FPGA Implementation Of A Seizure Detector Using Spectral Domain Feature Extraction

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***Abstract*—This paper describes a patient-specific algorithm for classification of epileptic seizures using intracranial electroencephalography (iEEG). The method consists of extracting statistical features from the average signal of all electrodes and its discrete wavelet transform (DWT) coefficients. A total of forty features is computed and used as the input of a linear support vector machine (SVM) classifier. The data for testing consist of 25 seizures from 16 different patients. It is shown the algorithm reaches a sensitivity of 98.0%, a specificity of 95.5% and a delay of 17.1 seconds. Finally, it is demonstrated that the algorithm is compatible with FPGA implementation by testing on 3 randomly selected patients.**

I. Introduction

A. Epilepsy

Epilepsy is a chronic neurological disorder that affects around 1% of the world's population. About 50 million people suffer from it [1]. It is defined as an abnormal electrical activity of the neurons in the brain which might have catastrophic consequences. Around a third of the patients' seizures are said to be drug-resistant, which means that they cannot be stopped using a classical treatment [2]. For these patients, it is capital to monitor them to avoid lethal consequences. A device that would be able to detect or even predict them would remove a weight on the patient. That device needs to be small and computationally light as it would be carried at all time.

B. Seizure detection

The main idea behind detection is to look at the electrical activity of the brain through an electroencephalogram (EEG). The task is to find features and a classifier that will separate the samples in two categories: either ictal (seizure) or non-ictal phase. In the literature, various features have been used for detection such as statistics computed from the Fast Fourier Transform [3] and [4], but EEG signals are non-stationary and thus it is not the most effective. For this reason, other researches have focused on using the Wavelet transform instead [5], [6], [7] and [8]. After computing the wavelet coefficients, one can compute statistics such as mean, energy, standard deviation and others. These values will for certain patients highly change between ictal or non-ictal epochs and thus allow to detect a seizure. Finally, the same statistics can be computed from the original signal directly without applying a transform [9], [10] and [11]. In this research, it was decided to use features from Wavelet transform and the original signal as it was shown that a detector using them can get really good results, as high as 99% accuracy for Xie et Krishnan [8].

After the features have been extracted, they will be given to a classifier which roles is to decide if the patient is currently suffering from a seizure or not. In the literature, three main classifiers were used along with wavelets features. First there are Random forest proposed by Mursalin et al. [12] which give good results. Übeyli [13] showed that neural network can also be used as a classifier and get up to 94% of accuracy,. Finally, Faust et al. [6] did a review of various papers using wavelet transform for epilepsy detection and many used a support vector machine (SVM) which showed good results. An advantage of SVM over the two others is the fact that it requires less computation and thus will consume less power. For this paper, the final system would be implemented on a FPGA board and for this reason an algorithm light in computation would be better. Thus, the choice was to use a linear SVM.

A diagram of the entire system built can be seen in figure 1, the rest of the paper will explain each of its elements, the results it got and will finally discuss them.

II. Detection process

A. Dataset

The short-term dataset used is from the Sleep-Wake-Epilepsy-Center (SWEC) of the University Department of Neurology at the Inselspital Bern and the Integrated Systems Laboratory of the ETH Zürich, also used in their research [14]. It is composed of various seizures from 16 different patients. The data was first pre-filtered between 0.5 and 150 Hz and then digitally converted on 16 bits at a rate of 512 Hz. All recordings have been verified by a certified EEG board-certified experienced epileptologist (K.S.) for identification of seizure onsets and endings. The number of seizures of each patient vary from 2 up to 13. For each seizure, the data is composed of a 3-minute pre-ictal segment, a 3-minute post-ictal one and the seizure (lasting between 10 and 1002 seconds). Originally the data contain each channel of recordings from all the electrodes, for this paper it was decided to keep only the average of all the channels for each seizure.

