Seizure Prediction using Hilbert Huang Transform on Field Programmable Gate Array

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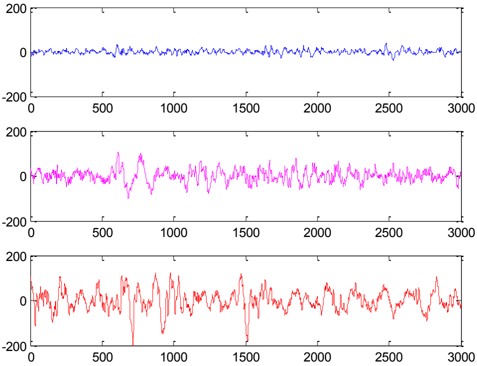
Introduction and Background

- About 50 million people suffer from epilepsy worldwide
  - Approximately 25% of them don't respond positively to medication or surgery
  - Unpredictability of epileptic fits
  - Patients are susceptible to injuries, burns etc.
- Most Brain-Computer Interfaces (BCIs) including platforms developed for classifying between the inter-ictal and pre-ictal states exist in software
- BCIs in hardware and mobile platforms are at an early stage
- Hardware architecture to classify between the pre-ictal and inter-ictal states using scalp EEG

Introduction and Background Cont'd

- During a seizure EEG signals exhibit higher amplitudes and less irregularity
  - Change from normal to seizure state is gradual
  - *Pre-ictal* period exists



Literature Review

- Zhu *et al.* [1] used complexity based features of Intrinsic Mode Functions (IMFs) to train a Neural Network achieving 74.38% accuracy (Single channel EEG)
- Ozdemir and Yildrim [2] decomposed intracranial EEG (iEEG) into 6 IMFs for feature extraction and Neural Network based classification obtaining a sensitivity of 93.1%
- Ozdemir and Yildrim [3] classified statistical properties such as maxima, minima, mean, standard deviation etc. of iEEG IMFs using a Support Vector Machine (SVM) with a sensitivity of 89.66%
- Ozdemir and Yildrim [4] used groupiness factor values and standard deviation of different energy bands in iEEG IMFs to train patient-specific Bayesian Networks and obtained a sensitivity of 96.55%

Literature Review Cont'd

- Parvez *et al.* [5] classified temporal correlations of iEEG IMFs extracted using the Discrete Cosine Transform using an SVM and obtained a 100% accuracy using the 1^{st} IMF
- Bajaj and Pachori [6] proposed using amplitude and frequency modulated (AM and FM) bandwidths of IMFs for *detecting* seizures. They obtained an accuracy of 100% when using the 2^{nd} IMF with a Morlet kernel
- Parvez *et al.* claim that AM and FM bandwidth features perform poorly on a large dataset when applied to the *prediction* problem

Our Approach

- Most previous methods used iEEG
  - Surgery poses additional risks (infection, hemorrhaging)
  - Implanted chips have unknown long-term consequences
  - Scar tissue may develop around electrodes rendering them ineffective
- Good classification accuracy can be obtained using AM and FM bandwidths in the *prediction* problem using *patient specific* classifiers
- Hardware architecture on FPGA

Feature Extraction

- Signal $x(t)$ is decomposed into n IMFs and a residue using Empirical Mode Decomposition (EMD)

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

- Hilbert Transform is then applied to each IMF and the analytic signal $z(t)$ is defined

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

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

Feature Extraction Cont'd

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

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

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

- The center frequency $\langle\omega\rangle$ of $z(t)$ is defined as,

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

Feature Extraction Cont'd

- Finally, the AM and FM bandwidths are defined as follows.

