Adaptive Rate EEG Signal Processing for Epileptic Seizure Detection

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Abstract– *A big number of people all over the world is affected by epilepsy. Electroencephalography (EEG) is a crucial component in the evaluation of epilepsy. Onset seizure detection is essential to prevent the seizure activity and improve patients' life quality. Presurgical treatment, precise assessment, seizure prevention, and emergency alerts all depend on the quick detection of seizure onset. Moreover, manual examination of EEG signals is boring and time-consuming task. Numerous automated epileptic seizure detection schemes have been developed to help neurologists. This paper focus on the realization of an efficient adaptive rate solution for the epileptic seizure detection. The signal is respectively digitized and segmented with an event-driven ADC (EDADC) and an activity selection algorithm (ASA). The segments are uniformly resampled and conditioned. In next step, the autoregressive (AR) Burg modelling is employed to extract the features. Afterwards, the extracted features are utilized for classification. It is demonstrated that the suggested system-processing load is adjusted as a function of the incoming signal disparities. It allows the suggested solution to attain a remarkable reduction in the processing activity and consumption of power compared to the counter classical ones. The overall system classification precision is also compared with the counter classical one. It confirms that the prospect of using the suggested system for an effective automatic epileptic seizure detection.*

Index Terms – *Adaptive Rate Processing, EEG, Epileptic Seizure, AR Burg, Classification.*

I. Introduction

Signs are Electroencephalogram (EEG) is used to measure the pulses which reproduce the electrical activity of the human brain. EEG is popular in several applications and employed broadly in cognitive psychology, cognitive science, neuroscience, and psycho physiological research. Since EEG signals involve big amount of data, the computer-aided analysis of EEG signals should be developed for a better understanding of mental states of brain. In order to acquire EEG signals, an electrode cap is placed on the scalp. Computers analyses and recognize the EEG signal patterns for different states of the brain [1].

Electroencephalography (EEG) signals are utilized to detect epileptic seizures. Epilepti form EEG patterns can be employed in the diagnosis and detecting seizures [2]. EEG signal analysis utilized as a diagnostic test, has been used for detection of epileptic seizure [3]. But, EEG-based seizure detection is not easy as it includes huge amounts of acquired EEG signal recording collected from multiple scalp electrodes [4].

This paper focus on the realization of an effective portable EEG processing modules for an efficient verdict of the patient's cerebral system. In this framework, the adaptive arte signal processing tools are intelligently used.

The proposed framework guideline is portrayed in Section II. Section II, also examines the utilized materials and strategies, utilized to implement the formulated framework. An outline of the suggested framework execution confirmation comes about is examined in Section III. The work is concluded in Section IV.

II. Materials and Methods

The proposed solution's block level diagram in Figure 1 shows that the EEG pulses, from the dataset of epileptic seizure signals [10], are employed as the EDADC input [8-9]. These pulses are firstly passed through an antialiasing band-pass filter with [F_{Cmin}=0.5; F_{Cmax}=35]Hz. This choice of pass band allows focusing on the EEG intended components while attenuating the unwanted components and noise [11, 15]. Therefore, it improves the performance of post features extraction and classification modules. The EDADC output is segmented with the Activity Selection Algorithm (ASA) [7-8]. In next step, the signal is resampled uniformly. Afterwards it is denoised with an adaptive rate filter [7] and its distinctive features are extracted with AR Burg [13] and are later on employed by the classifiers. The classification outcomes provide status about the patient cerebral health.

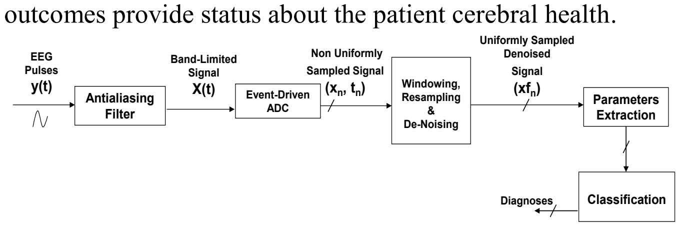

Fig. 1. The proposed system block diagram.

