Age-related differences in sensorimotor responce during VR-based task performance: time-frequency analysis and functional connectivity

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Abstract—In the present research, we show the results of time-frequency and functional connectivity analysis of electroencephalography data recorded during VR-based sensorimotor integration experiment. We focus on the differences in visually cued motor reaction processing between two age groups of subjects. Our results provide evidence of compensatory mechanism engaged by elderly adult group of subjects for sensorimotor integration task performance. Besides, young adults demonstrate post-movement beta-rebound, which wasn't found in older group of subjects.

Index Terms—sensorimotor integration, age-related changes, virtual reality, beta-rebound, functional connectivity, compensatory mechanism

I. INTRODUCTION

Studying age-related changes in brain functionality is crucial not only in the fundamental meaning of understanding the neural mechanisms underlying these changes, but also for development of systems of early diagnostics of neurodegenerative diseases [1]. In this context, one of the most discussed topics is a motor-related activity, since the age-related decline in motor functions is one of the most prominent and affecting quality of life [2], [3]. Besides, human motor system tends to engage with other areas of the brain in a complex manner, which is provides an extencive source of information about brain functioning in advanced age [4]–[7].

In the present paper, we propose a whole-scalp electroencephalography (EEG) analysis of dataset obtained from two age groups during an experiment based on virtual reality (VR). We implemented a multistage computational strategy based on time-frequency analysis, functional connectivity analysis and statistical testing aimed to provide extensive results on age-related changes in neural responce during motor-related

activity. We demonstrated that two age groups implement different strategies of processing VR-based sensorimotor task. In particular, elderly adults tend to involve larger amount of brain resouces to process motor action following a visual cue compared to young adults. Our findings are in line with modern ideas about how healthy aging affects brain electrical activity.

II. METHODS

A. Experimental paradigm

EEG signals were recorded using BrainAmp EEG amplifier with sample frequency 500 Hz and 64 sensors placed on the subject's head according to the international 10-20 system [8]. Each participant was seated in the special EEG chair and instructed to react on target cues by pressing the button on the gamepad. The cues were presented in VR-based fishing imitation environment using Oculus Rift headset. There were two types of cues: visual and audial, each one could be target and non-target:

1) Target visual cue – sinkage of a float;
2) Non-target visual cue – the float twitches, but does not sink under water;
3) Target audial cue – frog croaking;
4) Non-target audial cue – crow cawing.

We used data of two groups of subjects: young adult group (YA, 27 subjects, 18-35 y.o., 12f) and elderly adult group (EA, 18 subjects, 56-76 y.o., 12f). All participants signed an informed consent. Experimental paradigm was approved by ethical committee of Samara State Medical University. All aspects of the research conformed to the tenets of the Declaration of Helsinki.

B. Dataset and preprocessing

For the present research, we used EEG data recorded during target visual cue presentation only. Before proceeding with time-frequecy and functional connectivity analysis, EEG recordings were band-pass filtered (1-100 Hz), and the notch filter (50 Hz) was applied. We also applied an artefact-removal procedure using independent component analysis (ICA).

We selected 30 visual cue tasks for each participant. All epochs were sliced on 6-second time series [-2,4] s centered at the visual cue presentation.

C. Time-frequency analysis

We estimated spectral power in the range [1,40] Hz for each set of epochs using Morlet complex-valued wavelet and performed the baseline correction by substracting the mean of 2.5 seconds baseline preceeding the visual cue and dividing by the mean of the baseline values. We chose the number of cycles in the wavelet transform as f for each frequency f. The obtained spectral power values were then averaged over epochs for each subject.

To compare obtained time-frequency representations between groups and select the frequency ranges of interest, we applied spatio-frequency permutation cluster test using the tools provided by MNE library for Python [9], [10] ($df1 = 1$, $df2 = 43$, $p = 0.001$, $F_{critical} = 12.47$) with $r = 2000$ random permutations. To compare the temporal dynamics of spectral power, we used spatio-temporal cluster test with the same set of parameters.

D. Functional connectivity

We chose phase lag index (PLI) as a functional connectivity measure due to it being less sensitive to the intrinsic EEG properties such as noise and artefacts. The frequency-domain PLI defined as:

$$PLI_{i,j} = |\langle sign(Im[S_{i,j}(f)])\rangle|, \qquad (1)$$

where $S_{i,j}$ is a complex-valued Fourier-based cross-spectrum of i-th and j-th time-series, f corresponds to the frequency band of interest, and operator $\langle \cdot \rangle$ represents averaging over the time points k.

We calculated the adjacency matrix 62×62 for each epoch during the post-motor interval [0.5,1.5] s with baseline correction. For each subject, we calculated the mean connectivity matrix averaged over epochs and then performed between-groups analysis using element-wise comparison of mean connectivity matrices using one-tailed t-test for independent samples.