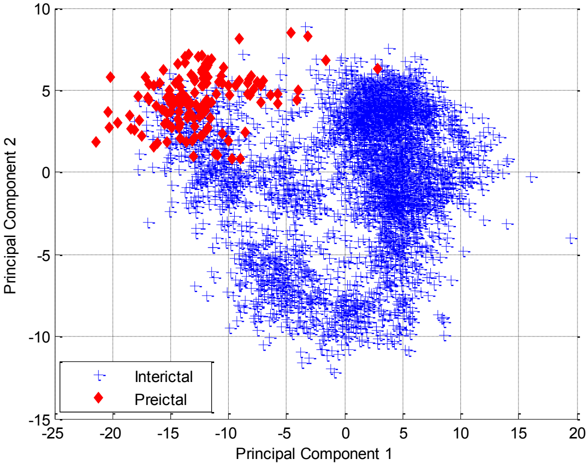
$$BW_{AM}^2 = \frac{1}{E} \int \left[\frac{dA(t)}{dt} \right]^2 dt \tag{7}$$

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

Feature Extraction Cont'd and Classification

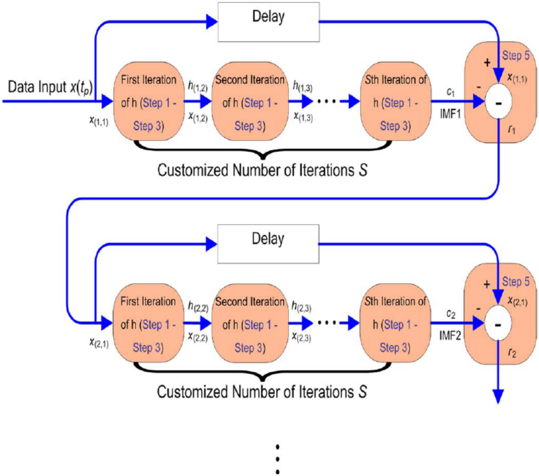
- We use the MIT-CHB Scalp EEG Database [7]
- We define the pre-ictal period commencing 5 min. prior to the start of an annotated seizure event and leading up to it
- Each of the 23 EEG channels are split into 15s epochs which are decomposed into 5 IMFs
- Each IMF yields 2 feature values and hence a $23 \times 5 \times 2 = 230$ dimensional feature vector characterizes each epoch
- We then randomly select 100, 15s epochs per record from the other records not containing seizures and similarly extract features
- Patient-specific SVM (RBF kernel) and a Logistic Regressor (LR) were evaluated in MATLAB

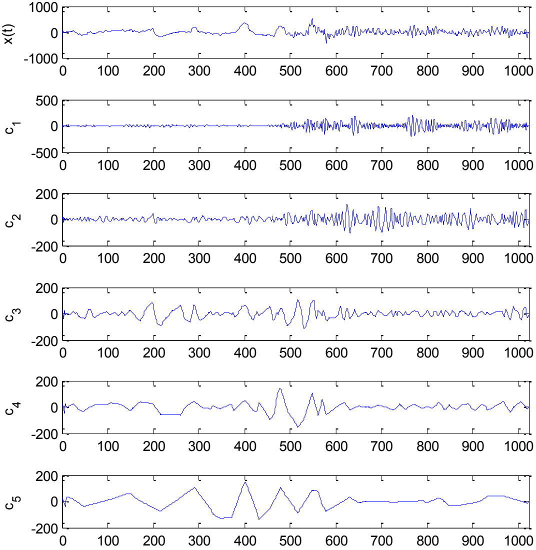
Feature Extraction Cont'd

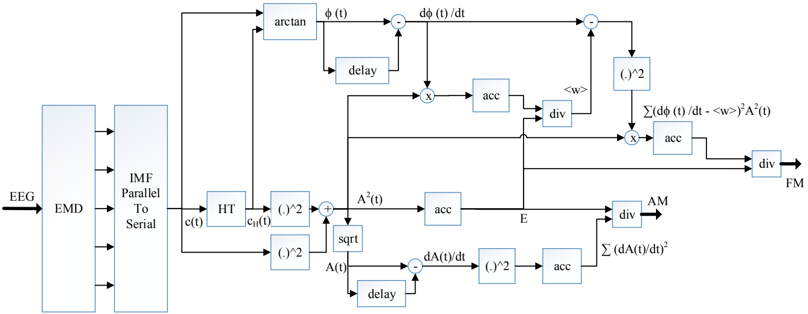


Hardware Implementation

- EMD on FPGA using the architecture proposed in [8]
  - S-number termination criteria ($S = 4$)
  - Sawtooth interpolation instead of cubic-spline interpolation
- Remaining components using adders, multipliers, CORDIC elements etc.

