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Application of empirical mode decomposition and artificial neural network for the classification of normal and epileptic EEG signals

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ABSTRACT

Epilepsy is a neurological disorder affecting more than 50 million individuals in the world. Analysis of the electroencephalogram (EEG) is a powerful tool to assist neurologists for diagnosis and treatment. In this paper a new feature extraction method based on empirical mode decomposition (EMD) is proposed. The EEG signal is decomposed into intrinsic mode functions (IMFs) by the EMD algorithm and four statistical parameters are calculated over these IMFs constituting the input feature vector to be fed to a multilayer perceptron neural network (MLPNN) classifier. Experimental results carried out on the publicly available Bonn dataset show that an accurate classification rate of 100% is achieved in the discrimination between normal and ictal EEG, and an accuracy of 97.7% is reached in the classification of interictal and ictal EEG signals. Our results are equivalent or outperform recent studies published in the literature.

1. Introduction

The electroencephalogram (EEG) is a time varying signal generated by brain electrical activity recorded either from intracranial electrodes inside the brain or by using scalp electrodes on the surface of the head [1]. The study of the EEG signals could be an effective tool for the analysis of neurological diseases. Epilepsy is one of the most common neurological disorder affecting more than 50 million individuals over the world [2]. Traditionally, neurologists utilize a visual inspection of the EEG recordings in order to detect epileptic seizures, this process becomes annoying and time consuming especially with long term recordings, besides to be a subjective detection. Hence, the need of an automatic method of diagnosis.

In the last two decades, many researchers addressed the problem of automatic seizure detection. It has been shown [3] that all the methods fall into four categories: (a) time domain, (b) frequency domain, (c) time–frequency domain, and (d) nonlinear methods. Liu et al. proposed time-domain method

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searching periodic and rhythmic patterns in EEG [4], while Subasi and Gursoy used principal and independent component analysis (PCA and ICA) for the classification of epileptic EEG signals [5]. In the frequency domain, spectral analysis by Fourier methods is a common technique used in EEG analysis. Polat and Gunes [6] developed a system for two-class epilepsy detection based on the nonparametric Welch method. Owing to the fact that Fourier method assumes the assumption of the stationarity (i.e. main statistical properties do not change over time) of the signals being processed which is unfortunately not the case for EEG signals [7,8], many authors tried time–frequency methods like the wavelet transform which do not impose the underlying hypothesis of the stationarity of data [9], among them Ocak [10] who used discrete wavelet transform (DWT) for automated detection of epilepsy and Acharya et al. [11] used wavelet packet decomposition (WPD) for detecting epileptic stages using higher order spectra (HOS) cumulants. The last category of methods are nonlinear methods as it has been shown that the EEG signals exhibit nonlinearity [10]. Nonlinear parameters such as largest Lyapunov exponent (LLE) [12], correlation dimension (CD) [13], and entropies [14] were successfully used in EEG analysis algorithms.

Empirical mode decomposition (EMD) is a new technique proposed by Huang et al. [15] developed for nonlinear and non-stationary signal analysis. EMD decomposes adaptively a given signal into a finite number of intrinsic mode functions (IMFs). Recently, the energy measure of IMFs [16], the weighted frequency of each IMF [17], the instantaneous area of analytic IMFs [18], the coefficient of variation and fluctuation index of IMFs [19] all computed from the application of EMD to raw EEG signals, were used as features for epileptic seizure detection.

In his paper, we propose four statistical parameters for the classification of non-seizure (normal, interictal) and seizure (ictal) EEG signals. These statistical parameters calculated on IMFs obtained from the decomposition of EEG raw signals by the EMD method, have been used as feature inputs to an artificial neural network (ANN). The type of the ANN considered in this study is the well known multilayer perceptron neural network (MLPNN) as it has demonstrated its powerful ability in the discrimination of complex nonlinear signals [20].

2. Materials and methods

2.1. Dataset

The dataset used in our experiments is from the department of epileptology at the University of Bonn, which is publicly available and described with more details in [21]. The dataset consists of five sets (denoted A–E), each containing 100 single-channel EEG signals of 23.6 s, sampled at frequency of 173.61 Hz with bandpass filter settings at 0.5–40 Hz (12 dB/octave). Sets A and B have been taken from surface EEG recordings of five healthy volunteers, while sets C and D have been measured in seizure-free intervals from five patients. Set E contains seizure activity selected from all recording sites exhibiting ictal activity. Therefore, in the present work three dataset A, D, and E corresponding respectively to normal EEG recordings (healthy subjects set A), interictal activity (set D) and ictal activity (set E) was classified. Note that the signals of set E are taken from patients during a seizure activity, while the signals of set D are from the same patients in seizure-free intervals.

2.2. Empirical mode decomposition (EMD)

The empirical mode decomposition (EMD) method decomposes any nonlinear and non-stationary signal $x(t)$ into a finite number of intrinsic mode functions (IMFs). Each IMF satisfies two fundamental conditions [22]: (1) the number of extrema and the number of zero crossings must be the same or differ by at most one; (2) at every point, the mean value of the envelope defined by the local minima and the envelope defined by the local maxima is zero.

A signal $x(t)$ can be expressed in terms of its M IMFs as:

$$x(t) = \sum_{m=1}^{M} imf_m(t) + r_m(t) \tag{1}$$

where M is the number of IMFs, $imf_m(t)$ is the mth IMF, and $r_m(t)$ is the final residue.

The complete procedure for getting IMFs for the signal $x(t)$ can be summarized as follows [19,23]:

Initialization: $m = 0$; $r(t) = x(t)$

(i) Find the local minima and the local maxima of $x(t)$.

(ii) Get the lower and upper envelopes $e_l(t)$ and $e_u(t)$ by connecting respectively the minima and the maxima with cubic spline interpolation.

(iii) Determine the mean $M_n(t)$ as:

$$M_n(t) = \frac{e_l(t) + e_u(t)}{2} \tag{2}$$

(iv) Extract $h(t)$ as:

$$h(t) = x(t) - M_n(t) \tag{3}$$

if $h(t)$ satisfies the IMF conditions, $m = m + 1$, $imf_m(t) = h(t)$, go to (v) else $x(t) = h(t)$ and repeat (i)–(iv).

(v) Define:

$$r(t) = r(t) - imf_m(t) \tag{4}$$

if $r(t)$ is a monotonic function, terminate the procedure, else, $x(t) = r(t)$ and go to (i).

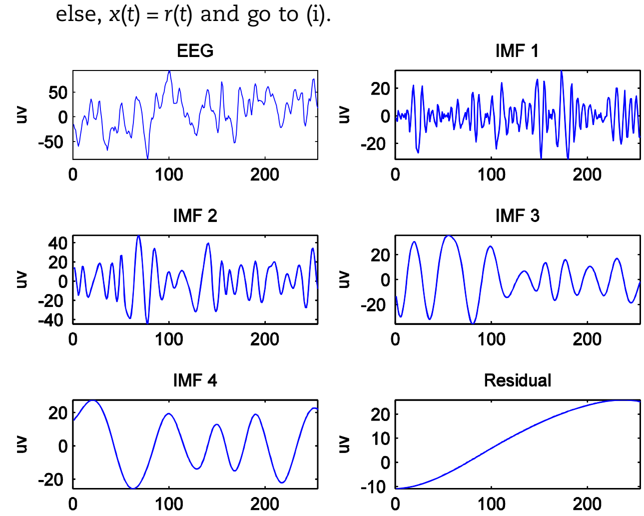

Fig. 1 – Normal EEG signal, its first four IMFs and a residual.