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Algorithm based on the short-term Rényi entropy and IF estimation for noisy EEG signals analysis

Jonatan Lerga[a,*], Nicoletta Saulig[b], Vladimir Mozetič[c]

[a] University of Rijeka, Faculty of Engineering, Department of Computer Engineering, Vukovarska 58, HR-51000 Rijeka, Croatia
[b] University of Rijeka, Faculty of Engineering, Department of Automation and Electronics, Vukovarska 58, HR-51000 Rijeka, Croatia
[c] University of Rijeka, Faculty of Medicine, Ulica Brace Branchetta 20/1, HR-51000 Rijeka, Croatia

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A B S T R A C T

Stochastic electroencephalogram (EEG) signals are known to be nonstationary and often multicomponential. Detecting and extracting their components may help clinicians to localize brain neurological dysfunctionalities for patients with motor control disorders due to the fact that movement-related cortical activities are reflected in spectral EEG changes. A new algorithm for EEG signal components detection from its time-frequency distribution (TFD) has been proposed in this paper. The algorithm utilizes the modification of the Rényi entropy-based technique for number of components estimation, called short-term Rényi entropy (STRE), and upgraded by an iterative algorithm which was shown to enhance existing approaches. Combined with instantaneous frequency (IF) estimation, the proposed method was applied to EEG signal analysis both in noise-free and noisy environments for limb movements EEG signals, and was shown to be an efficient technique providing spectral description of brain activities at each electrode location up to moderate additive noise levels. Furthermore, the obtained information concerning the number of EEG signal components and their IFs show potentials to enhance diagnostics and treatment of neurological disorders for patients with motor control illnesses.

1. Introduction

Most of biomedical signals, including electroencephalogram (EEG) records, are nonstationary and often multicomponental stochastic. Such signals are widely used in clinic diagnostics to detect illnesses and abnormalities in functioning of the central nervous system. Those nonstationarities often contain significant information concerning underlying clinical pathophysiological processes [1–6]. The traditional approach to their analysis includes empirical visual pattern recognition of pathology features done by medical experts. However, more recent approaches complement the traditional approach by computer-aided signal processing methods resulting in a more accurate and objective EEG analysis technique capable to quantify and categorize EEG signal features [7–12].

Some of the first computer-aided quantitative approaches to analyzing EEG time-series utilized the Fourier transform for the spectral analysis, followed by applying topographies mapping, compressed spectral arrays, as well as nonlinear dynamic methods [13,14]. The Fourier transform of EEG signals results in their spectral decomposition enabling quantification of their features in the frequency domain. However, being a stationary time-series analysis tool, the Fourier transform does not render significant information concerning spectral peak timing [15]. Furthermore, in the case of the EEG signals being obscured by the additive noise, traditional visual inspection of the EEG signals, as well as classical mathematical tools, such as the Fourier transform, exhibit strong limitations [16]. Also, filtering the EEG signal in order to suppress additive noise using the standard methods in frequency domain may be applied if the noise is located and limited only to a specific pre-known frequency band. However, this is not the case in most of the EEG signal processing applications. Furthermore, standard frequency-domain filtering is well-known to be highly dependant to the proper filter parameters selection and the chosen filter design, as well as to cause unavoidable effects to morphology of low frequencies when filtering the high ones (significant EEG spectral information is low-frequency in the range of 1–20 Hz) [16,17].

Therefore, the EEG signals analysis requires utilizing computationally more demanding tools suitable for nonstationary signal analysis both in noise and noise-free environments, such as joint time-frequency processing techniques, i.e. time-frequency distributions (TFDs) [1]. TFDs provide a two-dimensional representation of the EEG signal frequency content varying over time, and thus enable

* Corresponding author.
E-mail addresses: jlerga@riteh.hr (J. Lerga), nsaulig@riteh.hr (N. Saulig), vladimir.mozetic@ri.t-com.hr (V. Mozetič).

