Eur. Phys. J. Spec. Top. (2023) 232:605–608
https://doi.org/10.1140/epjs/s11734-022-00711-6

THE EUROPEAN PHYSICAL JOURNAL SPECIAL TOPICS

Regular Article

Extended detrended cross-correlation analysis of electrocorticograms

A. A. Koronovskii Jr.[1], I. A. Blokhina[1], O. N. Pavlova[1], O. V. Semyachkina-Glushkovskaya[1], and A. N. Pavlov[1,2,a]

[1] Saratov State University, Astrakhanskaya Str. 83, 410012 Saratov, Russia
[2] Regional Scientific and Educational Mathematical Center "Mathematics of Future Technologies", 410012 Saratov, Russia

Received 1 June 2022 / Accepted 26 October 2022 / Published online 7 November 2022

Abstract An extension of detrended cross-correlation analysis (DCCA) for processing interrelated nonstationary time series is considered using electrocorticograms (ECoG) in mice as an example. The application of this approach to the case of wakefulness and 1-day sleep deprivation is discussed. It is shown that, although the DCCA method enables to detect changes in ECoG caused by sleep deprivation, its extension improves the separation of the dynamics and may reduce the amount of data required to identify the state of the brain electrical activity.

1 Introduction

Cross-correlation analysis is widely used to quantify the cooperative dynamics of interacting units in various complex systems and, in particular, in network physiology [1–3]. Despite the fact that this tool provides an informative characterization of the dynamical features of such systems, physiological time series are often nonstationary, which limits the applicability of the classical cross-correlation function. A possible way to get around this limitation is to use detrending procedures, supposing that nonstationarity effects are low-frequency, and pre-filtering enables to exclude the nonstationary part of the data. However, there is another limitation of the traditional approach, namely, a decrease in the correlation function for random data sets, accompanied by a significant growth in the error of quantifying long-range correlations.

Detrended fluctuation analysis (DFA) [4, 5] is an alternative correlation analysis technique that improves the characterization of experimental datasets in terms of long-range correlations due to two features. On the one hand, DFA includes a detrending procedure as an intermediate stage of the computational algorithm. On the other hand, it deals with signal profiles and introduces a rising function, the slope of which is a numerical measure of the correlations in the datasets. Although detrending is involved, this does not mean that signal analysis can be performed without any data preprocessing [6–8]. The presence of various types of nonstationarity can lead to misinterpretation of the results obtained, and knowledge of such effects is an important issue [9]. The more stationary the process is considered within the framework of the DFA, the less problems with incorrect interpretations arise. Therefore, this method also requires pre-processing of the signal.

There is a modification of DFA to study cooperative dynamics based on two time series, namely detrended cross-correlation analysis (DCCA) [10, 11]. Both methods, DFA and DCCA, are applied under the assumption of a sufficiently homogeneous structure of the signals. They average fluctuations of signal profiles around local trends without focusing on the distributions of these fluctuations over different parts of the datasets. Often, the fluctuations in some segments can significantly outperform those in other parts of the signals, and taking into account such distributions provide important information about the dynamics under study.

Recently, we proposed an extended DFA (EDFA) that deals with two scaling exponents [12]. The first exponent is the quantity estimated within the original DFA approach, while the second exponent describes the inhomogeneous structure of the signal profiles, i.e., the impact of nonstationarity. We also modified this approach for the case of two signals within the extended DCCA (EDCCA) and showed how this modification quantifies the nonstationary entrainment phenomena in the dynamics of interacting systems with chaotic oscillations [13]. In fact, we proposed to consider scaling

[a] e-mail: pavlov.alexeyn@gmail.com (corresponding author)

features for the distributions of local fluctuations as an independent measure of the dynamics. The advantages of this approach for the case of EDFA were discussed in [14, 15].

