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by Saadat Nasehi, Hossein Pourghassem, and Afshine Etesami
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"Emotion Recognition from Brain Signals Using Hybrid Adaptive Filtering and Higher Order Crossings Analysis"
by Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis
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Online Epilepsy Diagnosis Based on Analysis of EEG Signals by Hybrid Adaptive Filtering and Higher-order Crossings

Saadat Nasehi, Hossein Pourghassem*, Afshine Etesami
Department of Electrical Engineering,
Najafabad Branch, Islamic Azad University,
Isfahan, Iran.
Email: h_pourghasem@iaun.ac.ir

Abstract— **This paper presents a novel epilepsy diagnosis algorithm based on analysis of EEG signals by hybrid adaptive filtering (HAF) and higher-order crossings (HOC). In this algorithm, HAF is developed to isolate the seizure and non-seizure EEG characteristics and facilitating the task of the feature vector extraction. Furthermore, HOC analysis is employed to select the effective feature from the HAF-filtered signals. The extracted features by HAF-HOC scheme can create maximum distinction between two classes. Finally, Quadratic Discriminant Analysis (QDA) and Mahalanobis Distance (MD) is used for classification and recognition of seizures through EEG signals. The proposed algorithm is implemented on CHB dataset and its performance has been evaluated for three measures. The results indicate that the algorithm can recognize the seizure with smaller delay and higher good detection rate that are important factors from a clinical viewpoint.**

Keywords — epilepsy, EEG, hybrid adaptive filtering (HAF), higher-order crossings (HOC), Quadratic Discriminant Analysis (QDA), Mahalanobis Distance (MD)

I. INTRODUCTION

There are still many individuals with pharmacoresistant epilepsy despite treatment by one or multiple anti-epileptic drugs. These types of seizures are known as medically intractable seizures [1]. Intractable seizures limit the independence and mobility of an individual and can effect in social isolation and economic hardship [2]. Society incurs an annual loss of 12.5 billion dollars in health care costs and losses in productivity [3]. So a novel therapy that better control seizures as well as technology that helps both the individual and their family to cope with the consequences of seizures.

Recently therapeutic and prosthetic devices have been used for the treatment of patients with neurological conditions such as epilepsy [4]. In these systems, a detector is designed to intelligently diagnose the seizure onset that may ease the burden of intractable could warm the patient of the seizure prior to the development of debilitating symptoms, or could notify a family member so that the consequences of a seizure are limited [5]. The goal of a seizure event detector is to identify seizures with the largest possible accuracy, but not necessarily with the smallest delay [6]. They are suited for applications requiring an accurate account of seizure activity over a period of time.

Seizure event diagnosis is most often accomplished through analysis of the EEG signals. Typically, a set of EEG channels develops rhythmic activity that reflects underlying neuronal hyper synchrony with onset of a seizure. The location of EEG channels and spectral content of the rhythmic activity varies across individuals.

Gotman present a seizure event detector [7] that searches for the EEG channels for the presence of rhythmic activity with a dominant frequency between 3-20 HZ. Gotman algorithm is not successful in detecting seizures consisting of EEG containing a mixture of frequencies or those with low amplitude high frequency activity.

In this paper, an epoch-based epilepsy diagnosis algorithm is proposed. In this algorithm a hybrid adaptive filtering (HAF) and higher-order crossings (HOC) scheme is used for signal segmentation. The role of HAF is to isolate the seizure and non-seizure EEG characteristics and facilitating the task of the feature vector extraction. The output of HAF is then used as input of the HOC in order to the efficient extraction of the feature vectors. We use two classifiers, Quadratic Discriminant Analysis (QDA) and Mahalanobis Distance (MD) for an extensive evaluation of the classification performance of the HAF-HOC scheme.

The remainder of this paper is structured as follows. We describe the proposed seizure diagnosis algorithm including of feature extraction based on HAF-HOC scheme and classification based on QDA-MD in section II. The performance of algorithm is evaluated on Children's Hospital Boston (CHB) dataset in section III. Some conclusion is discussed in section IV.

