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Age-related distinctions in cooperative dynamics of brain rhythms during sleep-wake transitions

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Abstract A promising topic in the study of brain rhythms is their consideration within the framework of the phenomenon of network interactions, when attention is focused not on individual EEG waves, i.e. the electrical activity of the brain in the particular frequency bands, but on their continuous coordination and varying cross-communications with changes in the functional state of the organism. In this paper, we discuss the age aspect in the cooperative dynamics of EEG rhythms. We report significant differences in pairwise rhythm interactions for groups of subjects of different ages and show that, regardless of the type of correlations between individual brain waves, they increase with age, which is manifested in the state of wakefulness. The corresponding differences are less pronounced during deep sleep.

1 Introduction

Analysis of the relationship between certain brain rhythms and distinct states of the body is a traditional neurophysiological approach. Over the past decades, many facts have been accumulated confirming change in the characteristics of various rhythms (primarily amplitude) with a change in the functional state [1–4]. However, along with the study of individual rhythms, the issue of their coordination, i.e., the simultaneous and coordinated response in the characteristics of several rhythms, is actively discussed. Examples of such coordination have been demonstrated for some pairs of EEG waves when studying perception, consciousness, cognitive functions and working memory [5–8]. Along with the consideration of pairwise interactions, the concept of rhythm coordination as a network, discussed in the works [9, 10], is of interest. The authors of these studies proposed a conceptually different way to the analysis of physiological states and functions, based on dynamic network interactions between various rhythms of the brain. They showed [9] that distinct coupling form and strengths are typical for different pairs of rhythms, and established characteristic positive correlations, anti-correlations and mixed correlations. It was also demonstrated that the type of correlations (for some pairs) can change during transitions between physiological states [10].

Based on the concept and methodology proposed in [9, 10], in this paper we focus on an issue that was left out of consideration by the authors of these studies, namely, the age aspect in cooperative dynamics of brain rhythms. Age causes numerous changes in the human body, including the electrical activity of the brain. In addition to the formation of various disorders of brain activity [11–13], healthy aging is also accompanied by a number of significant changes, including decreased cognitive functions, reduced coordination and motor control [14, 15]. In older adults, additional brain areas are recruited during motor activity to overcome structural changes in brain dynamics [16, 17], and the latter represents a kind of compensatory mechanism [18, 19], leading to differences in motor task performance depending on age [20, 21]. Based on the approach of functional brain networks [22, 23] it was shown that network connectivity and topological characteristics are appropriate to reveal the effects of healthy aging [24]. Consideration of pairwise rhythm interactions may provide further insight into the effects of age. In particular, we demonstrate that correlations among brain waves (both positive and anti-correlations) increase with age, and this phenomenon is more pronounced during wakefulness than during sleep stages.

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The paper is organized as follows. Section 2 shortly describes the experimental data and correlation analysis of brain waves based on normalized relative spectral power. Section 3 discusses age-related distinctions in cross-communication of brain rhythms during sleep-wake transitions. Section 4 summarizes the main findings of the research.

2 Methods

2.1 Experimental data

The study was conducted using the SIESTA [25] EEG database that includes recordings of healthy subjects carried out during night-time sleep in various sleep centers of the European Union. The protocols were approved by the local institutional review boards of the laboratories involved. All subjects provided written informed consent. For analysis, 63 multichannel recordings with a sampling rate of 200 Hz (both men and women) were selected, each containing fragments of at least 5 min duration for the following states: wakefulness (W), light sleep (LS), deep sleep (DS), and rapid eye movement (REM) sleep. Three age groups were chosen: (1) up to 40 years, (2) over 40 and up to 60 years, (3) over 60 years. The number of subjects in the groups was 18, 20 and 25, respectively. The analysis was performed using EEG signals from channels O_1 and O_2.

2.2 Relative spectral power

The approach proposed in [9] was used, according to which bandpass filtering of EEG signals was performed in the frequency bands of δ-wave (0.5–3.5 Hz), θ-wave (4.0–7.5 Hz), α-wave (8.0–11.5 Hz), σ-wave (12.0–15.5 Hz), and β-wave (16–19.5 Hz). Frequency gaps of 0.5 Hz were applied for better rhythm separation.

