Epileptic State Classification based on Intrinsic Mode Function and Wavelet Packet Decomposition

Dinghan Hu*, Jiuwen Cao*†, Xiaoping Lai*, Junbiao Liu†

***Abstract*—The scalp electroencephalogram (EEG) signal based epileptic seizure analysis has been comprehensively studied in the past. But existing researches are generally concerned with the seizure/non-seizure detection. Few attention has been paid to the epileptic preictal state classification, which is found to be evidently more important to the injury prevention. In this paper, we study the epileptic preictal state classification for seizure prediction. The one hour preictal EEG signal is divided into non-overlapped equilong segments. Statistical features of the first intrinsic mode function (FIMF) of the empirical mode decomposition (EMD) of the EEG signal as well as the 4-level wavelet packet decomposition (WPD) of the FIMF are extracted for the EEG signal representation. A five-state classification problem is formulated, including one interictal, three preictal, and one seizure states. Experiments on the benchmark epilepsy EEG database collected by the Children's Hospital Boston and the Massachusetts Institute of Technology (CHB-MIT) using several popular classifiers are provided for the effectiveness demonstration.**

***Index Terms*—Seizure detection, Epileptic state classification, EMD, WPD, FIMF**

I. Introduction

Epilepsy is a stubborn brain disorder characterized by abnormal electrical discharges of brain neurons that manifest as seizures or fits [1]. Epilepsy has the characteristics of sporadic and repetitive. The sudden onset of seizure generally makes an epileptic lose consciousness, which may cause damages due to the loss of control of the body, such as suddenly falling down, head trauma, etc. Therefore, in some ways, an accurate prediction of the preictal state before onset is more significant than the seizure detection.

The scalp electroencephalography (EEG), which contains a lot of information on brain activities, has been found effective in epilepsy analysis. Up to now, extensive EEG based epileptic seizure detection approaches have been presented. To name a few, Polat and Gunes [2] studied the seizure classification using the frequency domain statistical features of EEG. Zandi et al. [3] employed the wavelet packet transform (WPT) of EEG signals to detect the seizure/non-seizure states. Riaz et al. [4] applied the empirical mode decomposition (EMD) of EEG signals to distinguish epileptics from healthy people. Besides, the nonlinear analyses of EEG signals were studied for epilepsy classification by Iqbal et al. [5], Hsu et al. [6] and so on. Recently, Ahmedt-Aristizabal et al. [7] shows the deep learning based epileptic signal classification via using the long-short term memory networks.

It is readily found that the existing literature mostly focuses on the seizure/non-seizure detection but few attention has been paid to the preictal state classification. By dividing the one-hour preictal EEG signal into three consecutive, non-overlapped and equal-duration segments, we obtain a five-state classification problem, where the five states include one interictal, three preictal and one seizure states. The seizure can then be predicted by identification of the preictal states. To obtain effective features for EEG signal representation, we derived the first intrinsic mode function (FIMF) of the EMD [8] of the EEG signal. We computed the energy and variance of the FIMF and the energy ratio of the FIMF to the EEG signal, and variance of the FIMF. We then merged these features with the skewness and energy features of the wavelet package decomposition (WPD) of the FIMF. Popular classifiers, including the random forest (RF) and the K-Nearest Neighbor (KNN), are then adopted for feature learning and epileptic state classification. The effectiveness of the proposed algorithm is validated through experiments for comparisons with several state-of-the-art algorithms on the benchmark CHB-MIT epilepsy EEG database.

II. Methodology

A. EMD

The EMD [9] of an EEG signal $x(n)$ can be expressed as

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

where $c_i(n)$ is the i-th IMF and $r(n)$ is the residual component. The IMFs are iteratively obtained by $c_i(n) = r_{i-1}(n) - m_i(n)$ for $i = 1, \ldots, k$ with $m_i(n) = \frac{e_i^u(n)+e_i^l(n)}{2}$. Here, $r_{i-1}(n)$ denotes the residue signal in the $(i-1)$-th iteration, $e_i^u(n)$ and $e_i^l(n)$ represent the upper and lower envelopes derived by the cubic spline interpolation using the local maximum and minimum at the i-th iteration. EMD is capable of denoising through the decomposition. In general, the deeper the decomposition is, the better the denoising performance tends to be, but more useful information may be lost along with the decomposition. Therefore, the FIMF is an appropriate

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one as it can simultaneously achieve denoising and carrying enough useful information. Besides, FIMF actually contains the information of all IMFs in the subsequent decompositions. In [8], Amert et al. estimated the energy level of each IMF of the EMD by discrete Fourier transform and then used the change of the energy level caused by adaptive PSDs of the IMFs to detect the epileptic seizure. This method is only suitable for seizure detection, and not applicable to preictal state prediction. To alleviate this deficiency, we propose the FIMF based statistical features for multiple EEGs representation in this paper.