II. THE PROPOSED SEIZURE DIAGNOSIS ALGORITHM

The overall structure of the proposed seizure diagnosis algorithm is shown in Fig. 1. In this algorithm, Q-second epochs from seizure and non-seizure EEG signals are decomposed by HAF-HOC scheme within efficient-feature vectors. The HAF applying Genetic Algorithms to the representation of the seizure and non-seizure EEG signals on the Empirical Mode Decomposition (EMD) domain. The HOC form the effective feature vector via the oscillatory pattern of the HAF- outputted EEG signal instead of the EEG signal itself. Finally, QDA and MD classifiers are used to classify the extracted features from seizure and non-seizure EEG epochs.

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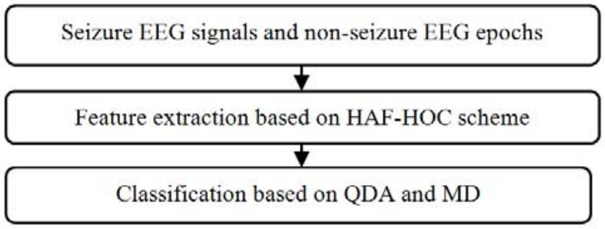

Figure 1. structure of the proposed seizure prediction algorithm

A. feature extraction using HAF-HOC scheme

The structure of HAF-HOC scheme is illustrated in Fig. 2. In this scheme, the seizure and non- seizure EEG signals is inputted to the HAF section after the pre-processing stage for signal segmentation and de-noising. The goal of HAF [8] is to isolate the EEG characteristics, facilitating the task of the feature vector extraction. To achieve this, the HAF combines the Empirical Mode Decomposition (EMD) and a simple Genetic Algorithm (GA) optimization concept to construct a filtering process to determinate the characteristics of the filtered signal. The EMD is qualified by Flaudrin [9] as a adaptive filter bank due to it's ability to decompose a signal into modes and residuals, which are explained as spectral representation. To improve the capability of the EMD algorithm, a GA-based approach is employed to select the optimum modes that correspond to a specific feature of a signal. The used GA is based on the realization strategy in [10], including of initialization, pair selection, cross-over, mutation, elitist strategy and termination. So the EEG signal is decomposed through an iterative sifting process [11] into a series of Intrinsic Mode Functions (IMFs) that correspond to different oscillatory modes of the EEG signal. At the sifting procedure, the oscillation mode is qualified as an IMF according to two conditions:

- for the entire dataset, the number of extrema and the number of zero crossings are either equal or differ at most by one
- the mean value of the envelope defined by the local maxima and the mean value of the envelope defined by the local minima is zero any point

At the end of the EMD process, the data series can be decomposed into M intrinsic mode functions and a residue. Then, the GA extracts the optimum IMFs by using energy or fractal dimension-based fitness function (FF). The selected IMFs can be combined through a reconstruction process to produce a reconstructed EEG signal (R-case) or used directly, without employing any reconstruction process (NR-case). In this paper, two FFs are used: energy (EFF) and Fractal Dimension (FDFF). The goal of EFF is to conduct a filtering procedure, by selecting the IMFs which embed the majority of the signal energy. The EFF is expressed by (1).

$$f(s)=\frac{\sum_{\{S|sr=1\}} E\{c_r(n)^2\}}{\sum_{i=1}^{M} E\{c_i(n)^2\}}, n=1,\ldots,N \tag{1}$$

Where S_r is the set of the elements of S with value 1, and S is the string of 1s and *c(n)* represents an IMF. As aresult, a bunch of IMFs that are more likely to embrace the majority of the initial signal energy is selected. The FDFF can be considered as a relative measure of the number of basic building blocks that form a pattern [12]. It consists of estimating the dimension of a time-varing signal in the time domain which allows significant saving in program run-time. The goal of FDFF is to capture the variations in the complexity of EEG signal. The FDFF is calculated by (2).

$$f(s)=\sum_{\{S|s_r=1\}} FD\{c_r(n)\}, n=1,\ldots,N \tag{2}$$

where FD{.} is expressed by (3).