The normalized relative spectral power S was estimated as the ratio of the spectral power for a selected brain wave to the total spectral power in all five bands. This measure was estimated in 2 s moving window and then averaged using 14 s moving window with 1 s resolution [9]. Further analysis of correlations between different brain waves was performed for 30 s segments of the relative spectral power S.

2.3 Correlation analysis

To analyze changes in the cooperative dynamics of brain rhythms during changes in the state of the body (sleep-wake transitions), the Pearson correlation (C) was estimated within segments

$$C = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}}. \tag{1}$$

Here, x_i and y_i are 30 s segments of the normalized relative spectral power of two rhythms, $\bar{x}$ and $\bar{y}$ are mean values. The value of C quantifies the type of correlation between brain waves, ranging from $C = -1$ (the strongest negative correlation or anti-correlation) to uncorrelated dynamics ($C = 0$) and further to $C = 1$ (the strongest positive correlation).

3 Results and discussion

As expected, transitions between wakefulness and different sleep stages lead to changes in the characteristics of brain rhythms, varying the normalized spectral power for each of them. Figure 1 shows examples of the corresponding changes for δ, θ, and α activity. In this example, 5-min fragments of the recording were selected for one of the subjects (channel O_1), which show pronounced differences in S values between wakefulness and deep sleep. Visually, the distinctions between wakefulness and REM sleep are less noticeable. The highest normalized spectral power appears in the δ activity range, varying on average from about 40–80% depending on the sleep stage.

The estimates demonstrate the presence of various types of correlations between pairs of rhythms, including anti-correlations, positive and mixed correlations in full agreement with the results and conclusions of the work [9]. In particular, according to Fig. 2, $C(\delta, \theta)$ takes negative values (anti-correlations) for most of the considered 30-second fragments, but if in the waking state the spread of $C(\delta, \theta)$ values is relatively large, including the case of $C(\delta, \theta) > 0$, then in the deep sleep state this spread is significantly reduced, and an increase in the degree of anti-correlations is observed with a tendency for $C(\delta, \theta)$ to approach -1.

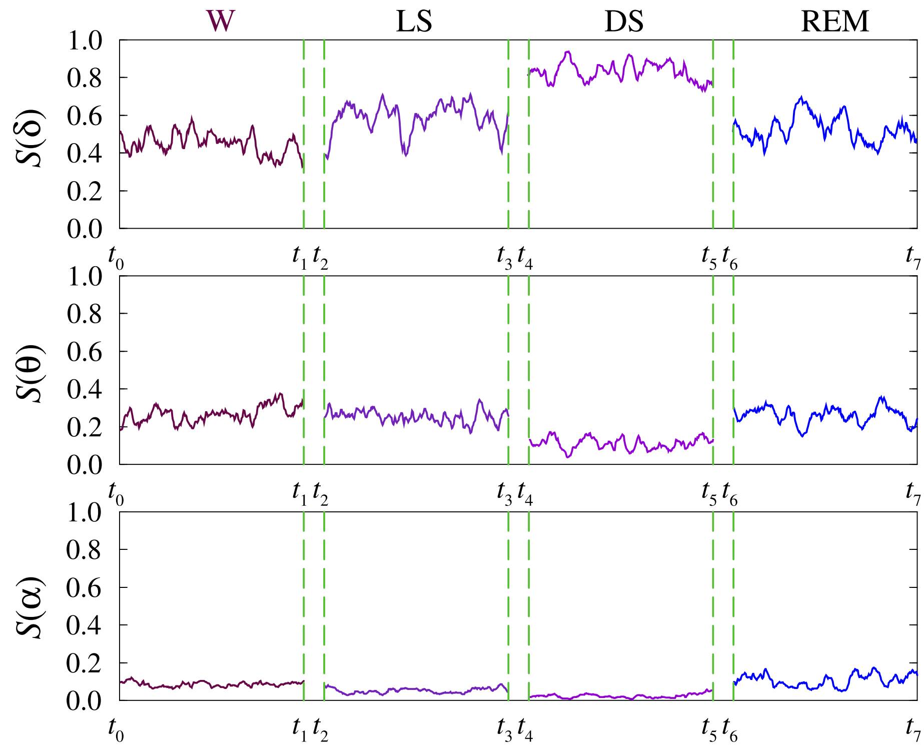

Fig. 1 Examples of changes in normalized relative spectral power during sleep for EEG waves δ, θ, and α