The extended DCCA is less explored for experimental data. To show its effectiveness for diagnostic studies, here we apply this method to ECoG signals in mice using sleep deprivation experiments. Sleep plays an important role in maintaining the health of the central nervous system [16, 17] and affects many processes in the organism [18]. It is important for attention, learning, decision making, etc. [19, 20]. Prolonged wakefulness (more than 10 days) causes various cognitive impairments [21]. Brief wakefulness is less crucial; however, it can also cause some changes in the electrical activity of the brain, which can be detected and identified from electrocorticograms (ECoG). In this work, we analyze two-channel ECoGs in mice for two conditions: the background dynamics of awake animals and ECoG after 1-day sleep deprivation (SD), and show the possibilities of EDCCA in characterizing these conditions. The paper is organized as follows. Section 2 contains information on the proposed extension of the DCCA and a brief description of the experimental procedures. Section 3 describes the main results of cross-correlation analysis of ECoGs in mice together with their discussion. Concluding remarks are given in Sect. 4.

2 Methods and experiments

2.1 Extended detrended cross-correlation analysis

Detrended cross-correlation analysis (DCCA) was proposed as a modification of DFA for the case of two interrelated time series $\{x_i\}$ and $\{\tilde{x}_i\}$, $i = 1, \ldots, N$, produced by time-varying dynamics of complex systems. The method consists of the following steps:

(1) Construction of profiles

$$y_k = \sum_{i=1}^{k} x_i, \quad \tilde{y}_k = \sum_{i=1}^{k} \tilde{x}_i. \tag{1}$$

(2) Dividing the profiles into $N - n$ overlapping segments of $n + 1$ samples and estimating the local (in the simplest case linear) trends z_k and $\tilde{z}_k$ within each segment ($i \le k \le i + n$).

(3) Computation of the cross-correlation

$$f^2_{\mathrm{DCCA}}(n,i) = \frac{1}{n-1} \sum_{k=i}^{i+n} (y_k - z_k)(\tilde{y}_k - \tilde{z}_k). \tag{2}$$

(4) Averaging over all segments

$$F^2_{\mathrm{DCCA}}(n) = \frac{1}{N-n} \sum_{i=1}^{N-n} f^2_{DCCA}(n,i). \tag{3}$$

The estimated dependence is usually a power-law function

$$F_{\mathrm{DCCA}}(n) \sim n^{\lambda}, \tag{4}$$

where λ is the scaling exponent.

The extended DCCA proposed in our recent paper [13] introduces an additional measure of the distributions of local fluctuations of the profiles around the trends by computing these local fluctuations

$$\begin{aligned} F_{\mathrm{loc}}(n,i) &= \frac{1}{n-1} \sum_{k=i}^{i+n} (y_k - z_k), \\ \tilde{F}_{\mathrm{loc}}(n,i) &= \frac{1}{n-1} \sum_{k=i}^{i+n} (\tilde{y}_k - \tilde{z}_k), \end{aligned} \tag{5}$$

estimation of their standard deviations $\sigma(F_{\mathrm{loc}}(n))$, $\sigma(\tilde{F}_{\mathrm{loc}}(n))$ and building the function

$$\mathrm{d}F_{\mathrm{EDCCA}}(n) = \sqrt{\sigma(F_{\mathrm{loc}}(n)) * \sigma\left(\tilde{F}_{\mathrm{loc}}(n)\right)} \sim n^{\mu}. \tag{6}$$

This function takes small values for stationary processes with similar local fluctuations in various segments. In the case of strong differences between local fluctuations, $\mathrm{d}F_{\mathrm{EDCCA}}(n)$ increases. The application of this approach for the quantitative evaluation of chaotic synchronization in coupled systems with self-sustained oscillations and a more detailed description of the method are given in [13].