$$FD=\frac{\log_{10} N}{\log_{10} N+\log_{10}\left(\frac{N}{N+0.4N_{\Delta}}\right)}, \tag{3}$$

where N is the length of the binary sequence, and N_{Δ} is the number of dissimilar pairs in the binary sequence. The output of HAF is used as input to the HOC section. The HOC analysis [13] provides the spectrum-related attitude of the signals and it is highly dependent on the dominancy of certain frequency in a specific sub-band of the whole frequency spectrum by rigorously analysing the signal in the time domain and without employing spectral transform. The goal of HOC is to select the effective feature vector (FV). In this paper, the HOC-based FV extraction method is implemented in two different approaches: the R-case and NR-case strategy. The feature vector is constructed by HOC analysis, formed as (4). where J denotes the maximum order of the estimated HOC and L the HOC order up.

$$FV^{HOC}=[D_1, D_2, \ldots, D_L], 1<L<J \tag{4}$$

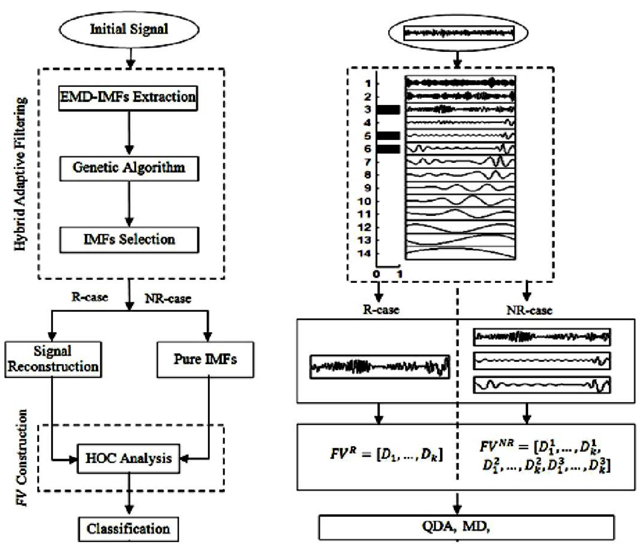

Figure 2. The HFA-HOC scheme for feature vector extraction

B. classification

We use two classifier, Quadratic Discriminant Analysis (QDA) [14] and Mahalanobis Distance (MD) [15] to classify the extracted features from seizure and non-seizure EEG signals by HAF-HOC scheme.

The QDA is based on the quadratic discriminant function:

$$d_p(FV) = -\frac{1}{2}\log\left|C_q\right| - \frac{1}{2}(FV-\mu_q)^T C_Q^{-1}(FV-\mu_q) + \log P_q \quad (5)$$

Where C is the covariance matrix for each class, q = 1,2 is the number of classes, μ is a vector with the mean values of each variable consisting the FV an P is the prior probability for each class. If C_q, μ_q are calculated from the training part whereas each FV from the test set is classified into one of the two classes by (6). where $g(FV)$ is the class of FV.

$$g(FV) = \arg\max_q d_q(FV) \quad (6)$$

The MD is the distance between a case (FV) and the centroid for each group in attribute space (n-D space). There is a MD for each case and each case is classified as belonging to the group for which the MD is minimized. The MD between two FVs, FV1 and FV2, assuming the same distribution and a corresponding covariance matrix C, is defined (7).

$$d_s(FV_1, FV_2) = \sqrt{(FV_1 - FV_2)^T C^{-1}(FV_1 - FV_2)} \quad (7)$$

III. EXPERIMENTED RESULTS

In this section, we evaluate the performance of our diagnosis algorithm. First, the used dataset is introduced. Then, the performance measures are defined. Finally, the results of algorithm are tested by two classifiers.

A. CHB-MIT scalp EEG dataset

This dataset consists of EEG recording from pediatric subjects with intractable seizures which collected at the Children's Hospital Boston. Subjects were monitored for up to several days following withdrawal on anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention. Recordings, grouped into 23 cases, were collected from 22 subjects (5 males and 17 females). All signals were sampled at 256 HZ samples per second with 16-bit resolution. Table I shows the details of CHB dataset. Further information about this data is available in [16].

