Immediate effect of neurofeedback in passive BCI for alertness control

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***Abstract*—We develop a passive brain-computer interface (BCI) which uses neurofeedback to maintain a high level of attention during the accomplishment of a prolonged task. The attention degree is estimated from EEG signals using methods of nonlinear and statistical time-frequency analyses. We find that the feedback increases the duration of the maximum interval during which the subject maintains substantial attention (150$\pm$40 s with feedback versus 100$\pm$20 s without feedback). However, the mean degree of attention during this interval is 27% lower than without feedback. The obtained result evidences that the cognitive reserve is limited, and therefore, to maintain high performance for a prolonged time, the brain operates in a "safe-mode" regime.**

***Index Terms*—Passive BCI, alertness control, mental fatigue, EEG analysis, brain resource.**

I. Introduction

The general aim of BCIs is to repair or improve human performance, for example, to help paralyzed people to control prosthetic devices [1] and interact with environment [2]. Currently, there are two types of BCIs, active and passive.

Active BCIs imply that the operator voluntarily generates specific patterns of his/her brain activity which can be automatically detected in real time. The resulting information can be translated into control commands and used as an input modality for controlling a technical device by thought [3].

Passive BCI utilize biomarkers derived from the operator's brain signals to improve his/her performance with no aim of voluntary control of the system [4].

Both types of BCI require a permanent information exchange between brain and computer, i.e., two-way data transfer in the BCI, where the information arriving from the brain to the computer allows continuous monitoring of the brain state evolution and generation of control commands for hardware. On the other hand, the information which comes back to the operator, is used either by the operator for self-control of his/her brain activity or by hardware/software to affect the brain directly. Such exchange of information between brain and computer is known as *biological feedback*.

Obviously, the feedback is a key part of human-machine systems. At the same time, its effective use for controlling brain dynamics requires a deep understanding of basic principles of neural brain activity under this type of control.

It is known that feedback control can dramatically change the behavior of a nonlinear system. In the same way, the human brain, being a strongly nonlinear system, can also be affected by feedback in an unpredictable way. Unfortunately, the main principles of the brain feedback control are not yet established. Although it is known that cognitive training allows enhancing cognitive performance, the possibility to immediately enhance human performance using the BCI system was not considered, to the best of our knowledge [5].

In the present work, we are interested in how feedback control affects human attention during visual perception. To quantify visual attention, we develop an algorithm based of the analysis of the time-frequency structure of EEG signals. The effect of this control can be described as follows. As soon as the subject's attention falls, an audio signal is sent to inform his/her about it, and after that the attention increases. We expected that such feedback control will maintain a high mean level of attention during the whole experimental session. However, our assumption was wrong. The results of the present work showed a rather unexpected outcome. Although the feedback control did enlarge time intervals of a relatively high level of attention, the mean level of attention during these intervals was not so high as in the group without feedback control.

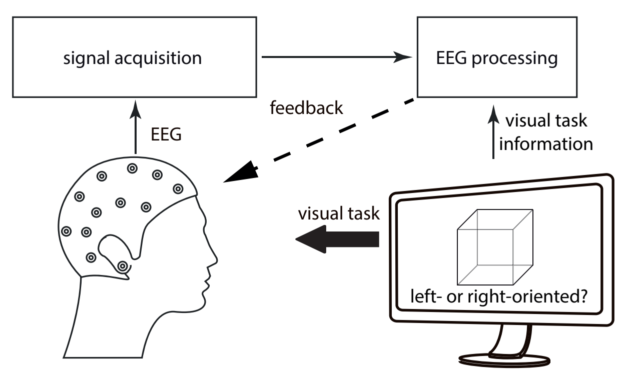

Fig. 1. Passive brain-computer interface for alertness estimation and control of attention via neurofeedback.

II. Methods

A. Subjects and stimuli

Twelve healthy subjects, males and females, between the ages of 20 and 28 with normal or corrected-to-normal visual acuity participated in the experiments. All participants provided informed written consent before participating in the experiment. The experimental studies were performed in accordance with the Declaration of Helsinki and approved by the local research Ethics Committee.

As a visual stimulus, we used the Necker cube [6]. This is a popular bistable image widely used in psychological and neurophysiological experiments and theoretical models [7], [8]. Since this cube has transparent faces and visible edges, an observer without any perception abnormalities perceives it as a 3D-object due to the specific position of the ribs (Fig. 1). Bistability in perception of the Necker cube consists in its interpretation as either left- or right-oriented, depending on the contrast of the inner edges. The task was to quickly classify presented Necker cubes according to their orientation. As was recently shown, this visual task required sustained attention of the observer [9].

