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Principles of time–frequency feature extraction for change detection in non-stationary signals: Applications to newborn EEG abnormality detection

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ABSTRACT

This paper considers the general problem of detecting change in non-stationary signals using features observed in the time–frequency (t,f) domain, obtained using a class of quadratic time–frequency distributions (QTFDs). The focus of this study is to propose a methodology to define new (t,f) features by extending time-only and frequency-only features to the joint (t,f) domain for detecting changes in non-stationary signals. The (t,f) features are used as a representative subset characterizing the status of the observed non-stationary signal. Change in the signal is then reflected as a change in the (t,f) features. This (t,f) approach is applied to the problem of detecting abnormal brain activity in newborns (e.g. seizure) using measurements of the EEG for diagnosis and prognosis. In addition, a pre-processing stage for detecting artifacts in EEG signals for signal enhancement is studied and implemented separately. Overall results indicate that, in general, the (t,f) approach results in an improved performance in detecting artifacts and seizures in newborn EEG signals as compared to time-only or frequency-only features.

1. Introduction

1.1. Change detection in non-stationary signals

Change detection in signals is the process of identifying differences in the state of an object or phenomenon by observing the signal generated by the process at different times. It has attracted widespread interest due to a large number of applications in diverse disciplines, including medical diagnosis [1,2].

The goal of this study is to propose and test new features that can be used to detect changes in non-stationary signals that appear because of transition of an object from a normal state to an abnormal state or from one abnormal state to another abnormal state. For example, the appearance of seizure in EEG signals is a transition from a normal state to an abnormal state that can result in death or long term handicap. For applications involving non-stationary signals for which the spectral characteristics change with time, time–frequency (t,f) methods have proved a valuable tool based on their ability to highlight and describe such time-varying characteristics [1]. For such signals, time–frequency distributions (TFDs) allow greater insight into the nature of the information carried by the signal. In particular, TFD's ability to show how the energy of the signal is distributed over the 2D (t,f) domain helps identify important features such as the number of signal components, rate of change, and regions of energy concentration. In general, such information cannot be obtained directly from signals representations in time or frequency domains and therefore it is desired to test the hypothesis that (t,f) methods should allow for more accurate change detection in non-stationary signals. For these reasons, this paper aims to present (t,f) features that are extracted from the TFD of a signal and exploit the additional information provided by signal variations in terms of non-stationarities observed in the (t,f) domain. Such (t,f) features can therefore be considered suitable for monitoring and change detection in non-stationary signals.

1.2. Paper contributions and organization

The main technical novelties of this study are three-fold: first, it introduces new (t,f)-based features suitable for change detection in non-stationary signals. Second, it presents a methodology for extending time-domain (t-domain) and frequency-domain (f-domain) features to the joint (t,f) domain. Third, it uses the

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introduced features to detect changes in EEG signals such as those caused by the presence of artifacts and brain abnormal brain activities.

Without loss of generality, this paper considers an illustrative application on a specific biomedical signal, namely, the newborn electroencephalography (EEG), and presents methodologies for detecting changes in the internal structure of signals as well as changes caused by external corrupting artifacts. As the signal characteristics vary in the transition from normal EEG to abnormal EEG, change detection techniques can be applied to newborn EEG signals for automatic diagnosis of abnormal brain activities and for signal enhancement. Traditional methods for detecting changes in EEG signals mostly concentrate on visual inspection which is a laborious and time-consuming task especially in the case of long recordings [1]. It also requires skilled interpreters; i.e. a neurophysiologist, who could be prone to subjective judgment and error that can result in serious consequences such as death or long term handicap. This paper tests the 2 point hypothesis that (a) TFDs are well-adapted for detecting variations such as EEG abnormalities [1,3] using a combined (t,f) pattern recognition and machine learning approach, and (b) that an improved performance can be obtained when we replace t-domain or f-domain features by their corresponding extended (t,f) features.