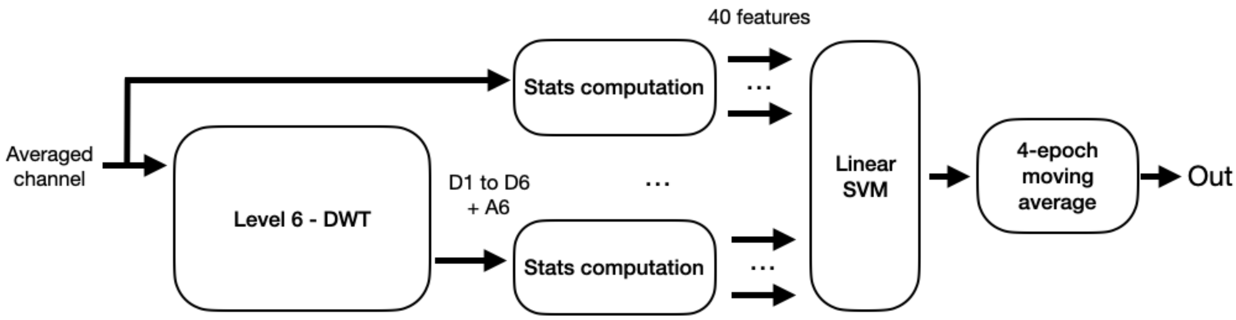

Fig. 1. Diagram of the entire system, the features extraction is done by the DWT and computation of statistics, the linear SVM is the classifier.

B. Discrete wavelet transform

The discrete wavelet transform (DWT) is a mathematical tool that allows to do a time-frequency analysis of a given signal. One of its main advantage over the Fourier transform is the ability to study non-stationary signals such as EEG. It decomposes the input signal into various sub-bands, each at a different scale thus capturing different information. The implementation that was chosen is the filterbank one as it is easy to do and fast. The input signal is filtered by two separate finite impulse response filters: the scaling filter which acts as a lowpass filter and the wavelet filter which acts as a high pass, both are also downscaled as they represent complementary frequencies keeping all the coefficients would be redundant. This gives two new signals: the approximation (low frequencies) and the details (high frequencies). They are said to be of level one. Then the same process can be repeated using the approximation as the new input, giving the approximation and details of level 2 (a complete system can be seen in figure 2). Each new signal will be a reconstruction of the original one using a different frequency band.

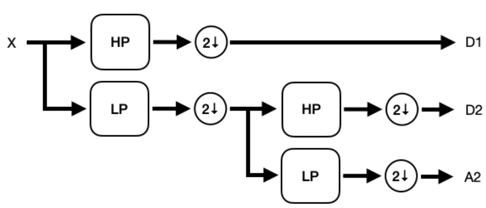

Fig. 2. Block diagram for a level 2 DWT. X is the input signal, HP is a highpass filter, LP a lowpass filter. The outputs are details of level 1 (D1) and 2 (D2) and approximation of level 2 (A2).

This transform is broadly used in signal processing for different domain and a lot of different filters can be found in the literature. The review of Faust et al. [6] shows that the wavelet Daubechies 4 (db4) is often used for epilepsy detectors and was also used for this paper. At first, the DWT was computed up to level 8 but it appeared that when the machine learning was performed to find the optimal SVM no features of higher level than 6 were used, therefore the final system only went up to level 6. This implies that all features are computed for the original signal and 7 new sub-bands (6 details D1 to D6 and approximation A6).

Finally, the implementation itself was done on Simulink using the add-ons HDL Coder which will generate the VHDL code required for the FPGA implementation. Meyer-Baese et al. [15] showed how it could be achieved in details.

C. Statistics extraction

The features from the 8 different signals were computed based on epochs of $N = 512$ samples which correspond to a one-second epoch. It was chosen because 512 samples were enough to represent the information but one second is short enough to reduce the delay before detection. Dong et al. [16] and Guo et al. [17] showed that the following statistics were interesting for epilepsy detection: energy (E), standard deviation (σ), curve length (L), maximum (M) and minimum (m) of the signal. The mean (μ) of the epoch is also computed though not used for the features as it showed no advantages but required for standard deviation. The statistics are computed for each of the eight signals as follows:

$$E = \frac{1}{N}\sum_{n=1}^{N} x_n^2 \tag{1}$$

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x_n - \mu_n)\cdot(x_n - \mu_{n-1})} \tag{2}$$

$$L = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \tag{3}$$

$$M = \max_n x_n \tag{4}$$

$$m = \min_n x_n \tag{5}$$

This gives a total of forty features to train the SVM. For each patient, the features were ranked by computing the average of each feature for the ictal epochs and dividing this by the average for the non-ictal ones. This was done on the training set (see section II-D).