B. WPD

The WPD is an extension of wavelet decomposition that performs signal decomposition on both the low and high frequency components of a signal [10]. Instead of using the original signal, the WPD is applied to the FIMF of the EEG signal in this paper to achieve a better characterization. For illustration, the FIMFs of the pre-1 state signals and their 1st-level WPDs are drawn in Fig. 1. Here, the one-hour preictal EEG signal is segmented into three non-overlapped pieces, each with a duration of twenty minutes, as shown in Fig. 2. The prediction of the seizure onset can thus be transformed to a classification problem for the five states: the one interictal state, the three preictal states (Pre-1, Pre-2, and Pre-3), and the one seizure state. An accurate classification of the preictal states may provide a prediction of the seizer with a resolution of 20 minutes ahead.

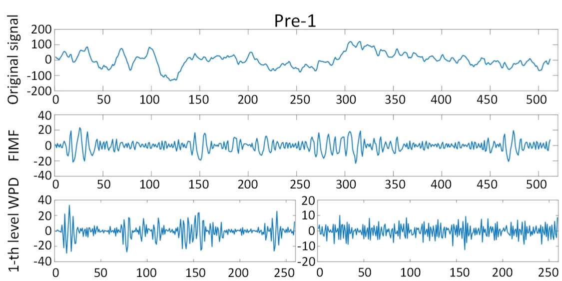

Fig. 1: Pre-1 signals, FIMFs and 1st level WPDs.

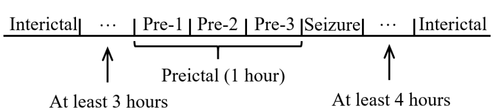

Fig. 2: Segmentation of the preictal state EEG signal.

C. Feature extraction

The statistical features extracted from the FIMFs of multi-channel EEG signals and their WPDs are concatenated for the EEG signal representation. For each channel, the energy of the FIMF, the energy ratio of the FIMF to the original EEG signal, and the estimated variance of the FIMF are calculated as

$$E_{\text{FIMF}} = \sum_{n=1}^{N} c_1^2(n), \tag{2}$$

$$E_r = \frac{\sum_{n=1}^{N} c_1^2(n)}{\sum_{n=1}^{N} x^2(n)}, \tag{3}$$

$$\sigma = \frac{1}{N}\sum_{n=1}^{N}(c_1^2(n) - \bar{c})^2, \tag{4}$$

where $\bar{c}$ represents the estimated mean of the FIMF.

It is shown in [11] that the 4-th level discrete wavelet transform has the maximum normalized energy, appropriately all frequency content in the Fourier domain and the highest correlation coefficient. In this paper, a 4-level WPD is performed on the FIMF for each channel resulting in 16 frequency subbands of the FIMF. The skewness and energy of each frequency subband are then extracted by

$$S_p = \frac{\sum_{k=1}^{K}(y_p(k) - \bar{y}_p)^3}{\sigma_p^3 K}, \tag{5}$$

$$E_p = \sum_{k=1}^{K} y_p^2(k), \tag{6}$$

where $y_p(k)$ is the reconstructed signal of the p-th subband ($p = 1, \ldots, 16$), $\bar{y}_p$ and σ_p are the associated estimated mean and standard deviation, and K is the length of the subband signals.

For the M-channel EEG signals, we obtain a vector of the FIMF energies $\boldsymbol{E}_{\text{FIMF}} \in R^M$, a vector of the FIMF energy ratios $\boldsymbol{E}_r \in R^M$, and a vector of the FIMF variances $\boldsymbol{\sigma} \in R^M$. We also get a vector of the WPD subband signal skewness features $\boldsymbol{S}_p \in R^{16 \cdot M}$ and a vector of WPD subband energies $\boldsymbol{E}_p \in R^{16 \cdot M}$. All these feature vectors are then concatenated to a single vector as follows:

$$\boldsymbol{v} = [\boldsymbol{E}_{\text{FIMF}}^T, \boldsymbol{E}_r^T, \boldsymbol{\sigma}^T, \boldsymbol{S}_p^T, \boldsymbol{E}_p^T]^T. \tag{7}$$

It is shown by the experiment in Section III that, the concatenated feature vectors for the five epileptic states have relatively smaller intra-class distances than the inter-class distances. This validates the good representational capability of the proposed features. Fig. 3 shows the flowchart of the proposed feature extraction scheme. With the above extracted feature vectors of the EEG signals as the inputs, a five-category classification problem is then constructed, where the random forest (RF) [12] is adopted as the classifier. RF is a popular learning algorithm that performs data classification based on the weighted results of multiple decision trees.

