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Automatic signal abnormality detection using time-frequency features and machine learning: A newborn EEG seizure case study

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ABSTRACT

Time-frequency (TF) based machine learning methodologies can improve the design of classification systems for non-stationary signals. Using selected TF distributions (TFDs), TF feature extraction is performed on multi-channel recordings using channel fusion and feature fusion approaches. Following the findings of previous studies, a TF feature set is defined to include three complementary categories: signal related features, statistical features and image features. Multi-class strategies are then used to improve the classification algorithm robustness to artifacts. The optimal subset of TF features is selected using the wrapper method with sequential forward feature selection (SFFS). In addition, a new proposed measure for TF feature selection is shown to improve the sensitivity of the classifier (while slightly reducing total accuracy and specificity). As an illustration, the TF approach is applied to the design of a system for detection of seizure activity in real newborn EEG signals. Experimental results indicate that: (1) The compact kernel distribution (CKD) outperforms other TFDs in classification accuracy; (2) a feature fusion strategy gives better classification than a channel fusion strategy; e.g. using all TF features, the CKD achieves a classification accuracy of 82% with feature fusion, which is 4% more than the channel fusion approach; (3) the SFFS wrapper feature selection method improves the classification performance for all TFDs; e.g. total accuracy is improved by 4.6%; (4) the multi-class strategy improves the seizure detection accuracy in the presence of artifacts; e.g. a total accuracy of 86.61% with one vs. one multi-class approach is achieved i.e. 0.91% more than the binary classification approach. The results obtained on a large practical real data set confirm the improved performance capability of TF features for knowledge based systems.

1. Introduction

This study is intended to be applicable to all types of non-stationary signals regardless of their nature or origin, but without loss of generality we will consider EEG signals for illustration purposes. The EEG is a well-known non-invasive test used in a wide range of applications such as epilepsy studies. It consists of several electrodes that are placed on a patient's scalp to record electrical activity from the brain. These EEG signals, like most real signals, have been shown to possess non-stationary characteristics [1]. But the two classical signal representations i.e. time-domain representation and frequency-domain representation, in both cases, treat the signal as stationary, which is a rough simplification. These conventional representations (in time or frequency) have been shown to be inadequate for non-stationary signals, and instead joint time-frequency (t, f) domain representations were found to be better adapted to process such signals. In particular, there are features that represent subtle change which may not be visible in the time domain or frequency domain, but are clearly visible in the joint time-frequency domain (see Appendix A for two illustrative examples). Recent studies have also found that time-frequency (TF) signal classification using such (t, f) domain features can outperform conventional time-only or frequency-only signal classification approaches as they allow more discriminative information to be extracted from the signal [1]. Fig. 1 illustrates the TF feature extraction methodologies and approaches that form the basis of this study.

There are two basic TF approaches to signal classification [1,2].

(1) Visual analysis for manual classification [3]: for this approach to be effective, it is important to select a TFD that offers high resolution to avoid blurring or mixing up unrelated components [1].

(2) Automated classification using template matching or machine learning approach: to detect abnormal changes in a signal as soon as it occurs without human intervention, an automated implementation is necessary. For a TF approach, one can use: (a)

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0950-7051/

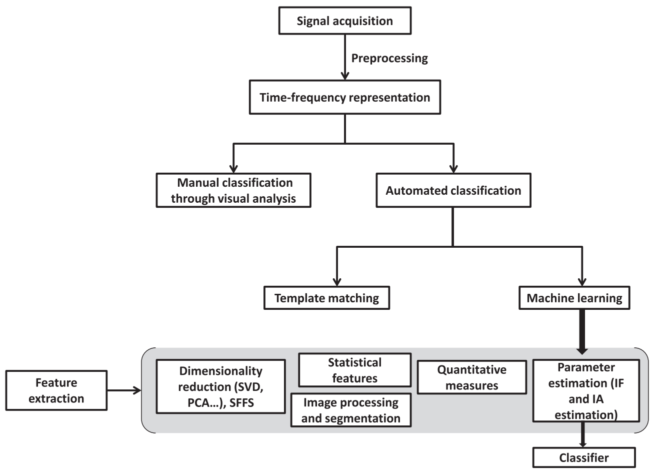

Fig. 1. Time-frequency approaches to signal classification. *(The feature extraction stage uses a variety of advanced methods such as dimensionality reduction, statistical features, image processing, quantitative measures and IF estimation features).*

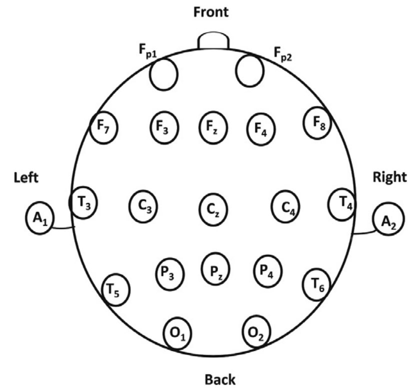

Fig. 2. The 10–20 EEG system. Each point on this figure to the left indicates a possible electrode position. Each site has a letter (to identify the lobe) and a number or another letter to identify the hemisphere location. The letters F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal and Occipital. (Note that there is no "central lobe", but this is just used for identification purposes.) Even numbers (2,4,6,8) refer to the right hemisphere and odd numbers (1,3,5,7) refer to the left hemisphere. The z refers to an electrode placed on the midline.)