2.2 Experiments

Experimental procedures were carried out on 10 male mice according to the Guide for the Care and Use of Laboratory Animals and protocols approved by the Local Bioethics Commission at the Saratov State University. Two-channel cortical ECoGs (Pinnacle Technology, Taiwan) were acquired by means of two silver electrodes with a tip diameter of 2–3 µm, which were placed at a depth of 150 µm in coordinates (L: 2.5 mm, D: 2 mm) from the bregma on both sides of the midline. For this, anesthesia with 2% isoflurane at a rate of 1 L/min N_2O/O_2—70:30 was applied. Small burr holes were drilled in the head plate to insert ECoG wire leads and fix them with dental acrylic. The experiments were started 10 days after the surgery.

Sleep deprivation was performed in accordance with the approach [22] by bringing new objects and sounds into the room [23], and observing that the animals study these objects. It was held from 20:00 to 8:00. ECoG signals were acquired before and after sleep deprivation for 4 h with a sampling rate of 2 kHz. Artifact removal was performed before signal processing.

3 Results and discussion

At the first stage of signal processing, we compared the inter-state differences in ECoG records in individual subjects. Our analysis showed that these states can be recognized based on the dependencies $\lg F_{\text{DCCA}}(\lg n)$ of the DCCA approach [10] and $\lg \mathrm{d}F_{\text{EDCCA}}(\lg n)$ of the extended method [13]. An example demonstrating the differences in $\lg F_{\text{DCCA}}(\lg n)$ and the corresponding values of the λ-exponent is shown in Fig. 1. According to this figure, stronger distinctions are associated with the region of long-range correlations, i.e., large values of $\lg n$. When these values decrease, the slopes of the dependencies approach each other. This is consistent with many studies of physiological datasets where long-range power-law correlations provided an informative characterization of the dynamics of physiological systems, e.g., [24–26]. Consideration of the distribution of $F_{\text{loc}}(n)$ within the framework of the extended method (EDCCA) provides similar distinctions (Fig. 2), although the difference in the slopes quantified by the μ-exponent becomes more noticeable.

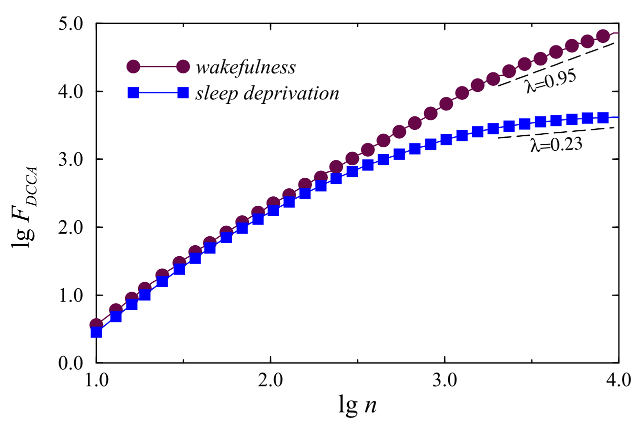

Fig. 1 An example of the dependencies $\lg F_{\text{DCCA}}(\lg n)$ for the states of wakefulness and sleep deprivation (one mouse)

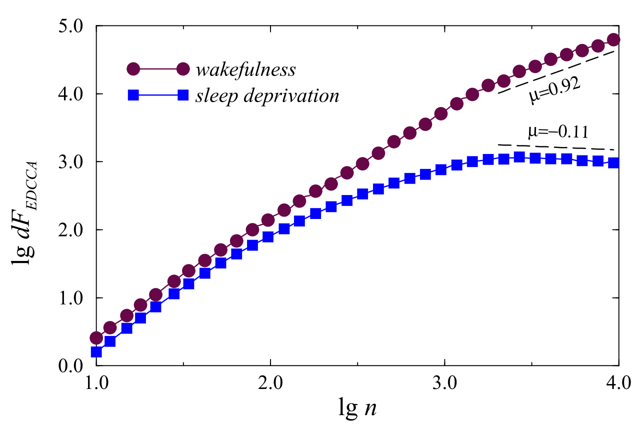

Fig. 2 An example of the dependencies $\lg \mathrm{d}F_{\text{EDCCA}}(\lg n)$ for the states of wakefulness and sleep deprivation (the same mouse as in Fig. 1)

Note that the μ-exponent can take negative values, similar to EDFA [12] and, therefore, the differences can be both quantitative and qualitative. Again, more pronounced distinctions are related to large values of $\lg n$.