B. Experimental design

All subjects were divided into two groups. In the first group (*Group1*) the feedback control was not used, while in the second group (*Group2*) the control was applied. The experimental procedure consisted of two sessions for all subjects. The subjects from *Group1* participated in both sessions without feedback control, whereas the subjects from *Group2* took part in the first session without feedback and in the second session with feedback control. The design of our experiment is illustrated in Fig. 1. All participants were instructed to press either left or right key on the input device depending on their first impression on the cube orientation at each presentation.

For all subjects, the second session was performed one month after the first session. Each session lasted 30 minutes. Each Necker cube was presented for short intervals between 1.0 and 2.0 seconds. Such a relatively short duration of the stimuli presentation was chosen to reduce the stabilization effect [10], because the probability of persisting interpretation of a previous image strongly depends on the stimulus duration. For the Necker cube, the required time of consistent observation was found to be about 1.0 second. Although the "memory" effect cannot be completely avoided, it can be significantly diminished by making the length of stimulus exhibition shorter than 2.0 seconds. Moreover, a random change in the control parameter g also prevents the perception stabilization. Lastly, to draw away the observer's attention and make the perception of the next Necker cube independent of the previous one, different abstract pictures were exhibited for about 5–6 seconds between subsequent demonstrations of the Necker cube images.

C. EEG acquisition and processing

EEG signals were recorded by five electrodes in occipital and parietal areas (O_1, O_2, P_3, P_4, P_z) with a 250-Hz sampling rate. Time-frequency EEG structure was analyzed with continuous wavelet transform [11]. The wavelet energy spectrum $E^n(f,t) = \sqrt{W_n(f,t)^2}$ was calculated for each n-th EEG channel in the 1–30 Hz frequency range. Here, $W_n(f,t)$ are the complex-valued wavelet coefficients and $n = 1, ..., N$ is the EEG channel number ($N = 5$). The mother wavelet function was the complex Morlet wavelet [12].

Wavelet energy spectrum $E^n(f,t)$ was analyzed in time-frequency domain. At the every moment of time the maximal values of wavelet energy were extracted and defined as the dominant spectral components of EEG signal. In order to analyze dynamics of dominant spectral components, we extracted frequencies of five of them ($f_1^n, \dots, f_5^n$) corresponding to maximal values of wavelet energy $E(f_1^n), \dots, E(f_5^n)$, and studied how the values of $f_1^n, \dots, f_5^n$ evolved in time. According to recent works, visual attention is associated with the interplay between α (8–12 Hz) and β (15–30 Hz) frequency bands in occipital and parietal areas. Therefore, we considered only those components for which the values $f_1^n, \dots, f_5^n$ belonged to these particular frequency bands.

We used spectral components to quantify the efficiency of the stimulus processing by the observer and compared the brain dynamics in 1-s intervals immediately before and after the onset of stimulus presentation. For this purpose, we introduced the values A_i^1, A_i^2, B_i^1, B_i^2 statistically described the location of the maximal spectral components, as follows

$$A_i^{1,2} = \sum_{n=1}^{N} \int_{t\in\Delta t_{1,2}^i} \left[\sum_{k=1}^{K} \xi_k^n(t')dt' \right], \qquad (1)$$

$$B_i^{1,2} = \sum_{n=1}^{N} \int_{t\in\Delta t_{1,2}^i} \left[\sum_{k=1}^{K} \psi_k^n(t')dt' \right]. \qquad (2)$$

These values were calculated using EEG data taken from all occipital and parietal channels before and after the onset of image presentation during presentation of i-th stimulus. Here, $\xi^n(t)$ and $\psi^n(t)$ defines the occurrence of the spectral components in α and β frequency bands, calculated as

$$\xi^n(t) = \begin{cases} 1/k, & \text{if} \quad f_k^n \in \Delta f_\alpha, \\ 0, & \text{if} \quad f_k^n \notin \Delta f_\alpha. \end{cases} \qquad (3)$$

$$\psi^n(t) = \begin{cases} 1/k, & \text{if} \quad f_k^n \in \Delta f_\beta, \\ 0, & \text{if} \quad f_k^n \notin \Delta f_\beta. \end{cases} \qquad (4)$$

Here, f_k^n is the location of the k-th maximal spectral component belonging to n-th channel, $K = 5$ is the number of analyzed spectral components, and $\Delta t_{1,2}^i$ indicate the 1-s time intervals preceding and following the i-th image presentation.

According to existing works on human attention, visual attention is associated with activation of an "attentional center" in the parietal cortex which operates at 15–30 Hz frequencies [13], i.e., β-waves. In addition, visual stimuli processing strengthens connectivity between occipital and parietal areas in α and β frequency bands [14], that in turn causes a growth of β-activity in occipital cortex. Finally, many studies evidence that visual information processing along with an increase in β-activity simultaneously inhibits α-wave activity. According to our recent study [15], the increasing visual attention causes a percept-related increase in β-activity accompanying by a decrease in α-activity.

