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Epileptic seizure detection in long-term EEG records using sparse rational decomposition and local Gabor binary patterns feature extraction

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ABSTRACT

In this paper, we address the problem of off-line supervised detection of epileptic seizures in long-term Electroencephalography (EEG) records. A novel feature extraction method is proposed based on the sparse rational decomposition and the Local Gabor Binary Patterns (LGBP). Namely, we decompose the channels of the EEG record into 8 sparse rational components using a group of optimal coefficients. Then, a modified 1D LGBP operator is applied, which is followed by downsampling of the data. The width of the largest LGBPs is finally computed for all the 8 rational components and the 23 channels of the EEG record. Hence, we characterize seizure patterns of one-second-long EEG epochs by 23 × 8 features. The effectiveness of the proposed feature extraction method is assessed using different classifiers which are trained with 25% of early EEG records of each patient. We performed an extensive comparative study over 163 h of EEG recordings from the CHB-MIT Scalp EEG database. The experiments show that the proposed technique outperforms other dedicated techniques by achieving the overall sensitivity of 70.4% and the overall specificity of 99.1%, in the patient-specific detection of epileptic EEG epochs. Moreover, it detects onset of seizures with the overall sensitivity of 91.13% and false alarms per hour rate of 0.35, on average.

1. Introduction

Epileptic seizures are symptoms of abnormal brain activities caused by electrical discharges and potential of neurons. Electroencephalography (EEG) is used for monitoring and recording brain activities. In epilepsy research, patients are diagnosed based on EEG records in order to predict or detect the occurrence of epileptic seizure events. One of the challenging tasks in seizure detection is to extract discriminative features from EEG signals in order to differentiate between seizure and seizure-free patterns. During a seizure event, EEG signal mostly appears with continuous rhythmic discharges containing amplitude oscillations and frequency fluctuations. In an automated seizure detection system, the final goal is to design a computer-aided system operating with a performance similar to the visual inspection of an EEG expert. Moreover, such a system might operate in patient-specific approach, where a dedicated classifier is trained and tested independently for each patient. In contrast, a non-patient-specific seizure approach can be trained with EEG signals of all patients and must be able to detect seizures in unseen EEG record.

Seizure detection systems are mainly divided into two main categories: (1) segment based methods which aim at distinguishing seizure epochs from seizure-free ones; (2) event based methods which are designed to detect/predict the occurrence of ictal events. The later category is mostly suitable for online detection or prediction of seizures where patients are monitored constantly and it is vital for clinicians to be alerted by onset of seizures. Segment based discrimination of EEG epochs can be employed as an early phase in seizure event detection. In this way, the prediction segment results of all channels are matched over time in order to distinguish seizure occurrence. In both categories, the main challenge is to represent seizure EEG activities in a discriminative feature space. Classical feature extraction methods have been widely used in supervised seizure segment and event detection techniques where features are extracted for each epoch of EEG channels [1,3,7,53,54,61]. In multi-channel EEG systems, it is possible to train a classifier for each channel individually. Subsequently, a meta-classifier can be fed with a class vector obtained by

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concatenating channel classifiers outputs, [11]. Such an architecture is mostly favored in the existence of a high dimensional feature vector [33].

Morphological analysis is a well-known approach used to characterize waveforms and spike discharges in EEG signals. In this approach, the EEG signal is divided into several parts containing background and current signal activities in order to monitor signal changes. It was shown in an automatic seizure detection method [64] that false positive rate is reduced by considering morphological features extracted from background activities. In a recent study, the application of 1D Local Binary Patterns (LBP) in characterizing EEG signal patterns was introduced for detection of epileptic segments among EEG time-series [30]. Time and/or frequency domain analysis techniques are developed in order to decompose EEG signals into several frequency sub-bands. EEG signal activities in ictal, pre/post-ictal and inter-ictal events are then characterized for each sub-band [17]. After decomposing EEG signals into principal sub-bands, other conventional feature extraction methods can be utilized in order to achieve a better interpretation of EEG patterns. Such a system was developed in [41], where a mixture of several spectral and time-frequency features was utilized in the detection of onset of pre-ictal events with a sensitivity of 100% and false alarms rate of 0.06 per hour. In [48], decomposition of EEG channels were utilized for mapping long-term epileptic EEG records into 2D space in order to perform a multivariate feature extraction. Additionally, both segment-based seizure detection systems in [33,48] were trained with a limited portion of early records in order to particularly confront the lack of sufficient annotated clinical data in a real world case.

Despite the existence of a wide variety of seizure detection algorithms, designing a reliable system which is able to emulate the neurologists task is an ambitious aim. In a real world application, long-term EEG records of a patient come along with large and highly imbalanced data. Feature extraction from a small set of multi-channel EEG records can also lead to the “curse of dimensionality” phenomena. Furthermore, the small training set provided by the neurologist is commonly insufficient for the system to cope with variability of epileptic seizure patterns due to over-fitting. Besides, due to the intrinsic variable characteristic of EEG, automatic elimination of electrophysiological artifacts are not always feasible. In this work, we design a supervised system suitable for off-line detection of seizures in long-term EEG records in such a way that it is capable of emulating the visual inspection task of a neurologist. Thus, the system is deliberately trained with 25% of EEG records, selected from the beginning of the recording, and tested on the remaining records.