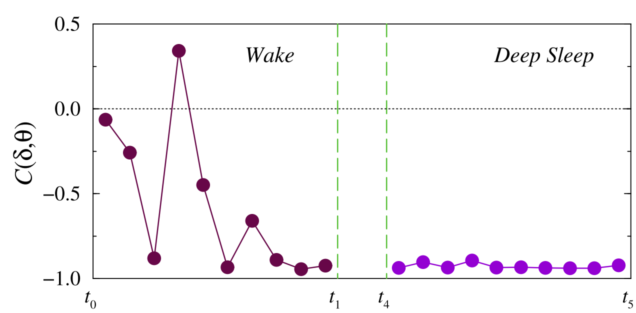

Fig. 2 Transition from mixed correlation to strong anti-correlation for $C(\delta,\,\theta)$

Considering that such studies have been previously conducted in detail in [9, 10], in this paper we focus on age differences in network interactions between brain rhythms. Figure 3a shows the results of statistical analysis of C for 10 pairs of rhythms in three age groups, which allow us to identify several characteristic features. Regardless of the type of correlations (positive or anti-correlations), they increase with age, accompanied by an increase in the absolute values of C. At the same time, reliable intergroup differences (for groups 1 and 3) are revealed for all pairs of rhythms (according to the Mann–Whitney test, $p < 0.05$). Differences between groups 1 and 2 are established for pairs $\delta{-}\alpha$, $\delta{-}\sigma$, $\alpha{-}\sigma$ and $\alpha{-}\beta$. Distinctions between groups 2 and 3 are identified for pairs $\delta{-}\alpha$ and $\delta{-}\beta$. Note that for pairs of rhythms with small values of the given measure, C often takes both negative and positive values (mixed correlations), but one of the types of correlations (positive or anti-correlations) is preferable. For other pairs, the dominance of one of the types of correlations is stronger. With age (group 3), the average values of C shift more towards the values $C = -1$ or $C = 1$, which is observed for all pairs of rhythms in Fig. 3a, indicating an increase in the coordination of brain rhythms.

In the light sleep stage, intergroup differences become less pronounced (Fig. 3b). Now, we can reliably identify an age-related increase in correlations only for several pairs of rhythms ($\delta{-}\alpha$, $\theta{-}\sigma$, $\alpha{-}\beta$ and $\sigma{-}\beta$ for groups 1 and 3, $\delta-\alpha$ for groups 2 and 3), although in general such a tendency is observed for 7 out of 10 pairs. At the same time, as in the case of wakefulness, anti-correlations are predominantly revealed for 7 pairs out of 10 (on average, negative values of C), and positive correlations appear in 3 pairs out of 10. These results show that the state of light sleep is less appropriate to reveal age-related distinctions in the cross-communication of brain waves.

The maximum differences in the cooperative dynamics of rhythms during sleep compared to wakefulness are observed in the deep sleep stage (Fig. 3c). Along with the growth of absolute values of C, there is a change in the type of correlations for some pairs (i.e. in the sign of the average values of C), in particular, for the pairs $\theta{-}\alpha$,

