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Efficient Epileptic Seizure Detection by a Combined IMF-VoE Feature*

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***Abstract*— Automatic seizure detection from the electroencephalogram (EEG) plays an important role in an on-demand closed-loop therapeutic system. A new feature, called IMF-VoE, is proposed to predict the occurrence of seizures. The IMF-VoE feature combines three intrinsic mode functions (IMFs) from the empirical mode decomposition of a EEG signal and the variance of the range between the upper and lower envelopes (VoE) of the signal. These multiple cues encode the intrinsic characteristics of seizure states, thus are able to distinguish them from the background. The feature is tested on 80.4 hours of EEG data with 10 seizures of 4 patients. The sensitivity of 100% is obtained with a low false detection rate of 0.16 per hour. Average time delays are 19.4s, 13.2s, and 10.7s at the false detection rates of 0.16 per hour, 0.27 per hour, and 0.41 per hour respectively, when different thresholds are used. The result is competitive among recent studies. In addition, since the IMF-VoE is compact, the detection system is of high computational efficiency and able to run in real time.**

I. INTRODUCTION

Epilepsy is a neurological disorder which affects about 50 million people worldwide. Epilepsy commonly leads to unexpected seizures with involuntary muscle contraction and loss of consciousness. Studies have shown that seizure patterns in EEG may present before major behavioral manifestations[1]. Thus it is valuable to automatically predict seizures from scalp EEG and trigger the prevention system before behaviors for epileptic patients.

During the past years, lots of efforts have been made in automatic seizure detection from scalp EEG signals [2]. A seizure detection method usually consists of a feature and a classifier. The proposed feature extraction methods include time and frequency analysis, entropy-based [3] and energy-based [4] approaches, component analysis [5], and empirical mode decomposition (EMD) [6]. Support Vector Machine (SVM) [7] and artificial neural networks (ANN) [5] are widely used for learning and classifiers. However, most existing methods can not well satisfy the requirements of practical uses. This is because: 1) some methods have long time delay in order to obtain a low false detection rate, which is not suitable for online application; 2) the features used in some methods are person-specific and lack of generalization to a large amount of patients. Consequently, it is still a problem to find a general feature which is able to reach high performance and short time delay.

In this study, we propose a new approach to detect seizure onsets from scalp EEG. To reflect various information of seizure state in EEG signals, multiple cues are extracted to constitute the feature IMF-VoE, including three intrinsic mode functions (IMFs) of the EMD and the variance of the range between the upper and lower envelopes. The experiments are tested on 80.4 hours of EEG data. The high sensitivity of 100% is achieved at a low false detection rates (FDR) of 0.16 per hour. The average time delays can be controlled at about 10 seconds.

II. OUR METHOD

Closely spaced spikes and slow waves are observable abnormal signals in seizure scalp EEG compared with the background signals [8]. This leads to relatively large variance of the range between upper and lower envelopes of signals, given a time window (see Fig. 2). Thus, we propose to use the variance of envelope difference (VoE) as one feature to characterize the seizure state. Besides, the EMD method can reduce given data into a collection of IMFs, which are simple oscillatory modes and have variable amplitude and frequency along the time axis. Due to the diversity of seizure EEG signals from different persons, we combine the VoE and a few IMFs to construct a powerful IMF-VoE feature for complementary purpose. Based on the feature, the detection stage can be performed by a simple threshold learned from background signals. In a real-time detection system, a two-threshold scheme is used to transform the seizure state to normal state in order for the detector to predict the next seizure. The framework of our method is shown in Fig. 1.

A. Feature Extraction

Raw EEG records are divided into segments by a sliding window with the size of 1s and the stride of 0.2s for subsequent processing.

1) Intrinsic Model Functions (IMFs): We compute the IMFs by the classical EMD method, which has been proved effective in seizure detection [9], [10]. The variance of the N^{th} IMF (VoIMF) in the t^{th} segment is:

$$\mathrm{VoIMF}_N(t) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2, \qquad (1)$$

where x_i is a data point in IMF_N and n is the sample number in the segment. As shown in Fig. 3, VoIMFs have larger values at seizure states while keep small at non-seizure points. In our method, the first three VoIMFs are used for feature combination.