III. Results and discussion

Fig. 1 shows the results of between-groups spatio-temporal and spatial-frequency permutaiton test. The frequency cluster shown on Fig. 1(A) occurs on the time interval [0.5,1.5] s that corresponds to the mean reaction time in both groups (YA – 528 ms, EA – 610 ms). Therefore, we suggest that the spectral power pattern in this time interval can be caused
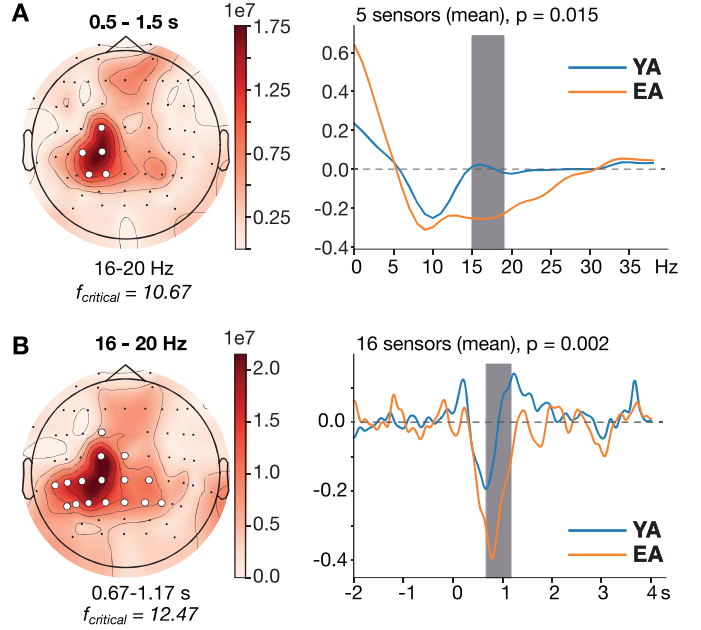

Fig. 1. **A** – Between-subject spatio-frequency cluster (left panel) and the full-range spectral power averaged over the sensors of the corresponding clusters (right panel) in the time interval [0.5,1.5] s; **B** – Between-subject spatio-temporal cluster (left panel) and beta-1 spectral power averaged over the sensors of the corresponding cluster(right panel).

by the motor execution (pressing a button). We can see that subjects from both groups experience decline of spectral power in motor-related rhythm starting approx. with 5 Hz. In YA group, the desynchronisation is localised in the frequency band corresponding to the alpha-rhythm, whereas EA subjects show extended frequency range. The between-groups spatial-frequency permutation test showed significant cluster in beta-1 range (16-20 Hz) that included sensors located on left motor cortex (C1, CP1, CP3) and left parietal cortex (P1 and P2), as shown on the left panel of Fig. 1(A). Due to the spatial and temporal location of this cluster, we suggests that it corresponds to motor-related event-related desynchronisation (ERD) caused by pressing a button as a reaction on visual stimulation. Beta-rhythm EEG oscillations are known to be actively involved in sensorimotor-related processes. ERD in beta-rhythm during motor-related tasks is well reported [11]–[13].