III. Results and Analyses

A. Experiment set-ups

We study the performance of the epileptic state classification for seizure prediction using the benchmark CHB-MIT database in this section. The database includes the scalp EEG signals of 22 pediatric patients, where 18 channels EEG signals are recorded for each patient with a sampling frequency of 256Hz. For each patient, three categories of the EEG signals belonging to the interictal, preictal and ictal states are recorded in the

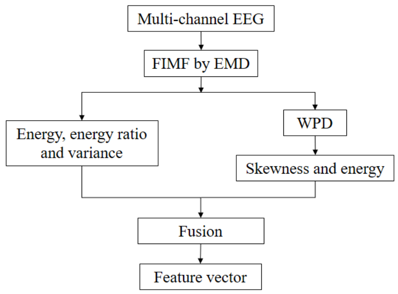

Fig. 3: The proposed feature extraction scheme.

original database, where the signal length of each state is one hour. In this experiment, we divide the one hour preictal state into three equilong and non-overlapped segments. The length of each segment is 20 minutes and the three preictal states are denoted as Pre-1, Pre-2, and Pre-3, respectively. A five-category classifier is built to perform the seizure prediction.

In order to extract the proposed statistical features from the FIMF and WPD, EEG signals are segmented into overlapped frames with a length of 2 seconds and an overlap ratio of 50%. By doing so, a total of 50000 EEG signal frames, 10000 frames for each of the five states, are obtained from all the EEG signals in the CHB-MIT database. The dimension of the FIMF+WPD feature vector for each frame are 630. To show the effectiveness of the proposed features and the associated classification, we compare with several state-of-the-art EEG feature extraction + classification algorithms in this section, which are briefly described in the following.

1) Wavelet package features + RF/KNN (WPF+RF/WPF+KNN): In WPF, the subband energy ratio, Shannon entropy, logarithmic energy entropy and norm entropy extracted from the 6-level WPD are used for the EEG representation. RF and KNN are adopted for the classifier, respectively.

2) Mean amplitude spectrum + Convolutional neural network + Support vector machine (MAS+CNN+SVM) [13]: The MAS computed for each of the EEG signals are served as inputs of the CNN. The output probability vector of the CNN are fed to SVM for classifier training.

3) Statistical features + RF (SF+RF): The mean, variance, median, skewness, and kurtosis of the subband WPD coefficients are derived for the EEG signal representation. The RF algorithm is employed as the classifier.

4) The proposed features + KNN (FIMF+WPD+KNN): The proposed statistical features based on FIMP+WPD in this paper is also tested using the KNN classifier for comparison.

B. Results and discussions

A five-fold cross validation is conducted for each algorithm, and the average result is reported for performance comparison. The number of decision trees in RF is optimized by a grid search over $\{10, 50, 100, 200, ..., 800\}$. Fig. 4 shows a curve of the average accuracy by the proposed algorithm with respect to (w.r.t.) different number of trees used in the RF classifier. It is observed that the accuracy increases with the number n of the decision trees when n is smaller than 600, but decrease slightly with n when $n > 600$. The classification accuracy reaches an maximum value of 91.60% when $n = 600$.

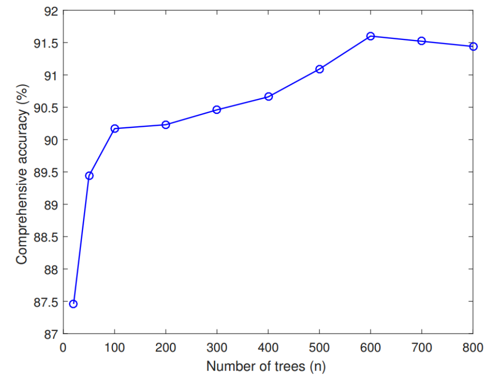

Fig. 4: Classification rate w.r.t. different decision trees of RF.

Table I shows the classification accuracies of the five epileptic states obtained by the proposed method as well as a comparison with other four aforementioned algorithms. One can see from Table I that the classification accuracies of the interictal and seizure states obtained by the proposed method are very high, as high as 98.10% and 98.65%, and the classification accuracies of the Pre-1, Pre-2 and Pre-3 preictal states also reach high values, i.e., 91.65%, 82.10% and 87.50%, respectively. As highlighted in boldface, the proposed method achieves higher classification accuracies than all the competing state-of-the-art algorithms for all five epileptic states. The average accuracy over the five epileptic states obtained by the proposed algorithm is 91.60%. The proposed algorithm obtains an increment of 6.33%, 11.34%, 6.8%, 11.12%, and 5.35%, respectively, over the FIMF+WPD+KNN, WPF+KNN, WPF+RF, SF+RF, and MAS+CNN+SVM algorithms. Meanwhile, with the same statistical features of FIMF+WPD, the RF algorithm is superior to KNN. Fig. 5 compares the classification rate confusion matrices of the proposed method and the second best algorithm MAS+CNN+SVM. As observed, the misclassification rates of the three preictal states obtained by the proposed method are far less than those by the MAS+CNN+SVM.