template matching, where a TFD of a given signal is compared with the TF templates of predefined patterns using methods such as matched filtering [4, Section 12.5] and distance measures [5]. Another approach, (b) machine learning, which classifies signals in three key stages i.e.: (i) transforming a signal into the time-frequency ((t, f)) domain using TFDs, (ii) extracting TF features from TFDs and (iii) training of a classifier; the critical step being the extraction of highly discriminatory features as one cannot use all TF features due to two constraints: one is the large number of redundant and irrelevant features (e.g. TFDs are sparse and therefore most (t, f) points have zero or negligible values [6]); the second constraint is to have more data requirements for training: TFDs have more samples than the original signal and increase the dimensionality of the problem [5].

Such TF Features can be extracted using several techniques:

(1) Dimensionality reduction approaches such as Singular Value Decomposition (SVD) [1], Principal Component Analysis (PCA) or Independent Component Analysis (ICA) [7], and non-negative matrix decomposition [2]. An alternative is to select specific (t, f) points using the information theoretic relevance measure [8] or sequential forward feature selection (SFFS) algorithm [9].

(2) TF regions that have maximum discriminatory information can be used as features, using some prior information or quantitative measures [10].

(3) TF energy concentration measures such as TF flatness can be used to discriminate signals whose energy is concentrated in the (t, f) domain from signals whose energy is spread in the (t, f) domain [1]. E.g. for EEG signals, seizure activity is sparse in the (t, f) domain, while the background is not [4, Section 16.3].

(4) Image features: Consider TFDs as images and use image processing methods to extract texture information [11]. Signal components may appear as pockets of energy concentration in the (t, f) domain. Thus, features that characterize the shapes of these pockets may be used to discriminate one class of signals from another [1,12], depending on the application.

(5) Using an AM-FM model [13, part I] with parameters such as instantaneous frequency (IF), instantaneous amplitude (IA), and total number of components extracted from TFDs [1,14]. An alternative for feature extraction is to separate signal components and then extract features from the separated components [15–17].

(6) Consider 2D TFDs as probability density functions (pdfs) so that the TFDs of normal and abnormal signals have different distributions. Then, standard TFD statistics such as mean, variance, skewness, kurtosis, and centroids can be used as features [18,19].

This paper focuses on the formulation and extraction of TF features from high resolution TFDs and their use in classification via machine learning approaches [1]. The application context is a large database consisting of 36 newborn patients and 20 channels recording per patient, with an average duration of 27 min. The study addresses several key issues that arise when implementing TF machine learning algorithms for detecting abnormalities such as: (1) which set of TF features is most discriminatory? (2) Which TFD gives the best classification performance? (3) How best to extract features from multi-channel recordings without increasing the dimensionality problem? (4) Can multi-class signal classification improve the performance of TF abnormality detection algorithms? More generally, the main objective is to define the best strategy to maximize the rate of detection of abnormalities in a large real database of recorded signals using TF features.

The rest of the paper is organized as follows. Section 2.1 presents the multi-channel EEG database used to illustrate the study methodologies. Section 2.2 describes the selection of state-of-the-art high resolution quadratic TFDs for EEG signal analysis and Section 2.3 compares them. Section 2.4 discusses the selection of TF features. Section 2.5 outlines the approaches for extracting and selecting features from multi-channel recordings. The proposed TF machine learning methodology is applied to detect abnormalities in EEG signals in Section 3. Finally, Section 4 concludes the study.

2. Material and methods

2.1. Database description

This study uses a large neonatal EEG database comprising 20-channel continuous EEG (cEEG) signals. The data were recorded according to the 10–20 international electrode placement system using bipolar montage, using a Medelec Profile system (Medelec, Oxford Instruments, Old Woking, UK) and sampled at $fs = 256Hz$. The channels are marked as: F_4-T_4, T_4-T_6, T_6-O_2, F_3-T_3, T_3-T_5, T_5-O_1, F_4-C_4, C_4-P_4, P_4-O_2, F_3-C_3, C_3-P_3, P_3-O_1, T_4-C_4, C_4-C_Z, C_Z-C_3, C_3-T_3, T_6-P_4, P_4-P_Z, P_Z-P_3, and P_3-T_5 (see Fig. 2). The EEG signals were pre-filtered using (1) an analog band pass filter with [0.5–70]Hz to avoid very low frequency noise and (2) an additional 50Hz notch filter to remove power line interferences. An anti-aliasing filter, i.e. a low pass-filter with cut-off frequency at 16 Hz is applied on the pre-processed signals and then the data are downsampled to 32Hz to reduce the computational load. This data was acquired from