D. Linear SVM

The goal of linear SVM is to find an hyperplane that will separate a features space into two regions, it will then check for any datapoint in which sides it stands. To do so, it uses the training data to optimizes two parameters: β, the normal to the hyperplane, and b, the intercept also called bias. It also has a miss-classification cost matrix that indicates to which degree false positives or false negatives should be optimized. After the training, the model can be used to assess if any epoch is ictal or not using its features vector x:

$$out = sign(\beta^T x + b) = \begin{cases} 1, & \text{if epoch is ictal} \\ -1, & \text{otherwise} \end{cases} \tag{6}$$

For each patient, around 75% of the data were used for training purposes but always keeping at least one seizure for the testing. This gave enough data to train while still being able to verify no overfitting occurred. A greedy algorithm was implemented to choose which features to used based on previously mentioned ranking. The following measures were used to assess the effectiveness of a model: sensitivity (number of seizures detected), specificity (number of true negatives over number of non-ictal epochs) and accuracy (average of both). At first, the algorithm added new features to the model and retrained it to maximize accuracy. Afterwards, the models were manually tuned, using the miss-classification cost matrix, to minimize the number of false positives while still detect seizures and with minimum delay. Finally, it was noted that the predictor ($\beta^T x + b$) was varying a lot for certain patients which resulted in a lot of false outputs. A way to mitigate this is not to use directly this value in the $sign$ function for equation 6 but instead to compute the moving average of the predictor over the last four epochs.

E. Implementation

For this paper, the explained work was implemented and tested in three different steps. First, to be able to implement it fast and to be able to build the models for each SVM it was done using MATLAB. Primary results were computed with this version in order to make sure the detector would work using a computer for all calculations. Then, the actual detector was programmed using Simulink and the HDL Coder library which allows to easily build a system that then can be implemented on a FPGA board. For this part and the next one, the models were not re-computed but instead it used the values found on MATLAB. Finally, a test for the system was built on the Intel D2-115 board using a Nios II CPU to communicate with the computer in order to check the results. This final test was realized to prove that the detector could indeed work and was performed for only three randomly selected patients.

III. Results and discussion

A. Results

The criteria that were used to determine if the results are good are the following:

1) **Seizure sensitivity:** number of seizures detected divided by total number of seizures.
2) **Specificity:** number of true negatives divided by total number of non-ictal epochs.
3) **Classification accuracy:** average of seizure sensitivity and specificity.
4) **Delay:** time between the moment a seizures is detected and the moment the epileptologist indicated the seizure started (the value was kept above 0 if the seizure was detected in advance).

These criteria were computed for all patients and for the three different testing phase of the algorithm as a manner of comparison. For MATLAB and Simulink, they are given in table I.

They are computed only for the testing dataset, which is composed of approximately 25% of the entire dataset. The result using the first implementation showed a specificity above 95% for all patients (except for patient 4) with an average of 97.2%. Furthermore, only one seizure was not detected (seizure 13 of patient 1). Sensitivity has an average of 98% and accuracy of 97.2%. Finally, the delay is on average of 14.9 seconds, note that for a single patient the given delay is the average over all tested seizures.

For the second phase, the sensitivity got the same results as before, meaning an average of 98%. The specificity is a bit lower but still above 91.7% for all patients, again except patient 4. The average specificity is at 95.5%. The accuracy thus also went lower, with a new average of 96.7%. The delay of detection is a bit higher and up to 17.1 seconds.

Finally, for the actual test on the FPGA three patients were randomly selected to make sure the detector also worked. Those were patients 2, 3 and 7. For all of them, the testing dataset consisted of one seizure. The results are given in table II. This shows an average of 100.0% of sensitivity. The specificity is at an average of 97.1% with a minimum of 91.9%. The accuracy is at 98.6%. Finally, the average delay is of 5.3 seconds. These results can be compared to the same patients for the MATLAB test. They had a sensitivity average of 100.0%, an average specificity 98.7% and accuracy of 99.4%. Finally, the delay was of 5.0 seconds.

B. Discussion

This method showed almost perfect sensitivity in the three implementations with all but one seizures detected, this proves the combination of chosen features along with linear SVM has a true potential for epileptic seizure detection. In the first stage of testing the specificity was above 95% which shows it is capable to distinguish a seizure with a low rate of false positive. Furthermore, the delay was of 15 seconds on average which is good for this application as it was shown by Hirsch et al. [18] that seizures appears on iEEG 20 seconds before clinical symptoms. The main drawback is that the detector is sometimes unable to work correctly as indicated with the results for patient 4 with the specificity going down to 70.1%. This might be due to the fact that epilepsy can either show local or global patterns but in this paper the input was always

TABLE I
PERFORMANCES FOR EACH PATIENT ON THE TWO FIRST TEST PHASES.