Taking into account the above observation, the subject's attention during visual stimulus processing can be quantified as

$$I(t_i) = \frac{(\overline{A}_i^1 - \overline{A}_i^2) + (\overline{B}_i^2 - \overline{B}_i^1)}{2}, \quad (5)$$

where $\overline{A}_i^{1,2}$ and $\overline{B}_i^{1,2}$ define the values of $A_i^{1,2}$ and $B_i^{1,2}$ averaged over six preceding events $(i-6,\dots,i)$. Such averaging is performed in accordance with our observations, that when stimuli are processed in a short time, the subject sometimes exhibits low attention I during a single event, even while demonstrating overall high attention during the whole session. One can see that $I(t_i)$ reaches a maximal positive value, if the values in both brackets in Eq. (5) are high and positive. It corresponds to a state of high attention when $\overline{A}_i^1 > \overline{A}_i^2$ and $\overline{B}_i^2 > \overline{B}_i^1$, i.e., α-activity decreases and β-activity increases. On the contrary, $I(i)$ reaches a minimal negative value when $\overline{A}_i^1 < \overline{A}_i^2$ and $\overline{B}_i^2 < \overline{B}_i^1$. Finally, $I(i)$ is zero when changes in α- and β-activity are insignificant.

The value of attention I was calculated after each visual stimulus was processed by the subject and compared to the threshold value $I_{\rm th}$. In our study, $I_{\rm th}$ was set to zero, and the feedback was organized as a short audio tone after the stimulus was processed, each time when $I \leq I_{\rm th}$. The subject was previously instructed to associate this sound message with a low attention state.

III. Results

Fig. 2 shows a typical change in the attention degree I for one subject from *Group2* during the first (a) and second (b) experimental sessions. One can see that the attention degree I oscillates with average period of $T \approx 150$ s. During each period, the subject processed about 20 visual stimuli. We suppose that the time intervals with $I > 0$ are associated with the states of increased attention. In these states, a large group of neurons actively participate in visual information processing. On the other hand, the intervals with $I < 0$ are related to a refractory state of neural dynamics.

One can see from Fig. 2 that feedback leads to an increase in the period of the attention $I(t)$ oscillations. At the same time, the amplitude of these oscillations becomes lower.

In order to statistically quantify these effects, we extracted maximal values $\delta_{I,II}^{\max}$ and $\gamma_{I,II}^{\max}$ obtained in the first and second sessions. These values correspond to the maximal time intervals during which the subject is able to maintain sustained attention. Then, we calculated the ratios between these values in the first and in the second session, i.e. $\gamma_{II}^{\max}/\gamma_{I}^{\max}$ and $\delta_{II}^{\max}/\delta_{I}^{\max}$ for both groups.

The obtained results are presented in Fig. 3 as mean$\pm$SD for subjects from *Group1* (white box) and *Group2* (black box). One can see that the ratio $\delta_{II}^{\max}/\delta_{I}^{\max}$ (Fig. 3(a)) for subjects from *Group2* is higher than that for subjects from *Group1* (1.6 ± 0.52 versus 1.1 ± 0.51). This evidences that feedback

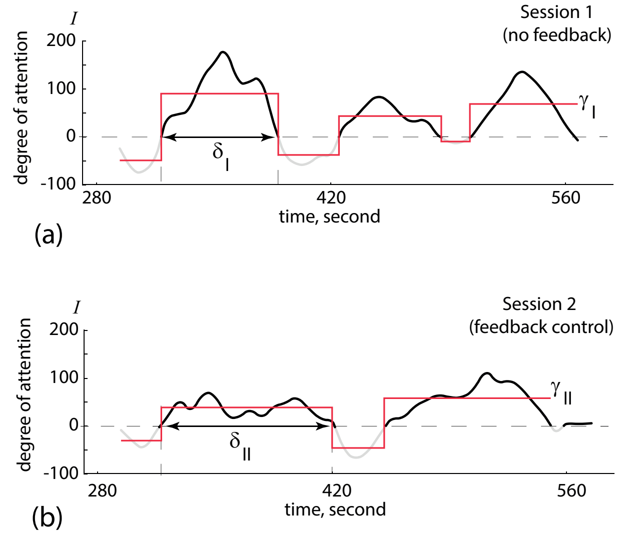

Fig. 2. Typical fragments of $I(t)$ dependency during (a) first (without feedback) and (b) second (with feedback) experimental sessions. The solid lines (above zero) show the traces of high brain response, while the transparent lines (below zero) indicate the refractory intervals of neural ensemble activity. The red line shows mean value of I achieved during each time interval.

control increased the maximum duration of the state of high attention for subjects from *Group2*. The statistical analysis of the values $\delta_{I,II}^{\max}$ obtained in the first and second sessions, performed via Wilcoxon signed-rank test yielded $p < 0.05$ for *Group2* and $p = 0.893$ for *Group1*.