B. Performance measures

We evaluated the performance of the proposed algorithm based on three measures:

- **Delay:** the delay between the expert-marked seizure onsets with the EEG detector declaration of seizure activity.
- **False Detection Rate:** the FDR is defined as the percentage of non-seizure epochs incorrectly identified as seizure epochs
- **Good Detection Rate:** The GDR is defined as the percentage of electrographic seizure event as labeled by an expert in neonatal EEG correctly identified by algorithm.

C. Results

We use the MATLAB to implement our algorithm. The data used in the experiments is labelled as seizure or non-seizure. We fixed the parameters Q = 1.5 second (EEG epoch length), F = 30 features (number of the extracted features by applying HAF-HOC scheme from each epoch) and 15 seconds following the seizure is used to train the QDA and MD classifiers. Then, we used two tests to evaluate the algorithm. In each test, one of classifiers is trained on the extracted features by HAF-HOC scheme from seizure and non-seizure EEG epochs. When the QDA is used as classifier, algorithm could achieve to GDR of 91.26% with a FDR of 13.51% and an average delay of 4.9 seconds. While, when the MD classifier is employed, algorithm could achieve to GDR OF 87.95% with a FDR of 14.77% and average delay 5.2 second. Table II show the obtained result by our algorithm with different number of the extracted features by applying HFA-HOC scheme. The best result obtain for F = 30 features. Our algorithm can reach a high GDR and low delay that can be very helpful for areas where medical resources are limited. It also does not require the occurrence of seizure activity during EEG recording. This merit reduces the difficulties in EEG collection since interictal data is much easier to collect than ictal data.

TABLE I. DETAILS OF CHB DATASET

patient	sex	age	No. seizures	non-seizures (hours)	seizure (min)
1	F	11	6	46	7.36
2	M	11	3	29	2.86
3	F	14	7	32	7.46
4	M	22	4	93	6.3
5	F	7	4	35	9.3
6	F	1.5	7	54	2.53
7	F	14.5	3	61	5.41
8	M	3.5	5	20	15.33
9	F	10	4	65	4.6
10	M	3	7	45	7.45
11	F	12	3	31	13.43
12	F	2	24	22	39.26
13	F	3	12	34	9.58
14	F	9	8	26	2.81
15	M	16	20	37	33.91
16	F	7	10	19	1.41
17	F	12	3	24	4.88
18	F	18	5	31	5.28
19	F	19	3	26	3.93
20	F	6	8	27	4.9
21	F	13	4	23	3.31
22	F	9	5	28	3.4
23	F	6	8	36	7.06
			163	844	201.76

TABLE II. PERFORMANCE OF PROPOSED EPILEPSY DIAGNOSIS ALGORITHM FOR DIFFERENT NUMBER OF THE EXTRACTED FEATURES BY HAF-HOC SCHEME

results	QDA			MD		
	M=20	M=25	M=30	M=20	M=25	M=30
FDR (%)	14.35	13.51	13.25	15.95	14.77	14.74
GDR (%)	85.42	91.26	91.44	70.21	87.95	90.12
Delay (s)	5.2	4.9	4.6	5.7	4.9	4.8

IV. CONCLUSIONS

We presented an online epilepsy diagnosis algorithm. In this algorithm, several features are extracted by HAF-HOC scheme. The HAF isolate the seizure and non-seizure EEG signals and facilitating the task of the feature vector extraction. The output of HAF is used as input of HOC in order to the efficient extraction of the feature vector. We used the QDA and MD classifier to evaluate the performance of the HAF-HOC scheme on CHB dataset. The best result obtain for F = 30 features. In this condition, algorithm could achieve to GDR of 91.44% and average delay of 4.6 second. The high GDR increase the capability of detector to recognize the seizures in order to initiate the just in time therapy methods and it is a important measure of the clinical utility of a epilepsy diagnosis algorithm.

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