ID	Number of seizures	MATLAB Sensitivity (%)	MATLAB Specificity (%)	MATLAB Accuracy (%)	MATLAB Delay (sec)	Simulink Sensitivity (%)	Simulink Specificity (%)	Simulink Accuracy (%)	Simulink Delay (sec)
1	3	67.7	96.1	81.9	2.5	67.7	94.6	81.2	4.3
2	1	100.0	97.5	98.8	0.0	100.0	97.8	98.9	1.0
3	1	100.0	99.7	99.9	8.0	100.0	99.4	99.7	6.0
4	2	100.0	70.1	85.1	12.5	100.0	74.3	87.2	16.4
5	3	100.0	99.1	99.6	34.7	100.0	98.1	99.1	33.7
6	1	100.0	96.9	98.5	0.0	100.0	94.4	97.2	0.0
7	1	100.0	98.9	99.5	7.0	100.0	97.8	98.9	11.0
8	1	100.0	97.2	98.6	7.0	100.0	97.5	98.8	10.0
9	2	100.0	97.1	98.6	35.0	100.0	98.3	99.2	38.0
10	1	100.0	100.0	100.0	3.0	100.0	99.4	99.7	4.8
11	1	100.0	100.0	100.0	21.0	100.0	99.4	99.7	24.0
12	3	100.0	97.9	99.0	4.7	100.0	98.0	99.0	15.3
13	1	100.0	98.1	99.1	5.0	100.0	91.7	95.9	6.5
14	1	100.0	98.3	99.2	9.0	100.0	94.7	97.4	9.0
15	1	100.0	98.9	99.5	74.0	100.0	97.2	98.6	75.0
16	2	100.0	96.1	98.1	15.0	100.0	95.4	97.7	18.0

TABLE II
PERFORMANCES OF THE FPGA DETECTOR ON THREE PATIENTS.

ID	Sensitivity (%)	Specificity (%)	Accuracy (%)	Delay (sec)
2	100.0	91.9	96.0	3.0
3	100.0	100.0	100.0	4.0
7	100.0	99.4	99.7	9.0

an average of all channels of the EEG which lose local information. As in this dataset it is only the case for one patient and the average accuracy is still at 97.2%, it was considered that doing a more extensive computation of features was not necessary.

The implementation using Simulink has a lower specificity, the average being at 95.5% against 96.4%. This result is still considered good, it is explained by the difference in the computation, this new model was built with the goal of a FPGA target and for this it required to limit the number of bits used thus some errors. For the same reason, the accuracy went down to 96.7%. The delay also went a bit higher to 17.1 seconds but it still lower than the goal of 20 seconds.

Finally, for the actual FPGA tests the results are very close to the ones from the original test phase for these three patients. This shows that the system designed for this paper can indeed be implemented on a FPGA board for low consumption and is able to detect most seizures in less than 20 seconds with a low false positive rate.

The results were compared to the paper of Burello et al. [19] who also worked on the SWEC-ETHZ database. They worked by combining local binary patterns with hyperdimensional computing. It was done using Python code and thus can be compared with the MATLAB results from this paper. They obtained a sensitivity of 99.4%, a specificity of 95.7% and a delay of 18.2 seconds. Their final test were ran on a graphics card (Nvidia GeForce GTX 1080) which consumes a lot of power. This shows their algorithm have a better sensitivity but a lower specificity and higher delay. One can note that the specificity they obtained was higher for 15 patients but drastically lower for one. The two algorithms thus seem comparable in results but both do not work well for certain patients. Another point is their algorithm is built for low memory usage while the one of this paper was for implementation on FPGA for low consumption.

IV. CONCLUSION

This paper shows that statistical features computed after applying a discrete wavelet transform and linear SVM can be used to detect epileptic seizures for different patients. The input signal is a pre-filtered average EEG over different electrodes and can be used in realtime with the detector. This was demonstrated through different implementations, first more theoretical one to make sure the system worked, and the final implementation was installed on a FPGA board to prove the low-power capability. It was able to detect, in a fast manner, seizures with a high sensitivity and specificity. The results are comparable to techniques which require a high power consumption.

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