Biomedical Signal Processing and Control 44 (2018) 168–180

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Classification of ictal and interictal EEG using RMS frequency, dominant frequency, root mean instantaneous frequency square and their parameters ratio

Arindam Gajendra Mahapatra*, Keiichi Horio

Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology,2-4 Hibikino, Wakamatsu-Ku, Kitakyushu 808-0196, Japan

ARTICLE INFO

Article history:
Received 19 August 2017
Received in revised form 28 February 2018
Accepted 9 April 2018

Keywords:
Electroencephalograph (EEG)
Epilepsy
Ictal
Interictal
Empirical mode decomposition (EMD)
Root mean square (RMS) frequency
Dominant frequency
Root mean instantaneous frequency square (RMIFS)
Support vector machine (SVM)

ABSTRACT

In this work, we have proposed to use root mean square (RMS) frequency f_r and dominant frequency f_d along with the ratio of their contributing parameters as features for classification of interictal and ictal electroencephalogram (EEG). Empirical mode decomposition (EMD) is used for decomposing EEG into a finite set of intrinsic mode functions (IMFs). IMFs are then represented into analytic form by applying Hilbert transform over it. Analytical form of these IMFs are utilized to extract the features. Kruskal–Wallis test was applied to determine features from first two IMFs to be used for classification purpose using support vector machine (SVM). A novel feature root mean instantaneous frequency square (RMIFS) f_R been proposed using relationship between RMS frequency and dominant frequency to define it as square root of the sum of time averaged instantaneous frequency spread around center frequency and square of center frequency. It is also been used along with its parameters ratio for ictal and interictal classification. The best results were observed using RMS frequency and its parameters ratio from IMF2 to discriminate ictal from interictal. The highest average accuracy and sensitivity observed was 99.91%, 100%. An adaptive thresholding method has also been proposed in this work to recover the false positives. Adaptive thresholding was able to recover the average accuracy.

1. Introduction

Electroencephalogram (EEG) is first-hand tool for diagnosis epileptic seizures. Epileptic Seizure is a generalized term which has broad classification depending on the reasons behind its occurrence [1,2]. Epileptic seizure or ictal can be considered as hyperactivity of neural network which disrupts normal brain functioning from few seconds to several minutes. Interictal is the period between two consecutive ictal or seizure. Previously, for epileptic EEG classification, Fourier based methods were in use [3] but these methods are fixed to basis functions. Short time Fourier transform (STFT) based time frequency methods had also been used [4]. But there exist trade-off between frequency and time resolution depending on the window size [5]. Wavelet based analysis [5–7] has also shown good results in classifying seizures. Guo et al. [8] has employed discrete wavelet transform to pre-analyse the EEG signals.

In conjunction with each method, feature extraction remains one of the important part of EEG classification process, influencing their results. The results are as good as the selection and combination of the features. Features like correlation dimension [9], fractal dimensions were applied previously [10]. Liang et al. in his research work [11] had extracted approximate entropy (ApEn) along with other spectral features. These features were used with auto regressive model and principal component analysis, was able to quantify irregularities of signals. Peak value, equivalent width and mean square abscissa features are derived from cross-correlation of signals and power spectral density was applied in [12]. Energy and curve length of the signal feature were extracted using genetic programming in [8]. Tang et al. [13] had used median Teager energy with SVM assembly for seizure detection. Tempko et al. [14] had used a total of 55 features, total power, spectral edge frequency are few of the spectral features. In time domain, the features were Hjorth parameters, zero crossing, root mean squared amplitude, nonlinear energy. Information theory based features were shanon entropy, singular value decomposition entropy, spectral entropy to name a few. Permutation entropy feature was applied in [15] to

* Corresponding author at: Horio Lab, Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology (KYUTECH), 2-4 Hibikino, Wakamatsu-Ku, Kitakyushu 808-0196, Japan.

E-mail addresses: mahapatra-gajendra@edu.brain.kyutech.ac.jp, arindammmahapatra@gmail.com (A.G. Mahapatra).

https://doi.org/10.1016/j.bspc.2018.04.007
1746-8094/

classify ictal data from non-seizure and interictal data for creation of seizure detection system. Strength and degree of horizontal visibility graph (HVG) features, a type of complex network were also used by Zhu et al. [16] for ictal classification purpose.

Lately, empirical mode decomposition (EMD), introduced by Huang et al. [17] has been used successfully to classify ictal EEG. In conjunction with EMD, parameters like weighted frequency [18], coefficient of variation, fluctuation index [19], mean, standard deviation, variance, skew, centroid [20,21] were employed for classification. Bandwidth's amplitude modulation and frequency modulation features are used for discriminating seizure from non-seizure using least square support vector machine (LS-SVM) in [22] along with EMD. Phase space representation was utilized to discriminate interictal from ictal by Sharma et al. [23]. RMS frequency was used along with another feature based on amplitude from Hilbert spectrum for the classification of seizure and non-seizure in [24].