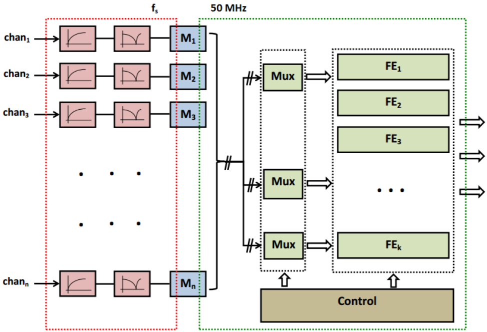

Delay
Data Input x(tp)
x(1,1)
First Iteration of h (Step 1 - Step 3)
h(1,2)
x(1,2)
Second Iteration of h (Step 1 - Step 3)
h(1,3)
x(1,3)
Sth Iteration of h (Step 1 - Step 3)
c1
IMF1
Step 5
+
-
x(1,1)
r1
Customized Number of Iterations S
Delay
x(2,1)
First Iteration of h (Step 1 - Step 3)
h(2,2)
x(2,2)
Second Iteration of h (Step 1 - Step 3)
h(2,3)
x(2,3)
Sth Iteration of h (Step 1 - Step 3)
c2
IMF2
Step 5
+
-
x(2,1)
r2
Customized Number of Iterations S


x(t)
1000
0
-1000
c1
500
0
-500
c2
200
0
-200
c3
200
0
-200
c4
200
0
-200
c5
200
0
-200
0 100 200 300 400 500 600 700 800 900 1000


arctan
ϕ (t)
dϕ (t) /dt
delay
(.)^2
acc
x
<w>
div
∑(dϕ (t) /dt - <w>)²A²(t)
EEG
EMD
IMF Parallel To Serial
HT
c(t)
cH(t)
+
A²(t)
E
AM
FM
sqrt
A(t)
dA(t)/dt
∑ (dA(t)/dt)²

Hardware Implementation Cont'd

- For implementation with a 23-channel EEG system , the multirate architecture proposed in [9] can be used
- Instead of calculating the $e^{-\mathbf{w}^T\mathbf{x}}$ term in the logistic function, classification can be done using $sign(\mathbf{w}^T\mathbf{x})$

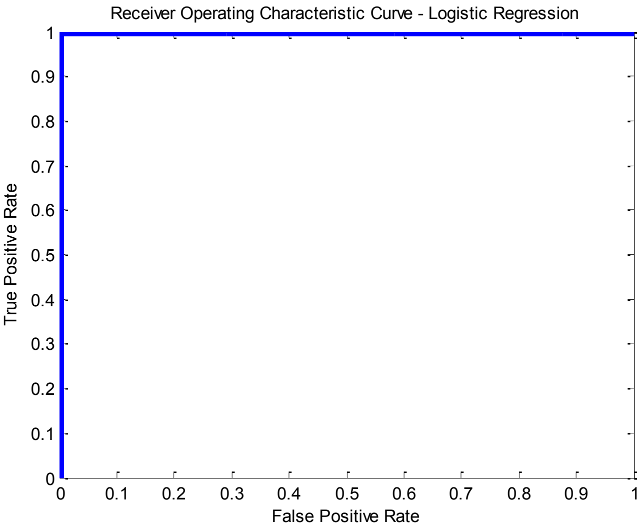


Results

- Area under the ROC (Receiver Operating Characteristic Curve) curve for classification using SVM and LR

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

Results Cont'd



Conclusions and Future Work

- Most methods utilizing the HHT for predicting epileptic fits employ iEEG
  - Would typically require surgery, implants etc.
  - Risky and have unknown long-term consequences
- Most systems are still in software
- Further research would include optimizing the design on FPGA even further
  - Large number of clock cycles available between reception of consecutive epochs
- Explore cubic-spline interpolation instead of sawtooth interpolation for improved accuracy
- Dimensionality reduction using statistical testing (Mann-Whitney)

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Thank You