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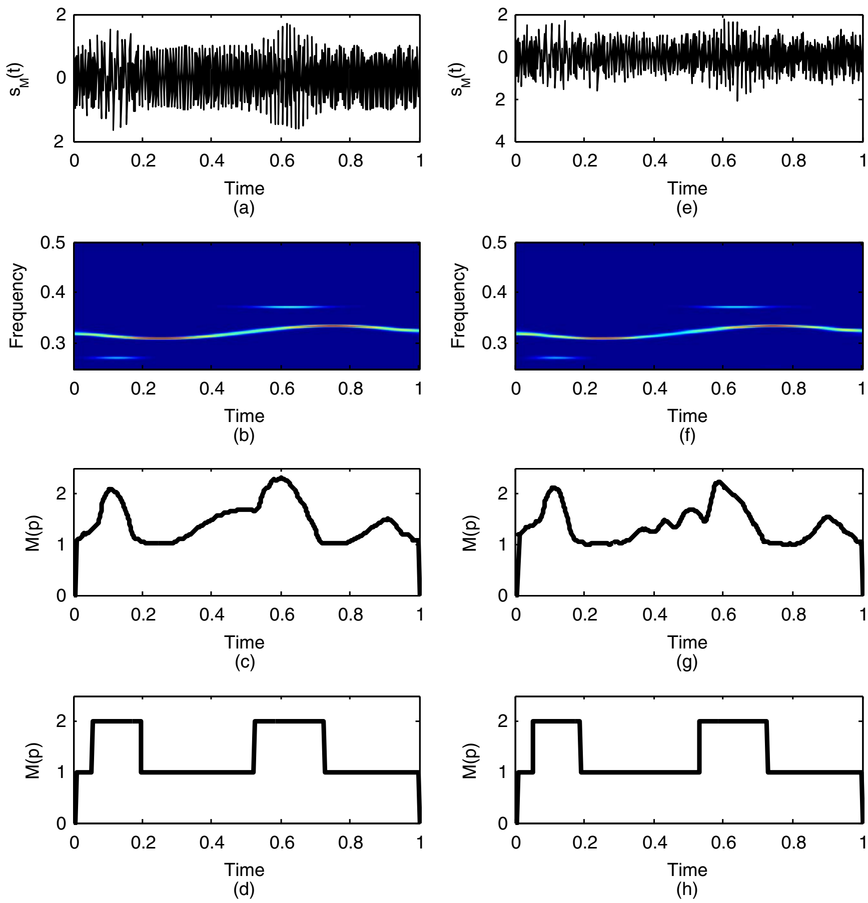

Fig. 1. An example of the number of signal components estimation using the STRE with and without additive noise. (a) Noise-free signal $s_M(t)$ time-series. (b) Noise-free signal time-frequency representation (spectrogram). (c) Noise-free signal local number of components $M(p)$ obtained by the non-iterative algorithm [39]. (d) Noise-free signal local number of components $M(p)$ obtained by the iterative algorithm [40]. (a) Noisy signal $s_M(t)$ time-series (SNR=10). (b) Noisy signal time-frequency representation (spectrogram) (SNR=10). (c) Noisy signal local number of components $M(p)$ obtained by the non-iterative algorithm (SNR=10) [39]. (d) Noisy signal local number of components $M(p)$ obtained by the iterative algorithm (SNR=10) [40].

detection of the number of signals components and their frequency range [1].

Exploiting important information packed in the EEG signal spectral energy variations, observed in joint-time frequency domain, has led to numerous methods for various features extraction from EEG signals and their classification [18–25]. TFDs also allow the estimation of signal instantaneous frequency (IF) (its variation in frequency with time), making them a natural approach for the EEG signal analysis and classification [26–31]. A time-frequency based approach upgraded by the modification of the Rényi entropy, called short-term Rényi entropy (STRE), for the EEG signal complexity detection has been proposed in the paper. The STRE was upgraded by the component extraction procedure that allowes an accurate IF estimation, and applied to EEG data records of a set of the right and left hand and leg movements captured by the scalp electrodes (both noisy and noise-free for various signal-to-noise ratios (SNRs)). As shown in the paper, the method was proved to be an efficient tool for detecting and analyzing neurological brain activities, and also robust to noise for up to moderate noise levels.

The paper is structured as follows: Section 2 gives an introduction to signal time-frequency analysis followed by the definition of signal complexity based on Rényi entropy of TFDs, presented in Section 3. The component extraction procedure and the IF estimation are elaborated in Section 4. A comprehensive discussion of experimental results is given in Section 5. Conclusion is found the Section 6.

2. Signal representation in the time-frequency domain

TFDs are used in order to introduce multi-dimensionality in the signal representation. In fact, TFDs are two variable functions, $C_z(t, f)$, that show how the frequency contents of signals changes in time [32–34]. Signal representations in the time-frequency domain find wide applications in various fields of engineering, including biomedicine, seismology, radar/sonar analysis, etc. Representing a signal in the time-frequency domain results in several advantages over the classic signal representations, such as the ability of identification of signal features (time and frequency variations) and number of signal components, as well as separation of signal components from the background noise.

In the following subsections some of the widely used TFDs are introduced, and their basic characteristics shortly summarized.

2.1. The spectrogram

The spectrogram, a simply formulated TFD, obtained by squaring the magnitude of the short-time Fourier transform (STFT) of signal $z(t)$ [32–34]

$$S_z(t, f) = |\mathrm{STFT}_z(t, f)|^2 = =|\int_{-\infty}^{\infty} z(\tau)w(t-\tau)e^{-j2\pi f\tau}d\tau|^2, \tag{1}$$

where $w(t)$ is smoothing window, and t and f are time and frequency, respectively. Unlike the STFT, obtained by limiting the analyzed signal with the window function $w(t)$, and hence being a linear time-frequency transformation, the spectrogram introduces nonlinearity in the time-frequency representation. In fact, the spectrogram of the sum of two signals, does not correspond to the sum of the spectrograms of the two signals [35]. However, this limitation of the spectrogram