TABLE I: Classification accuracies (%) by the proposed method and comparisons with state-of-the-art algorithms

Accuracy / State / Algorithm	Interictal	Pre-1	Pre-2	Pre-3	Seizure	Average accuracy
Proposed method	**98.10**	**91.65**	**82.10**	**87.50**	**98.65**	**91.60**
WPF+RF	97.67	81.52	69.19	79.52	97.10	84.80
WPF+KNN	92.86	68.71	67.57	78.81	93.33	80.26
MAS+CNN+SVM	98.06	87.04	73.29	75.28	97.67	86.25
SF+RF	95.76	75.71	62.81	73.19	94.95	80.48
FIMF+WPD+KNN	95.55	79.90	74.85	80.40	95.65	85.27

To further validate the effectiveness of the proposed statistical features of FIMF+WPD in classification of the five cate-

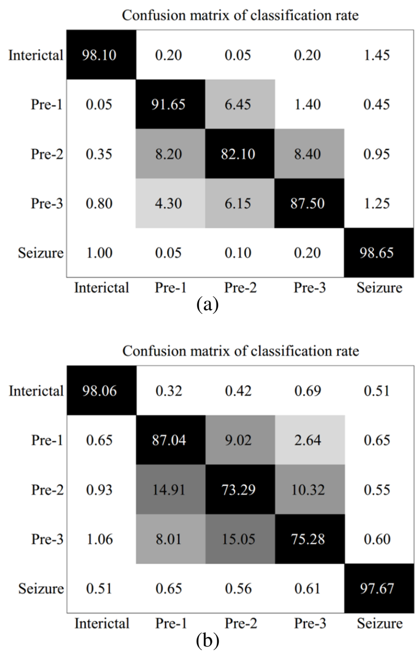

Fig. 5: Confusion matrices of (a) the proposed method and (b) the MAS+CNN+SVM.

	Interictal	Pre-1	Pre-2	Pre-3	Seizure
Interictal	0. 3926	3. 6285	4. 4591	4. 4750	4. 8255
Pre-1		0. 7773	5. 1665	5. 1382	5. 5003
Pre-2			0. 7896	4. 6511	4. 9490
Pre-3				0. 6237	3. 5923
Seizure					0. 7212

Fig. 6: The intra- and inter-class Chebyshev distances of the proposed features.

gories, the average intra- and inter-class Chebyshev distances of the five epileptic states are calculated for comparison. Fig. 6 shows the detailed intra- and inter-class feature distances. Obviously, for each state, the intra-class Chebyshev distance (shown in the diagonal line of Fig. 6) of the proposed features is much lower than the inter-class Chebyshev distances. It thus demonstrates that the proposed statistics of FIMF+WPD are distinctive features in characterizing the EEG signals of the five epileptic states.

Experiments on datasets with different training/testing sample ratios are also conducted in this section to test the robustness of the proposed method, where 500 decision trees are used in RF. Table II lists the detailed accuracies of each category and the associated average accuracy. We can see that even with the low sample ratio of 6:4 the proposed method can reach a high average accuracy of 89.74%.

IV. Conclusions

We studied the epileptic state classification in this paper. Rather than the seizure/non-seizure detection, an epileptic state classification was performed, where the epileptic states include one interictal state, three preictal states, and one seizure state.

TABLE II: Accuracies of the proposed method w.r.t. different ratios between training and testing datasets using 500 trees.

Accuracy / State / Sample ratio	Interictal	Pre-1	Pre-2	Pre-3	Seizure	Average accuracy
6:4	98.03	88.50	80.08	84.03	98.08	89.74
7:3	98.40	90.23	80.83	85.27	98.37	90.62
8:2	98.70	89.10	84.00	85.65	98.00	91.09
9:1	98.80	90.00	83.10	87.00	98.70	91.52

Novel statistical features extracted from the FIMF of EEG signal and its WPD were developed, and the RF algorithm was adopted as the classifier. Experimental studies on the CHB-MIT database with the one hour preictal signals being divided into three segments corresponding to the three preictal states show that an average classification accuracy of 91.6% has been achieved. Particularly, for the three preictal states, the lowest classification rate is as high as 82.1%.

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