: Preictal and interictal feature distributions for child 1 projected onto first 2 principal component axes

Based on these outcomes, Cohen and Lee [16] have suggested methods to compute the Amplitude Modulation (BW_{AM}) and Frequency Modulation (BW_{FM}) bandwidths of $c(t)$. The final results are shown in equations (7) and (8).

$$BW_{AM}^2 = \frac{1}{E}\int\left[\frac{dA(t)}{dt}\right]^2 dt \tag{7}$$

$$BW_{FM}^2 = \frac{1}{E}\int\left[\frac{d\phi(t)}{dt} - \langle\omega\rangle\right]^2 A^2(t)dt \tag{8}$$

We first define the preictal period of each child commencing from 5 minutes prior to the start of an annotated seizure event. This interval is divided into 15s non-overlapping epochs. Each single channel epoch segment is then decomposed using EMD. AM and FM bandwidths are calculated for the first 5 IMFs yielding a 10-dimensional feature vector per channel. This is repeated for all 23 channels in the epoch resulting in a 230-dimensional feature vector. 20 such feature vectors can be obtained from the 5 minute preictal period. Thereafter, we select records not containing seizure events and randomly select 100, 15 s epochs per record for extracting the same features. Preictal and interictal feature vectors for each child are fed into separate classifiers (a classifier for each child) for determining optimal patient-specific decision surfaces. Principal components of features extracted for child 1 in the preictal and interictal period using MATLAB are shown in Fig. 2.

C. Classification

We evaluate a Least-Squares SVM (LSSVM) with a Radial Basis Function kernel and a Logistic Regressor (LR) in classifying features.

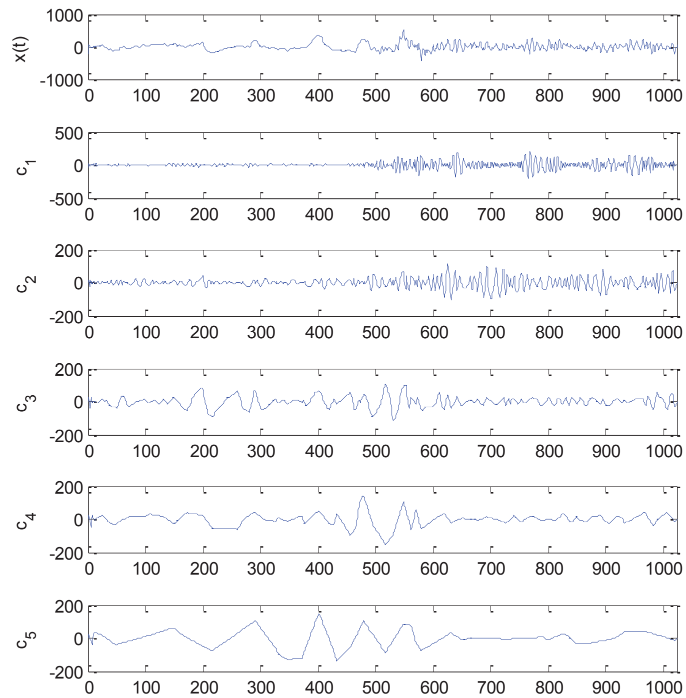

Fig. 3: EMD of an EEG epoch on FPGA

D. Hardware Implementation

We implement EMD on FPGA using the architecture proposed in [17]. The design utilizes sawtooth interpolation instead of the cubic spline interpolation used in software in order to facilitate continuously processing incoming data. An S-number termination criteria is used instead of the conventional convergence criteria involving the number of zero crossings and the number of local extrema of the signal. The authors in [17] suggest setting S to be between $3-5$ and we set $S = 4$. We decompose each epoch segment $x(t)$ into 5 IMFs (Fig. 3) and thereafter extract bandwidth features for each one using elements such as accumulators (acc), CORDIC blocks, multipliers etc. using the architecture shown in Fig. 4. Due to the recursive nature of the computations and smaller amplitudes of the components at successive iterations, we use 64-bit fixed point arithmetic in the design.

Calculating the proposed features in hardware utilizes a large amount of resources. Hence, having a separate feature extraction module per EEG channel is not feasible. As the sampling frequency of the EEG acquisition device is much lower than the typical clock frequency of the FPGA and since the same feature extraction operations need to be performed on all 23 channels only once every 15 s, the multirate architecture proposed in [18] for asynchronous BCIs can be used in an actual scenario.