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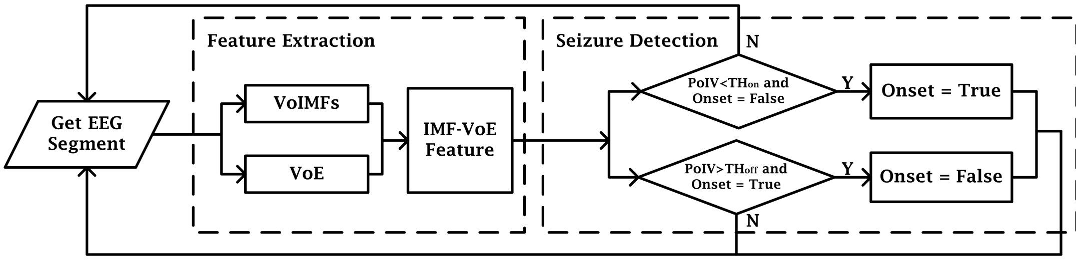

Fig. 1. A flow chart of seizure detection system

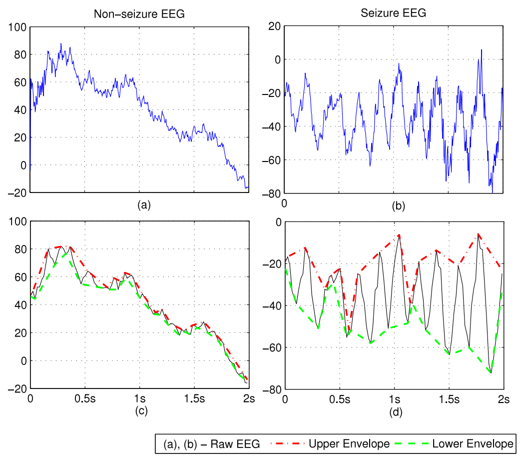

Fig. 2. The envelope computation of seizure and non-seizure data. (a, b) Raw EEG data. (c, d) Smoothed EEG data.

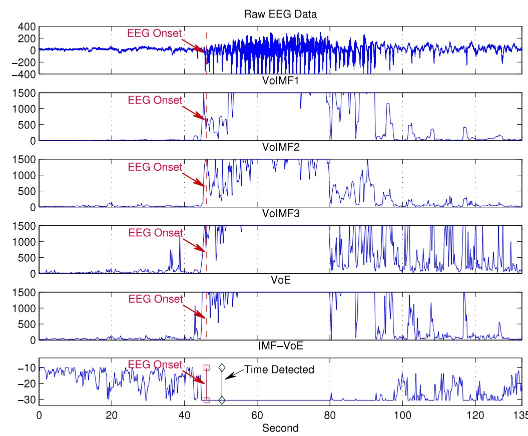

Fig. 3. The changes of single/combined features against seizure/non-seizure states.

2) Variance of Envelope Difference (VoE): Most seizure states cause the change of the range between the upper and lower envelopes of signals. As shown in Fig. 2, we compute the VoE by the following steps:

- Use a mean filter to remove densely located local maxima/minima;
- Compute the envelopes of the filtered data:
  - the upper envelope: find all the local maxima and connect them to be the upper envelope E_u;
  - the lower envelope: find all the local minima and connect them to be the lower envelope E_l;
- Compute VoE in the t^{th} segment:

$$\mathrm{VoE}(t) = \frac{1}{n-1}\sum_{i=1}^{n}(E_{uti} - E_{lti} - (\overline{E_{ut} - E_{lt}}))^2, \quad (2)$$

  where n is the number of the sampling points, E_{uti}/E_{lti} is the value of the upper/lower envelope at point i, and $\overline{E_{ut} - E_{lt}}$ is the mean difference between the upper/lower envelopes in the t^{th} segment.

Fig. 3 shows that larger values of VoE appear at seizure states. Thus, we use it as another feature for seizure detection.

3) IMF-VoE Feature: From Fig. 3, it can be found that only the VoIMF or VoE feature have some strength to identify seizure states, while none of them is always powerful along the whole duration of ictus. At the point that one feature is ineffective, the other features may be helpful. In order to benefit from both the VoIMF and VoE features, we combine them to build a IMF-VoE feature.