The proposed method contains a novel feature extraction technique, which utilizes earlier results from the generalized rational Discrete Short Time Fourier Transform (RDSTFT) [36]. We note that the competence of RDSTFT in epileptic seizure detection has been examined by Samiee et al. [49]. Namely, we showed that the RDSTFT spectra can outperform other state-of-the-art feature extraction methods like wavelets, entropy based algorithms [2], Welch PSD and all the Cohens class of *t–f* distributions. Furthermore, we examined how the parameters, e.g., inverse poles (**a**), window size (M), number of coefficients (N), etc. affect the classification performance. During these experiments, only the coefficients of the RDSTFT were used as features. Now, we propose the sparse variation of the RDSTFT decomposition, which is combined with Gabor filtering and local binary patterns. Although these are well-known feature extraction methods in image processing, we should adapt them to 1D signals. The final features are the LGBP widths, which increase the discrimination power of 1D LGBP features in differentiating between seizure and seizure-free EEG epochs. The performance of the proposed method is evaluated for both seizure segment and event detection tasks using different classifiers. Finally, an extensive comparative study using several state-of-the-art algorithms is performed to demonstrate the effectiveness of the proposed feature extraction. The comparison of the results obtained by the proposed technique with those of competing methods places the proposed technique as the premium alternative in off-line seizure detection systems where achieving low false alarms and high sensitivity rates is crucial.

The rest of this paper is organized as follows. First, we explain the background of the RDSTFT in Section 2. Furthermore, we extend the basic concept with sparse rational decomposition and close the section by the spatial and frequency analysis of the decomposition. In Section 3, we define the LGBP width feature extraction method, which is followed by the description of the dataset and the classifier in Section 4. The performance of the proposed algorithm for segment and event based seizure detection tasks are compared with other state-of-the-art methods in Section 5. Finally, in Section 7, we conclude the work and discuss possible directions for future research.

2. Rational EEG decomposition

Rational functions proved to be an efficient tool for classification of EEG signals [36,49,50]. In this section, we review the main concept of the original [36] and the sparse RDSTFT [50]. Then, we will show that the rational components of the EEG carry diagnostic information about both the spatial and the frequency content of the signal.

2.1. Rational DSTFT

Let us denote the complex plane by $\mathbb{C}$, the open unit disc by $\mathbb{D} := \{ z \in \mathbb{C} : |z| < 1 \}$, the unit circle by $\mathbb{T} := \{ z \in \mathbb{C} : |z| = 1 \}$ and the uniformly sampled $f(t)$ and $g(t)$ functions by $f[n]$ and $g[n]$, respectively. Then, the classical DSTFT over the compactly supported g window function can be defined as,

$$\mathcal{F}_g^{\epsilon} f[n,k] = \sum_{m=0}^{M-1} f[m-n]\overline{g}[m]\overline{\epsilon}_k[m] \quad (n \in \mathbb{N}), \tag{1}$$

$$f[m-n] \approx \frac{1}{M\overline{g}[m]} \sum_{k=0}^{M-1} \mathcal{F}_g^{\epsilon} f[n,k]\epsilon_k[m] \quad (n \in \mathbb{N}), \tag{2}$$

where $\epsilon_k[m] := e^{2\pi i k \frac{m}{M}}$ $(0 \le m < M)$ and M is the window size. In our case, M is also equal to the number of equally spaced frequency bins. The frequency content can be visualized by displaying the squared magnitude of the Fourier coefficients in each window. The resulting diagram is called the spectrogram of the signal f (see e.g., Chapter 5 in [42]).

Using the same terminology as in Eqs. (1) and (2) we can define the rational version of the classical DSTFT. This procedure can also be interpreted as a windowed Fourier transform, but now we are using different bases. More precisely, let us consider a vector of inverse poles $\mathbf{a} := (a_0, \ldots, a_{M-1}) \in \mathbb{D}^M$. Then the so-called Malmquist–Takenaka (MT) system, which was introduced by Malmquist [40] and Takenaka [60], can be written in the following form:

$$\Phi_k(z) = \frac{\sqrt{1-|a_k|^2}}{1-\overline{a}_k z} \prod_{j=0}^{k-1} B_{a_j}(z) \quad (z \in \overline{\mathbb{D}},\ 0 \le k < M), \tag{3}$$

where $B_a(z)$ is a Blaschke-function:

$$B_a(z) := \frac{z-a}{1-\overline{a}z} \qquad (z \in \mathbb{C} \setminus \{1/\overline{a}\}).$$

In order to construct the RDSTFT we replace ϵ_k in Eq. (1) by $\phi_k[m] := \Phi_k(e^{2\pi i \frac{m}{M}})$. Note that the perfect reconstruction in