While the maximal duration of the time interval during which $I > 0$ increased in the presence of feedback, the maximum mean value of I achieved on this interval, decreased. This decrease of attention is demonstrated via the ratio $\gamma_{II}^{\max}/\gamma_{I}^{\max}$ in Fig. 3(b). One can see that the ratio $\gamma_{II}^{\max}/\gamma_{I}^{\max}$ is equal to 0.71 ± 0.08 and 1.13 ± 0.44 for *Group2* and *Group1*, respectively. The Wilcoxon signed-rank test provided $p < 0.05$ for *Group2* and $p = 0.686$ for *Group1*.

Finally, we compared the mean values of attention during the first ($\overline{I}_I$) and second ($\overline{I}_{II}$) experimental sessions for every subject from *Group1* (without feedback) and *Group2* (with feedback) to find the difference $\Delta I = \overline{I}_{II} - \overline{I}_I$. As seen from Fig. 3(c), the mean difference between $\overline{I}_I$ and $\overline{I}_{II}$ in *Group2* is positive ($\overline{\Delta I} > 0$), while in *Group1* it is negative ($\overline{\Delta I} < 0$), in spite of a relatively large standard deviation (SD) among different subjects in the group. In order to define whether or not the change between $\overline{I}_I$ and $\overline{I}_{II}$ is significant for these groups, we applied the Wilcoxon signed-rank test, usually used to compare two related short samples. As a result, we obtained $p = 0.345$ and $p = 0.51$ for the first and second group, respectively. This evidences that the changes in the mean level of visual attention between the first and second sessions in both groups are insignificant. While for *Group1* this result was expected because the subjects demonstrated more or less the same mean value of I in two different sessions, for *Group2* the result was rather surprising. The reason for this kind of behavior can be understood if we suppose that the

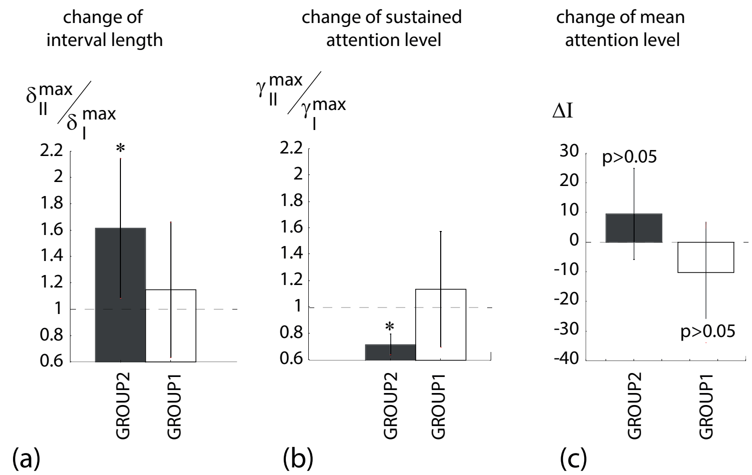

Fig. 3. Statistical analysis. (a) Changes in the mean value of attention I during the first and second sessions. (b) Ratio between values $\delta_I^{\max}$ and $\delta_{II}^{\max}$, characterizing a length of time intervals of sustained attention. (c) Ratio between values $\gamma_I^{\max}$ and $\gamma_{II}^{\max}$ characterizing mean degree of attention during these intervals. The results are obtained for the first and second sessions for subjects from *Group1* (white boxes) and *Group2* (black boxes). The data are shown as mean$\pm$SD (*$p < 0.05$ by Wilcoxon signed-rank test, $n = 6$).

cognitive reserve to maintain sustained attention for a long time is limited, so that the brain needs rest to recover its resource.

IV. Conclusion

The obtained results evidence the following two effects.

(i) The degree of attention (DA) estimated on the base of spectral properties of parieto-occipital EEG oscillates in time. The time intervals during which DA is high alternates with periods of lower DA.

(ii) Neurofeedback implemented via a sound message which informs the subject about decreasing DA, leads to an increase in the duration of intervals with high DA, but does not affect the mean DA during the session.

Having considered brain dynamics under the effect of increasing mental workload, one has to take into account the limited brain resource, that can cause the limitation of brain ability to consciously perceive and process information [16]. In this context, neurofeedback is aimed to increase the capacity limit of information processing in the brain. At the same time, according to our results, the capacity enhancement cannot be achieved during a single feedback control session. In order to increase the stimulus-related brain response amplitude, the functional structure of the brain network must be adjusted to process more complex workload. According to the recent review [5], this can be done using cognitive training which demonstrates a high efficiency in behavioral performances. It was demonstrated, that in addition to the training-induced changes in the brain activity, morphological changes can also be induced by cognitive training [17].

V. Acknowledgment

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