A. The Event-Driven A/D Conversion (EDADC)

The ADC is a basic element of the signal processing chain [6-8] that manages the overall system performance [8]. Ordinarily, signal acquisition is founded on the basis of Nyquist sampling and processing theory [8-9]. Thus, design parameters of these conventional ADCs are selected for the most noticeably awful case [12]. In this manner, within the case of moo movement arbitrary signals like Speech, Seismic signals, etc. such ADCs are not efficient [10-12]. The EDADCs can diminish this shortfall. It is done by altering their sampling frequency as a function of the incoming signal disparities. In this way only the related information is acquired while the rest of the signal is overlooked. Hence, a noticeable decrease in the post processing activity is achieved [6-8].

B. The Windowing, Resampling and Filtering

The ASA examines the distinctiveness of each segment and extracts its features, which are used to pilot the post-processing parameters and activity accordingly [8-9].

The selected segments are uniformly resampled [6-8]. It allows benefiting from both non-uniform and uniform verges [13].

The resampling is achieved via interpolation. For chosen system parameters, the interpolation error is a function of the used method [13-15]. For a given resolution, $\boldsymbol{M}$, and dynamic range, $\Delta\boldsymbol{V}$, the EDADC quantum, $\boldsymbol{q}$, can be calculated as $\boldsymbol{q} = \frac{\Delta\boldsymbol{V}}{2^{\boldsymbol{M}}-\boldsymbol{1}}$. The highest interpolation error is $\boldsymbol{q}$ [13]. The segments resampling is performed with a Nearest Neighbor Interpolation (NNI). The process of estimating an interpolated sample $\boldsymbol{xr_n}$ is accomplished as a mean of non-uniform samples $\boldsymbol{x_n}$ and $\boldsymbol{x_{n-1}}$ [13].

Let W^i be uniformly interpolated at a frequency Frs^i. The Frs^i is chosen as a function of F_{ref} and Fs^i. $Fref$ is the selected reference frequency, such that it is greater than and closest to $F_{Nyq} = 2.f_{max}$. f_{max} is the bandwidth of $x(t)$. The sampling frequency for W^i is given by $Fs^i = \frac{N^i}{L^i}$. Here, L^i and N^i are the length and the count of samples that exist in W^i. Nr^i are uniformly placed samples remain in W^i after resampling.

For the considered example, f_{max} =35Hz. It is because of the employed F_{Cmax}=35Hz. For the classical counterpart, the EEG pulses are acquired with a 12-Bit resolution ADC at an acquisition frequency of 1024Hz. Therefore, F_r=1024Hz is chosen. The interpolated uniform data is conditioned by using the adaptive rate filter [7, 15]. It improves the post classification accuracy. The filters bank is designed for a range of sampling frequencies, $Fref$, between 79Hz>2. F_{Cmax} to F_r=1024Hz. In this case Δ=15Hz is chosen. It results into a bank of Q =64 band-pass FIR filters. The resampling frequency, Frs^i, can be specific for each W^i and it is kept coherent with the sampling frequency, $Fref_C$, of online chosen reference filter, hc_k. It is realized by using the algorithm, shown in Figure 2.

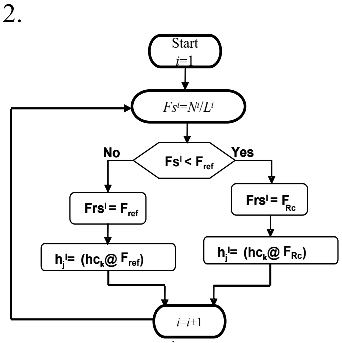

Fig. 2. The ASM chart for choosing Frs^i and a filter from the reference filters bank for W^i.

C. The Features Extraction

The denoised signal distinctive parameters are computed with the AR Burg [10]. It provides a higher resolution spectrum in comparison to the Fourier transform [10] and leads towards a better precision of classification.

D. The Classification Methods

Four classification techniques are used [14].