First, for each VoIMF or VoE, its probability density function is estimated from non-seizure signals. Suppose the values of the feature are in the range of $[a, b]$. Using a piece of training background signal of EEG, a histogram with m bins and a bin width of $h = (b-a)/m$ can be computed. After normalization, $P_{i,k}$ in the k^{th} bin represents the probability of feature i falling into a certain range in the non-seizure state. If $P_{i,k}$ is zero, it will be set to a small value for the numerical purpose. In our experiments, we find that $m = 150$ and $h = 10$ can sufficiently satisfy the requirement of detection.

After $P_{i,k}$ for VoE and each VoIMF is estimated, the IMF-VoE feature in the t^{th} segment is computed by

$$\mathrm{IMF-VoE(t)} = \log_2 \prod_{i=1}^{n} P_{i,bi}, \quad (3)$$

where n represents the number of features and $P_{i,bi}$ is the value in bin bi of the histogram in which the value of feature i falls. Fig. 3 shows the ability of the IMF-VoE feature. In the seizure state, it keeps small and exhibits more stable than the single features.

B. Seizure Detection

1) Probability of IMF-VoE: Since the dimension of the IMF-VoE feature is one, it is straightforward to learn a

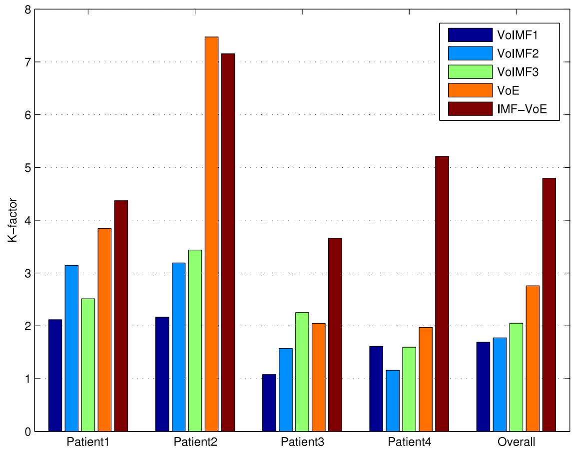

Fig. 4. The k-factors of single/combined IMF-VoE features for all patients.

threshold from the EEG signal to construct a classifier for detection. However, in practice, a fixed threshold can not well distinguish seizure states from background for different persons due to the diversity of signals from individuals. Thus we estimate the probability density functions of IMF-VoE for each patient with the training background data. Once the probability of IMF-VoE (PoIV) is less than a threshold which is general over individuals, a seizure onset was detected.

2) Detection system: In a real-time seizure detection system, it is necessary to switch the decision of classifier from the seizure state to the normal state so as to predict the next seizure. Thus, we use two thresholds, TH_{on} and TH_{off}, and a boolean state variable $Onset$ to address the problem. When $Onset$ is false and PoIV for current segment is lower than the TH_{on}, a seizure is detected. The state of the classifier will be turned back to non-seizure when PoIV is higher than TH_{off} during onset. The process of detection is described in Fig. 1.

III. Experiments

A. Materials and Settings

All EEG data used in the study are recorded during presurgical epilepsy monitoring by NicoletOne amplifier from the Second Affiliated Hospital of Zhejiang University College of Medicine. 32 channels of scalp EEG data are recorded according to the International 10-20 System of Electrode Placement. The sample rate is 256Hz. 50Hz notch and 1.6Hz-70Hz band pass filters has been applied in the acquisition. Only one channel recorded from within the epileptogenic zone is selected with the advice of the epileptologist for seizure detection.

B. Analysis of Features

To test the classification effects of VoIMFs, VoE and the combined IMF-VoE feature, we employ k-factor as the measure:

$$k\text{−factor} = \frac{|m_1 - m_2|}{\sqrt{(v_1 + v_2)/2}} \qquad (4)$$

where m_1 and m_2 are the means of feature values of seizure and non-seizure signals, v_1 and v_2 are the variances. The k-factor indicates the distance between two clusters of seizure and non-seizure signals classified based on given feature. High k-factor value indicates good classification performance [7]. The results are shown in Fig. 4. Diverse classification performances of the VoIMFs and VoE are observed for different patients. For example, the feature of VoE shows good classification effect for patient1, 2 and 4. While for patient 3, VoIMF3 has the best performance of distinguishing seizure from background signals. Despite the various classification capacity of VoIMF or VoE feature, the performance of combined IMF-VoE feature keeps relatively high. The overall k-factors also indicate that combined IMF-VoE feature as a integration of the four single features, has high and stable performance over patients.