Similar to the procedure followed when evaluating the system in software, 230-dimensional feature vectors comprising of B_{AM} and B_{FM} for each of the IMFs of each EEG channel may be extracted using hardware cosimulation. These features

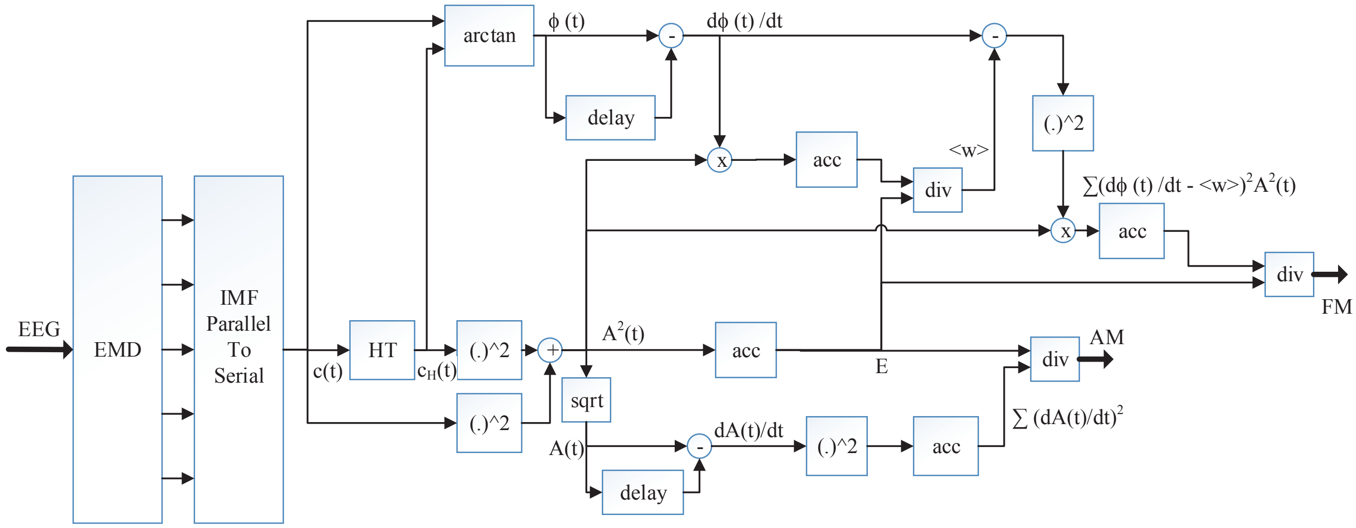

Fig. 4: The Feature Extraction Process

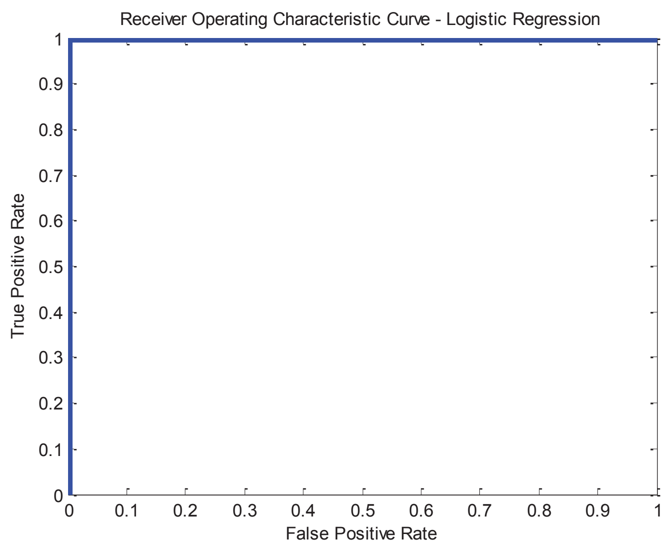

Fig. 5: ROC for LR classifier trained in software with features from child 1

can then be used to train an LR model. The LR is proposed as it may be implemented more easily than an SVM decision function in hardware. Instead of calculating the $e^{-\mathbf{w}^T\mathbf{x}}$ term in the logistic function, the decision could be made based on the sign of $\mathbf{w}^T\mathbf{x}$, where $\mathbf{w}$ is the weight vector and $\mathbf{x}$ is the 231-dimensional vector with a constant term 1 appended.

IV. Results and Discussion

The classifiers implemented in software were evaluated by the area under the curve (AuC) of the Receiver Operating Characteristic (ROC) curve. Table I shows the results obtained for a set of patients for whom feature extraction and classification were performed in MATLAB. An ROC resulting from training an LR is shown in Fig. 5.

Hardware implementation was done on a Virtex 7 FPGA.