1. The Support Vector Machine (SVM)

It conducts the nonlinear mapping to augment the dimensionality of training data. It allows discovering the most suited classifier which can correctly differentiate among different classes of the testing data [14]. The decision is made on the basis of distance metric.

2. The Artificial Neural Network (ANN)

It is known for its robustness against noise. It learns on the basis of a multilayer feed forward network in an iterative fashion and set weights for predicting the instances class labels [14].

3. The REPTree

It develops a prediction tree. The absent labels are treated by dividing the given dataset in sections [14]. The testing set is identified by using the templates through the added nodes coincidence removing effect [14].

4. The k-Nearest Neighbors (k-NN)

It learns and identifies the testing sample by comparing it with training ones. The k Training instances are used to identify the incoming sample. The decision is made on the basis of distance metric.

III. Results and Discussion

The EEG pulses from the dataset of epileptic seizure signals [10]. It is composed of three different classes of Normal, Ictal, and Interictal. Each EEG pulse is segmented for a time length of 1 seconds and with a 12-Bit resolution ADC. Therefore, for a given time length of 1 seconds and sampling frequency of 1024Hz, each digitized segment is composed of 1024 samples. 400 instances are considered from each class. Therefore, total 1200 instances are processed. In the proposed solution the EDADC and ASA allows to treat only the pertinent information [10, 12, 16, 19] (cf. Figure 3).

Figure 3 displays the interest of using the EDADC and the ASA. It confirms that they segment only the pertinent signal information. They also diminish the low amplitude noise by using their noise thresholding capability. It enhances the precision of post speech classification [6-8]. Additionally, signal is further conditioned by using the adaptive rate filter [7]. The suggested solution attains an overall 8.2 times reduction in the acquired samples compared to the counter classical one. It brings a noticeable reduction in the arithmetic complexity and the power consumption of the suggested solution over to the classical one.

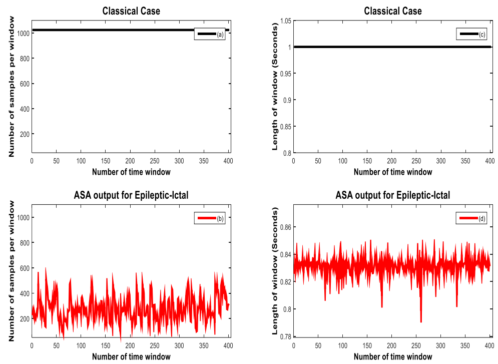

Fig. 3. The *number of samples per window versus number of windows, classical case (a), the length of window versus number of windows, classical case (b), the number of samples per window versus number of windows obtained with the ASA for class epileptic Ictal (c), the length of window versus number of windows obtained with the ASA for class epileptic Ictal (d).*

The signal is conditioned and its distinctive parameters are calculated with a MATLAB based system model [17]. WEKA is used for the classification [16]. The 10-fold cross validation is used. Results, obtained with different employed classifiers are summarized in Table 1.

Table 1: *Classification Performances for 3class EEG data*

	NORMAL	ICTAL	INTERICTAL	AVERAGE
SVM	0.968	0.785	0.973	0.908
k-NN	0.92	0.848	0.953	0.907
ANN	0.95	0.948	0.948	0.948
REPTree	0.92	0.873	0.94	0.911

Table 1, shows that the best average classification accuracy of 94.8%, is obtained with the ANN method. In this case, the ANN performs better because of its ability of only using the most relevant points to find a linear separation.

IV. CONCLUSION

An innovative event-driven method is suggested for the diagnosis of Epileptic Seizure. It is demonstrated that the integration of EDADC and ASA has diminished the number of needless samples to process. An 8.9 times decrease in the collected number of samples has been achieved over the classical approach. It demonstrates the devised system drastic computational complexity reduction over the classical counterparts.

It has been shown that the proposed module achieves the best classification accuracy of 94.8%. It demonstrates the potential of suggested approach in the realization of low power portable EEG modules.

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