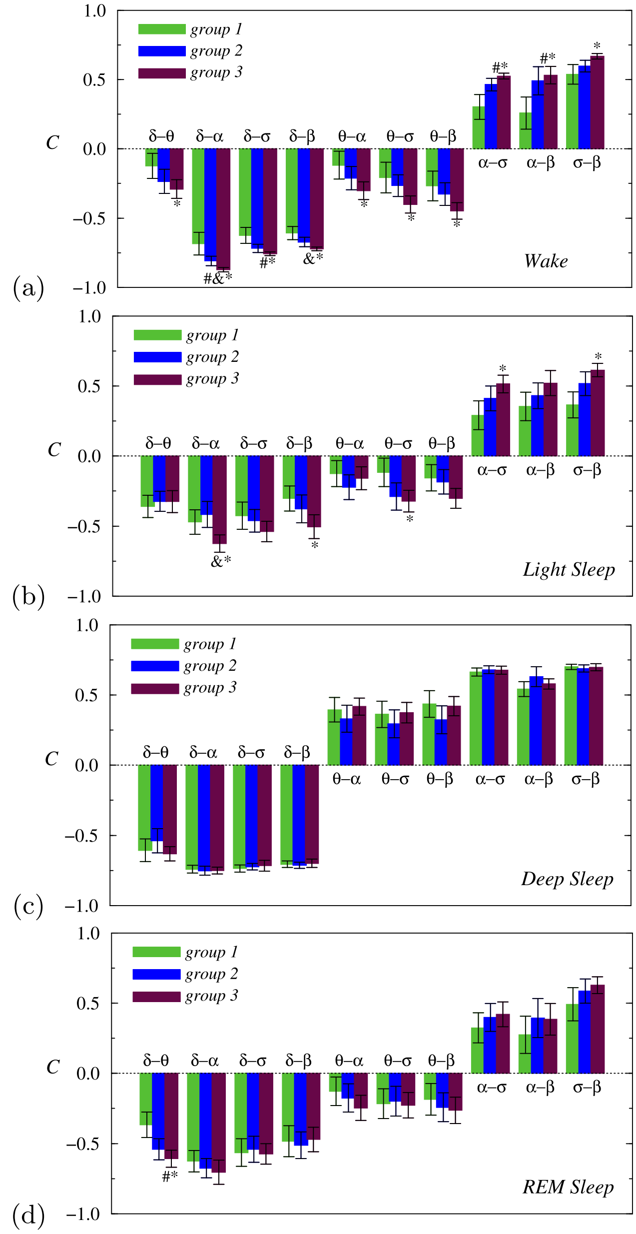

Fig. 3 Age-related changes in C-values during wakefulness (**a**), light sleep (**b**), deep sleep (**c**) and REM sleep (**d**). Data are shown as mean ± SE. Significant intergroup differences are marked by "#" for groups 1 and 2, "&" for groups 2 and 3, "$*$" for groups 1 and 3

$\theta-\sigma$ and $\theta-\beta$. However, from the point of view of age-related distinctions in cooperative dynamics, one can note the absence of reliable intergroup differences. Here, not a single pair of rhythms was identified with significant differences between any of the selected groups. Thus, the well-defined distinctions between groups 1 and 3 in the wakeful state become unreliable during deep sleep.

The REM sleep stage demonstrates less pronounced differences from wakefulness compared to deep sleep in terms of cooperation of rhythm pairs (Fig. 3d). There is $\delta-\theta$ pair with reliable differences for groups 1 and 3 as well as for groups 1 and 2, but in most cases, intergroup distinctions are not reliably identified, unlike wakefulness. The obtained results allow us concluding that age-related distinctions in cooperative dynamics of brain rhythms depend on the physiological state.

4 Conclusion

The paper discusses the concept of dynamic network interactions between various brain rhythms, which was applied with an emphasis on the study of age-related changes in EEG wave cross-communications. Using the Pearson correlation, significant differences in pairwise rhythm interactions were found for groups of subjects of different ages, most pronounced in the waking state. It is noted that older people demonstrate stronger correlations (or anti-correlations) for all pairs of rhythms under consideration. In the sleep state (especially in the deep sleep phase), age-related changes weaken, which is accompanied by a change in the type of correlations for some pairs of rhythms (i.e. a change in the sign of the average values of the correlation measure). We suppose that the results obtained are of interest in studying not only the effects of healthy aging, but also pathological changes in the electrical activity of the brain, including traumatic brain injuries.In particular, demonstrating the age-related differences between some EEG frequency bands in various physiological states paves the way for identifying brain age using the applied technique. Also, the method could potentially be extended for early prediction of Parkinson's and Alzheimer's diseases.

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Author contribution statement

Authors contributions are as followed: Conceptualization, A.N.P. and O.V.S.-G.; methodology, A.N.P.; software, G.A.G.; formal analysis, G.A.G. and V.V.A.; investigation, G.A.G. and V.V.A.; writing—original draft preparation, G.A.G. and A.N.P.; writing—review and editing, A.N.P. and O.V.S.-G.; visualization, G.A.G.; supervision, A.N.P. and O.V.S.-G.; project administration, O.V.S.-G.; funding acquisition, O.V.S.-G. All authors have read and agreed to the published version of the manuscript.

Data availibility statement The datasets analysed in the current study are available through the advisory board of the SIESTA Group (https://www.thesiestagroup.com) upon request.

Declarations

Conflict of interest The authors have no conflict of interest to declare that are relevant to the content of this article.

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