Despite the fact that we observe significance of this cluster in beta-1 only, we can see that EA group generally demonstrates broader interval of frequencies that exhibit the decline in spectral power, whereas the YA group shows a relative increase of beta-1 spectral power. This can indicate a rapid increase of beta-rhythm spectral power that often occurs after movement called a post-movement beta-rebound. To check this, we performed a two-samples spatio-temporal permutation cluster test in the frequency range of interest (see Fig. 1(B)). The test revealed a similarly-located cluster and showed that the short ERD after presentation of visual cue is followed by rapid increase of beta-1 spectral power in YA, but not in
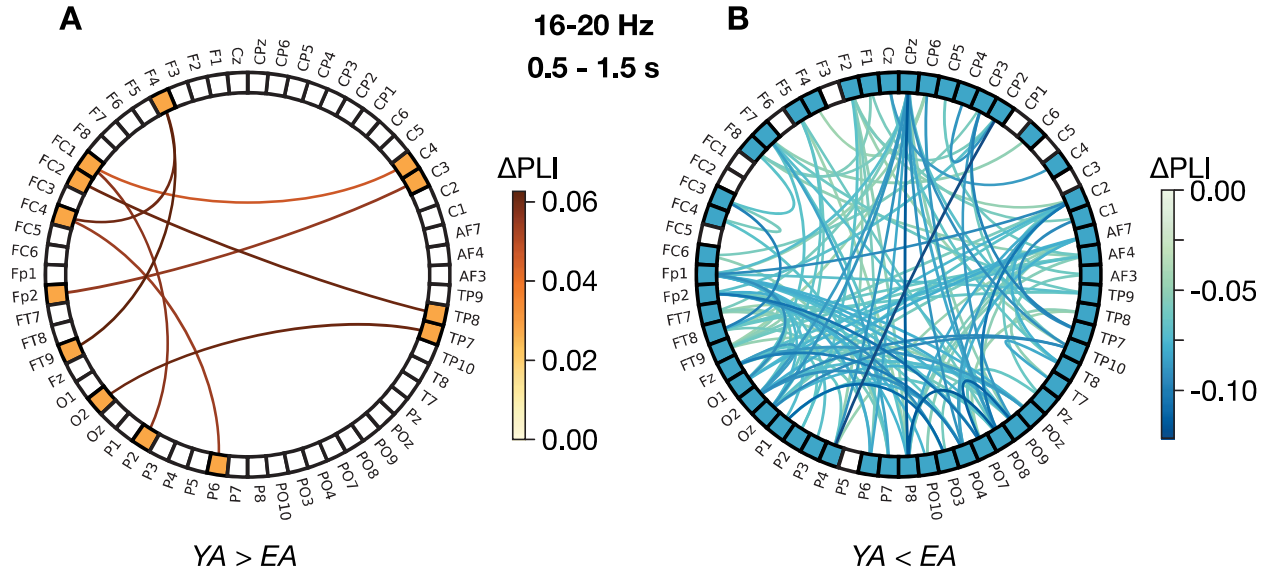
Fig. 2. Between-groups analysis of beta-1 band functional connectivity during motor execution cued by visual stimuli. **A** – The connections that are significantly stronger in YA group; **B** – the connections that are significantly stronger in EA group. Here, ΔPLI is the difference between mean functional connectivity (YA vs EA).

EA group. Despite the fact that ERD itself wasn't statistically significant, the beta-1 rebound was. Age-related decrease of beta-rebound amplitude was reported previously in a number of studies [14], [15]. Therefore, the differences demonstrated by spatio-frequency and spatio-temporal permutation tests are linked to age-related changes in neural response on motor action proceeded by visual cue.

We proceed with connectivity analysis in the previously discussed frequency range and time interval. On Fig. 2 we demonstrate the results of between-group analysis of beta-1 functional connectivity. Fig. 2 (A) shows the connections that are significally stronger in YA group. We see that YA group demonstrates the stronger connections in frontal and temporal areas.

Fig. 2(B) shows the connections that are significantly stronger in EA group compared to YA. EA group demonstrates stronger coupling in occipital, parietal and temporal lobes. We can also see hubs in CPz and C2 sensors connected to temporo-parietal, parietal and parieto-occipital lobes. Generally, we see that EA group is characterised by stronger local and distant coupling.

Motor execution cued by visual stimulation causes a broader connectivity pattern in EA group compared to YA. Such differences between functional connectivity network in beta-1 range could mean the different activation pattern forming in two age groups of subjects as a motor reaction on visual cue. We show that, despite the fact that functional connectivity network of both groups involves parietal, temporal, occipital and motor sensors, EA subjects involve much more sensors, demonstrating a strong almost full-scalp coupling pattern

during motor execution.

We reported a CPz sensor being a strong hub in EA group providing large-scale connections with temporal, parietal and occipital areas. In our previous studies on age-related changes in motor-related neural reactions, we reported the similar result in theta-rhythm and interpreted in as a sign of an age-related working memory decline [16]–[18]. However, we believe that the results provided in the present paper can be a strong evidence of the compensatory increase of number and strength of connections in EA group. Compensatory mechanism is a well-reported effect that is associated with pathological as well as age-related changes in brain structural properties [19].This is a reorganisation mechanism to prevent the cognitive decline by recruitment of additional regions to process a task that requires much less resources in control group [20]. It is possible to explain the functional connectivity pattern shown on Fig. 2 with an age-related demand for additional resources that causes much stronger coupling for processing a motor-related task in EA group that requires less connections in young healthy adults.

IV. CONCLUSION

We applied time-frequency and functional connectivity analysis to reveal the age-related differences in processing of VR-based sensorimotor task. First, we showed that motor execution cued by visual stimuli causes significant ERD of beta-1 frequency band in left-lateralized motor area that is more pronounced in elderly adults group. This difference is explained by post-movement beta rebound that occurs in young adult group, but not in elderly adults.

Second, we demonstrated that the functional connectivity pattern in elderly adults engages much more connections between remote areas as well as on the local level with particularly strong coupling in motor, parietal and occipital sensors. We believe that this result is an illustration of a well-known compensatory mechanism that elderly adults engage to compencate for age-related brain functionality loss.

Results presented in this paper are in line with both modern and classical ideas about age-related changes in brain functionality.

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