The design of an automatic abnormality pattern recognition system requires defining representations that are suitable to show these abnormality patterns in a clear way using a range of features, as well as allow feature extraction and selection. For the case of detection of newborn EEG abnormalities, the results in this paper confirm that TFDs and (t,f) based features can result in a reliable and accurate recognition system which is an improvement upon time-only or frequency-only features. A receiver operating characteristics (ROC) analysis is selected as a performance metric to evaluate the performance of each (t,f) feature when used to detect changes in newborn EEG signals. A comparison is also made between the performance of the (t,f) features extracted from different quadratic TFDs (QTFDs) including the extended modified B-distribution (EMBD) [1,4]. The results of applying those features to data sets of newborn EEG signals marked for seizures reveal that the selected (t,f) features consistently result in a high degree of discrimination between different states in the signals. Further, a baseline comparison between time-only or frequency-only features and their translated extended (t,f) features shows that the latter can improve the detection performance, thus justifying the (t,f) approach selected in this paper and verifying the research hypothesis.

The rest of the paper is organized as follows. Section 2 reviews relevant background about EEG signals. In Section 3, methodologies for automatic detection of artifacts and seizures in newborn EEG signals are described, including the key formulation of the (t,f) features. The results of applying such methodology to real data are provided in Section 4 and Section 5 concludes.

2. Newborn EEG signals

2.1. Newborn EEG seizures

EEG is the recording of brain electrical activities measured by electrodes placed on the scalp (see Fig. 1). As EEG signals can be collected non-invasively and most brain related abnormalities show clear abnormal variations on EEG recordings, they are widely used for assessment of brain diseases and disorders [1]. Previous studies have shown that background EEG activities often provide objective evidence of the degree and severity of the underlying cause and that abnormal activities are correlated with adverse physical and/or neurological outcomes. Specifically in newborns, the presence of seizures carry with them a high probability of poor neurodevelopmental outcome or even death [5]. Newborn EEG seizures exhibit variations in voltage, duration, frequency content, and waveform shape (see illustrative example in Fig. 2).

Fig. 1. Recording newborn EEG signals.

Techniques for automatic seizure detection using EEG signals include the use of time-domain statistics [6], spectral features [7], combination of time–only (t-only) with frequency-only (f-only) features [8], autoregressive (AR) modeling [9,10], and non-linear analysis [11]. The above are limited in their performance as they do not take into account the property of non-stationarity, and instead they use the assumption of stationarity. Previous studies have shown that (t,f) based techniques which account for non-stationarities have superior performance for detecting seizures in newborn EEG signals [12–14]. These findings motivated the need to define and assess the performance of the (t,f) features presented in Section 3.3.3 for automatic seizure detection in newborn EEG.

2.2. Newborn EEG artifact detection

A major problem with the implementation of a fully automatic EEG diagnostic system in neonatal intensive care unit (NICU) is the contamination of the EEG by various artifacts in sections of the EEG recording (see illustrative example in Fig. 3). These artifacts impede automated neonatal EEG analyses thereby limiting their usefulness to the neonatologist in the NICU. Any automated system that is considered for use in the NICU needs to have a pre-processing stage to detect artifacts.

This study is a contribution towards an overall plan to develop such an automated EEG diagnostics system. In order to develop and deploy such a system in NICUs, there is a need to design the pre-processing artifact detection system as a switch that passes artifact free signal segments to the automated EEG signal classification system but redirects artifact contaminated EEG segments to an artifact removal system; the objective being to ensure that artifact free segments are not distorted by unnecessary filtering that can degrade useful information. The overall block diagram is shown in Fig. 4. As previously mentioned, a major difficulty with all of the above objectives is that EEG signals are non-stationary [1], with spectral characteristics that change with time, and, therefore require a (t,f) approach, as detailed in Section 3. Note that the 2 stages of artifact removal and abnormality identification are shown only for context, as they are not included in the scope of this contribution.

A large number of methods for artifact detection have been developed in the case of adult EEG signals [15–18], but these methods cannot be applied to neonatal EEG signals as the latter have much more diversity in their patterns [19]. Previous studies used features based on spectral, temporal, statistical properties and wavelet decomposition to discriminate artifacts from other