TABLE I
COMPARISON OF AUC FOR AN LSSVM AND LR CLASSIFIER FOR FEATURES EXTRACTED IN SOFTWARE

Child ID	LSSVM (AuC)	LR (AuC)
child 01	1.0	1.0
child 03	1.0	0.98
child 06	1.0	1.0
child 10	1.0	1.0
child 13	1.0	0.972
child 14	0.997	0.937
child 18	1.0	1.0
child 19	1.0	0.987
child 20	1.0	1.0
child 21	1.0	0.98
child 22	0.995	0.928

V. Conclusion

The HHT has been utilized in a number of BCI applications due to its ability to analyze non-linear and non-stationary signals. Most studies where it has been used for feature extraction in predicting oncoming epileptic seizures have made use of iEEG and few have utilized scalp EEG. However, the long term side effects of implantable chips for EEG acquisition are unknown and can cause scar tissue to develop around the devices reducing contact with neuron populations and thereby rendering them ineffective. We present the FPGA implementation of a scalp EEG-based seizure prediction system using bandwidth features extracted from different IMFs. Good classification accuracy has been obtained using patient-specific classifiers. Future efforts would include optimizing the design even further by reusing hardware resources due to the availability of a large number of clock cycles in between the reception of successive epochs of EEG. Implementing EMD using cubic spline interpolation would also help increase the accuracy of the proposed system.

REFERENCES

[1] F. Mormann, R. G. Andrzejak, C. E. Elger, and K. Lehnertz, "Seizure prediction: the long and winding road," *Brain*, vol. 130, no. 2, pp. 314–333, 2007.

[2] J. R. Williamson, D. W. Bliss, D. W. Browne, and J. T. Narayanan, "Seizure prediction using EEG spatiotemporal correlation structure," *Epilepsy & Behavior*, vol. 25, pp. 230–238, 2012.

[3] J. C. Sackellares, "Seizure prediction," *Epilepsy Currents*, vol. 8, no. 3, pp. 55–59, 2008.

[4] L. Chisci, A. Mavino, G. Perferi, M. Sciandrone, C. Anile, G. Colicchio, and F. Fuggetta, "Real-time epileptic seizure prediction using AR models and Support Vector Machines," *IEEE Trans. Biomed. Eng.*, vol. 57, pp. 1124–1132, May 2010.

[5] T. Zhu, L. Huang, and X. Tian, "Epileptic seizure prediction by using Empirical Mode Decomposition and complexity analysis of single-channel scalp electroencephalogram," in *2nd International Conference on Biomedical Engineering and Informatics*, pp. 1–4, Oct 2009.

[6] N. Ozdemir and E. Yildirim, "Epileptic seizure prediction based on Hilbert Huang transform and artificial neural networks," in *20th Signal Processing and Communications Applications Conference*, pp. 1–4, April 2012.

[7] F. Duman, N. Ozdemir, and E. Yildirim, "Patient specific seizure prediction algorithm using Hilbert-Huang transform," in *IEEE-EMBS International Conference on Biomedical and Health Informatics*, pp. 705–708, Jan 2012.

[8] N. Ozdemir and E. Yildrim, "Patient specific seizure prediction system using Hilbert spectrum and Bayesian networks classifiers," *Computational and Mathematical Methods in Medicine*, vol. 2014, pp. 1–10, August 2014.

[9] M. Z. Parvez, M. Paul, and M. Antolovich, "Detection of pre-stage of epileptic seizure by exploiting temporal correlation of EMD decomposed EEG signals," *Journal of Medical and Bioengineering*, vol. 4, pp. 110–116, Apr 2015.

[10] V. Bajaj and R. Pachori, "Classification of seizure and nonseizure EEG signals using Empirical Mode Decomposition," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, pp. 1135–1142, Nov 2012.

[11] University of Freiburg, "Seizure prediction project Freiburg." (Online) http://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database.

[12] J. J. Shih, D. J. Krusienski, and J. R. Wolpaw, "Brain-computer interfaces in medicine," *Mayo Clinic Proceedings*, vol. 87, pp. 268–279, Mar 2012.

[13] A. Shoeb, "Application of machine learning to epileptic seizure onset detection and treatment," Ph.D. dissertation, Massachusetts Inst. of Technol., Cambridge, Sep, 2009.

[14] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, Jun 2000.

[15] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung, and H. H. Liu, "The Empirical Mode Decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," in *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, vol. 454, pp. 903–995, The Royal Society, 1998.

[16] L. Cohen and C. Lee, "Instantaneous bandwidth for signals and spectrogram," in *International Conference on Acoustics, Speech, and Signal Processing*, pp. 2451–2454, 1990.

[17] Y. Y. Hong and Y. Q. Bao, "FPGA implementation for real-time Empirical Mode Decomposition," *IEEE Trans. Instrum. Meas.*, vol. 61, no. 12, pp. 3175–3184, 2012.

[18] L. P. Wijesinghe, D. S. Wickramasuriya, and A. A. Pasqual, "A generalized preprocessing and feature extraction platform for scalp EEG signals on FPGA," in *IEEE Conference on Biomedical Engineering and Sciences*, pp. 137–142, Dec 2014.