After such a preliminary analysis using visual control of the dependencies $\lg F_{\text{DCCA}}$ $(\lg n)$, $\lg \mathrm{d}F_{\text{EDCCA}}$ $(\lg n)$ on a double logarithmic plot and numerical measures λ, μ, the states of wakefulness and sleep deprivation for the whole group of mice were compared at the second stage. To provide comparison of different ranges of $\lg n$, we estimated local slopes and computed t-values of the Student's t-test. Figure 3 shows the results of statistical analysis for both λ and μ exponents. It gives an opportunity to point out several important circumstances. First, both scaling exponents enable characterization of inter-state transitions in a wide range of $\lg n$. The dashed lines indicate the critical value t_c related to the significance level $p < 0.05$. Secondly, the EDCCA method provides higher t-values compared to the DCCA approach, i.e., the proposed modification of the detrended cross-correlation analysis seems to be useful for improving the diagnostic capabilities of DCCA. Thirdly, the EDCCA method enables inter-state characterization over a wider range of scales ($\lg n > 2.3$ compared to $\lg n > 2.6$), therefore, a reduced amount of data can be used for analysis and separation between two physiological states under consideration. For the example discussed in our study, this reduction is not crucial, because the necessary length of data sets is rather small compared to the total duration of the experimental records. For other studies with faster changes in functional conditions, this feature of the EDCCA method becomes more important.

Thus, the performed study not only showed the possibility of reliably characterizing the effects of sleep deprivation, but also demonstrated the advantages and potential of the extended version of the detrended cross-correlation analysis.

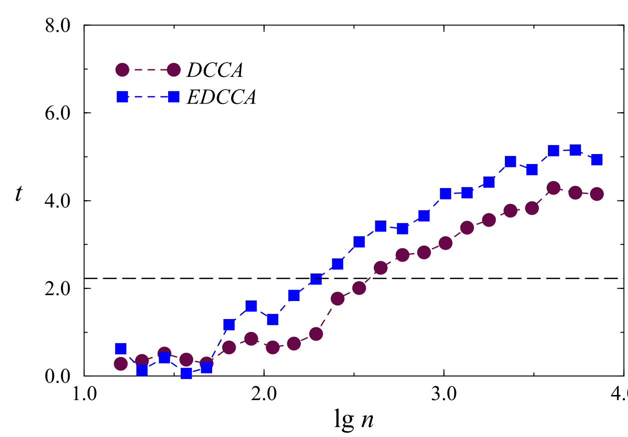

Fig. 3 The dependencies of t-values of the Student's t-test on the scale (lg n) showing differences between the states of wakefulness and sleep deprivation in a group of mice characterized by λ and μ exponents, respectively. Dashed line indicates the critical value t_c related to the significance level $p < 0.05$

4 Conclusion

Time-varying dynamics of complex systems, leading to nonstationary behavior of the resulting time series, limits the application of traditional methods for signal processing, such as the cross-correlation function. In order to avoid misinterpretation of data analysis results caused by various types of nonstationary behavior, detrended cross-correlation analysis was proposed and tested in several studies, as well as its extension—the EDCCA approach. In the current work, we considered the application of EDCCA to characterize changes in ECoG signals caused by 1-day sleep deprivation in mice. The obtained results indicate that while the DCCA method allows identification of wakefulness and sleep deprivation states, its extension can improve the quantification of the effects of sleep deprivation. The EDCCA method has been shown to be a useful extension of the detrended cross-correlation analysis for physiological time series.

Funding This work was supported by the Russian Science Foundation (Agreement 22-22-00065), https://rscf.ru/en/project/22-22-00065/.

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