The ability to discriminate between the ictal and interictal EEGs of epileptic patients is important for practical applications like seizure prediction, warning systems or closed-loop seizure control systems [11,25]. To create seizure detection system, features are required that can determine the presence of seizure from interictal data [26]. The first step is to have features showing good classification accuracy with high sensitivity for ictal EEG data. In this work, classification of ictal from interictal is done successfully first by using RMS frequency f_r and its parameters ratio. RMS frequency is the square root of the sum of square bandwidth and square of center frequency. Contributing parameters ratio is the ratio of center frequency square to square bandwidth. Dominant frequency f_d and its parameters ratio also been utilized for the same purpose. Dominant frequency have same physical relevance as RMS frequency but different by definition, i.e. square root of sum of square of instantaneous bandwidth and square of instantaneous frequency. The third feature used is by exploiting the equivalence of RMS frequency f_r and dominant frequency f_d to define root mean instantaneous frequency square (RMIFS) f_R as square root of sum of time averaged bandwidth square and center frequency square. These features are average measures which show good discrimination power in classifying ictal from interictal using SVM. These features, f_r and f_d also have an advantage of overcoming the drawback of square bandwidth and square instantaneous bandwidth which can be same for two different signals simultaneously. RMS frequency used in this work is different from generic root mean square analysis as in [27,28]. An adaptive thresholding algorithm is developed to address the issue of false positives, i.e. problem of wrongly classifying interictal data as ictal data by SVM. It was able to increase the specificity by 6.84% on average consequently increasing the average accuracy.

The paper is organized as Section 2 describes EMD, Hilbert transform, feature computation and SVM followed by Section 3 consisting of the description of the data used in this work, selection of the features and preparation of data for classification. Results are discussed in Section 4 with adaptive thresholding. Conclusion at the end.

2. Method

2.1. Empirical mode decomposition

EMD [17] analyse a signal adaptively without imposing any predefined model, completely dependent on the data. It decomposes the EEG signal into a number of oscillatory modes called intrinsic mode function (IMF).

EMD accept a decomposition as an IMF on two conditions:

1. The difference between the number of zero crossing and number of extrema must be either 0 or at most 1.
2. The mean calculated at any instant of time from the upper and lower envelope must result in zero.

EMD algorithm as follows:

1. Detect all the extrema of signal $z(t)$.
2. Use cubic spline to interpolate among the local maxima to obtain upper envelop $U_{max}(t)$.
3. Use cubic spline again to interpolate among the local minima to obtain lower envelope $L_{min}(t)$.
4. Take average of the envelopes $Avg(t) = \frac{1}{2}(U_{\max}(t) + L_{\min}(t))$.
5. Deduct the average from the original signal, $h(t) = z(t) - Avg(t)$.
6. Declare $h(t)$ as an IMF when it is in compliance with the two conditions and then assign $h(t)$ to $c(t)$.
7. Do $r(t) = z(t) - c(t)$. If $r(t)$ is not monotonic, assign $z(t) = r(t)$, go to step 1.

Recursively apply this whole process which is called sifting process [29,30] until residue $r(t)$ conform to be monotonic. In the end, original signal can be reproduced by summing all the IMF decompositions and the monotonic residue as represented in Eq. (1).

Fig. 1 depicts EMD decomposition of interictal EEG signal segment [31] and Fig. 2 presents decomposition of ictal EEG signal segment [31]. First eight decompositions or IMFs along with the residue have been presented in the figure.

$$z(t) = \sum_{i=1}^{K} c_i(t) + r_K(t), \tag{1}$$

where K represent the total number of IMFs and $c_i(t)$ represent the ith IMF. $r_K(t)$ is the monotonic residue at the end. EMD code used in this work is publicly available at http://perso.ens-lyon.fr/patrick.flandrin/emd.html.

2.2. Hilbert transform over IMF

Hilbert transform was applied on the IMF produced by the EMD. Hilbert transform takes the real valued IMF $c(t)$ to the time frequency domain by projecting it on the real axis of the complex domain, representing it in analytic form $s(t)$ as

$$s(t) = c(t) + jc_H(t), \tag{2}$$

where applying the Hilbert transform on $c(t)$ gives $c_H(t)$ defined as $c_H(t) = c(t) * \frac{1}{\pi t}$, $*$ represents convolution. By utilizing Hermitian symmetry, only the real part is considered for working, ignoring the imaginary part representing negative frequency. Eq. (2) can be represented as in [17]

$$s(t) = a(t)e^{j\varphi(t)}. \tag{3}$$

Instantaneous phase $\varphi(t)$ and amplitude $a(t)$ can be given by

$$\varphi(t) = \arctan\left[\frac{c_H(t)}{c(t)}\right]. \tag{4}$$

$$a(t) = \sqrt{c^2(t) + c_H^2(t)}, \tag{5}$$

Amplitude $a(t)$ is normalized. Instantaneous frequency is defined as derivative of instantaneous phase as in [32]

$$\omega(t) = \varphi'(t). \tag{6}$$

Prime represents differentiation in this work.