C. Seizure Detection Performance

The seizure detection method is tested on 80.4 hours of EEG data with 10 seizures of 4 patients. The performance is evaluated by three commonly used measures of sensitivity (proportion of seizures correctly detected), false detection rate (FDR, false detection times per hour) and time delay (TD, time latency between seizure onset detected and seizure onset marked by epileptologists). Results for different thresholds are shown in TABLE I.

The detection system obtains a sensitivity of 100% with low FDR of 0.16 per hour. The time delay can be controlled at about 10 seconds with an acceptable FDR of 0.41 per hour. The selection of TH_{on} can adjust the tradeoff between FDR and time delay. Given high sensitivity and low FDR, the system may serve as offline seizure detector to mark seizures in long-term EEG automatically instead of by epileptologists manually which is a labor-intensive task [11]. On the other hand, with short time delay the method is capable for online detecting work with high performance. Our results are competitive to former studies. Saab and Gotman reported a detection method with sensitivity of 78%, FDR of 0.86/h and TD 9.8s[12]. Meier's study reported a online system with sensitivity of 90%, FDR less than 0.5/h with TD less than 10s [7]. These methods need much more features to compute, while in this study, only few features are used and high performance is achieved with relatively lower computational cost. Furthermore, only small piece of background EEG data rather than large amount of seizure and non-seizure data are used in the training stage.

D. Analysis of FDR

Time delay is an important criterion for online seizure detection system. Short time delay unavoidably causes an increase in FDR, so that the control of FDR is a critical issue for performance improvement.

There are two kinds of false detections: interesting ones and uninteresting ones [12]. Interesting false detections (IFD) involve epileptic events such as spikes or rhythmic waves while uninteresting false detections (UFD) are non-epileptic events due to artifacts such as EMG or amplitude bursts. In

TABLE I

RESULTS OF THREE THRESHOLDS

Patients	Hours	Seizures	TH_{on}=0.0001,TH_{off}=0.1			TH_{on}=0.0003,TH_{off}=0.1			TH_{on}=0.0005,TH_{off}=0.1		
			TD(s)	FD	FDR(/h)	TD(s)	FD	FDR(/h)	TD(s)	FD	FDR(/h)
P1	15.5	S1	18.59	0	0	5.31	0	0	4.92	0	0
		S2	22.58			21.41			20.23		
P2	24	S1	25.48	3	0.13	12.98	9	0.38	5.56	13	0.54
		S2	4.06			4.06			4.06		
		S3	31.78			8.34			8.34		
P3	24.9	S1	9.69	5	0.20	9.30	5	0.20	8.93	6	0.24
		S2	4.94			4.94			4.94		
P4	16	S1	36.91	5	0.31	33.00	8	0.50	17.38	12	0.75
		S2	10.91			10.91			-12.53*		
		S3	29.47			21.66			21.66		
Total	80.4	10	19.44	13	0.16	13.19	22	0.27	10.67	31	0.41

TD refers to time delay; FD refers to false detection; FDR refers to false detections per hour.
*Since some studies regard minus TD as FD, this value is discarded in calculation of average TD.

our study, the majority of false detections are uninteresting ones. As we examine the false detections with synchronous video records, it turns out that most false detections are made because of rhythmic EMG artifacts while the patients are chewing. The statistics of false detections for TH_{on} = 0.0005 are shown in TABLE II.

TABLE II

FALSE DETECTIONS

Patient	IFD	UFD	UFD While Chewing
P1	0	0	0
P2	2	11	10
P3	1	5	5
P4	4	8	7
Total	7	24	22

IFD refers to interesting false detection;
UFD refers to uninteresting false detection.

Since up to 91% of the UFDs are caused by rhythmic chewing while eating, detection and removal of EMG is a necessary process to bring notable improvement to the performance.

IV. CONCLUSION

In this paper, a new efficient method for epileptic seizure automatic detection was proposed. The method showed high performance on 4 patients. This method only needed small amount of background EEG, and the computational complexity was low enough for embedded systems.

In future work, larger data sets will be applied to verify the performance of our method. In addition, with the EMG artifacts detected and removed, the false detection rate of the method could be decreased significantly. Algorithms such as ICA [13] would be used for EMG removal to improve the performance.

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