AGING EFFECTS ON THE PERFORMANCE OF A BRAIN-COMPUTER INTERFACE

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INTRODUCTION

Aging is accompanied by physical and functional changes in the brain, such as a decrease in long-term memory, inhibition, size, and white matter integrity [1]. PET and fMRI studies reported that compared to younger adults, older adults' brains displayed less lateralization when performing the same tasks [2], showing an overactivation of brain regions not activated in younger adults [3]. This pattern of asymmetry reduction has been termed the Hemispheric Asymmetry Reduction in Older Adults (HAROLD) [4]; more generally this age-related overactivation is accepted as compensatory, and termed the Compensation-Related Utilization of Neural Circuits Hypothesis (CRUNCH) [3].

This age-related change in cortical activations from a more focused and lateralized pattern to be more diffused and bilateral may fundamentally challenge older adults' ability to use brain-computer interfaces (BCI), because a large number of BCI methodologies are based on locality-dependent signal enhancement processing algorithms such as Common Spatial Pattern (CSP) and Laplacian filtering [5]. This may be a contributing factor in the limited effectiveness of BCI post-stroke rehabilitation methods when applied in practice [7]. Perhaps the effect of aging also plays a key role in the decreased BCI performance, in addition to the ailment itself.

Stroke rehabilitation is an application in which BCI rehabilitation has been considered a promising tool. As the world population ages [8], noncommunicable diseases such as stroke, which rises in prevalence with age, is causing an increase in mortality and long-term disability [8]–[10]. 80% of stroke survivors experience upper limb paresis – this is the most common post-stroke impairment [11]. Further recovery is often slow even with state-of-the-art physiotherapy [12]. BCI stroke rehabilitation is a promising tool because it overcomes the challenges presented by current therapies; constraint-induced movement therapy (CIMT) or bilateral arm training [12] are useful strategies, but residual movement are required for therapeutic feedback [13], [14]. As BCIs are solely based on brain activity, it can be used even if patients have severe limb weakness [15]. BCI can support recovery by substituting the loss of normal neuromuscular output or inducing activity-dependent brain-plasticity to restore normal brain functions [7], [12], [16]. Many BCI stroke rehabilitation training leverage locality-dependent BCI methodologies, such as SMR because it is related to motor movement,

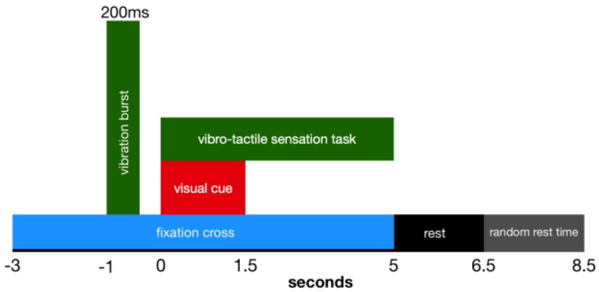

Figure 1 Experiment protocol for a single trial.

readable by electroencephalogram (EEG), and have a relatively high signal-to-noise ratio [7], [17]. However, its limited effectiveness in practice [7] may be due to the fact that the average population of BCI stroke rehab studies is aged 55+ [7], while the fundamental SMR processing algorithms were developed and validated on much younger populations [18]. While the neurophysiological changes induced by stroke certainly plays a role in the reduced effectiveness of BCI-based stroke rehabilitation, there is a lack of research regarding the effect of aging on neuroelectrophysiology and BCI.

This work is a preliminary investigation on the age-related changes in EEG and its ramifications on the performance of BCIs based on sensory-motor rhythm (SMR).

METHODS

Participants

11 older adults (age 56 – 83, 8 female), 11 younger adults (age 18 – 25, 6 female). All participants were BCI naïve, right handed, had normal or corrected vision. The study was approved by the office of Research Ethics of the University of Waterloo (ORE# 21401).

Experiment setup

The protocol included 2 runs of 40 trials each for a total of 80 trials (40 left, 40 right). A 2-4 min rest time was given in between runs. The sequence of each trial is shown in Figure 1. At -3s (the start of each trial), a white fixation cross appeared lasting through the entire trial. At -1s, subjects received 0.2s of vibration (175 Hz) on both wrists as a prompt for the vibro-tactile sensation task. At 0s, a sustained vibro-tactile stimulation of 5s was applied, either to the left or the right side, accompanied by its respective visual cue. At 5s, a 1.5s rest is given, as well as a random 0-2s rest time to prevent habituation.

Data analysis

Offline signal processing was performed and EEG data was manually corrected for artifacts using EEGLAB toolbox [20]. Artifacts were removed in two steps: 1) removal of trails containing non-ocular artifacts, and 2) use of independent component analysis (ICA) to remove ocular artifact components from remaining epochs [19]–[21].

Classification

A fourth-order Butterworth filter was applied to the raw EEG signals prior to further spatial filtering. Following, Common spatial filter was used prior to classification of EEG epochs into either left or right classes [22]. Linear discriminative analysis (LDA) was used for classification. The raw EEG data was used to simulate online BCI performance. Hence, no artifact removal was performed. Classification was performed with EEG data from 0 – 2s from each epoch. Due to the high inter-subject variation for discriminative frequency bands, sub-frequency bands were used in analysis:

Table 1: Classification accuracy

	Performance accuracy (%)	**Optimal Frequency band**
Older Adult 1	58.87 ± 1.81	β-
Older Adult 2	65.75 ± 2.90	α
Older Adult 3	63.75 ± 3.17	αβ
Older Adult 4	67.75 ± 4.16	θ
Older Adult 5	61.25 ± 4.49	α
Older Adult 6	55.13 ± 4.51	η
Older Adult 7	59.75 ± 3.11	θ
Older Adult 8	67.00 ± 4.09	β+
Older Adult 9	83.87 ± 2.08	β
Older Adult 10	58.00 ± 6.75	β-
Older Adult 11	67.87 ± 3.44	αβ
Younger Adult 1	89.25 ± 1.58	η
Younger Adult 2	80.50 ± 2.37	η
Younger Adult 3	99.50 ± 0.65	α+
Younger Adult 4	52.25 ± 2.27	β
Younger Adult 5	86.50 ± 1.84	α+
Younger Adult 6	99.50 ± 0.65	α+
Younger Adult 7	94.50 ± 1.05	α+
Younger Adult 8	71.75 ± 1.88	αβ
Younger Adult 9	97.50 ± 0.59	α+
Younger Adult 10	78.87 ± 2.97	β+
Younger Adult 11	87.63 ± 1.90	η

theta (6–8 Hz), lower alpha (8–10 Hz), alpha (8–13 Hz), upper alpha (10 – 13 Hz), low beta (13–20 Hz), beta (13–26 Hz), upper beta (20–26 Hz), alpha-beta (8 – 26 Hz), and gamma (10–16 Hz). 10x cross validation was performed on all sub-frequency bands to evaluate BCI performance [22], the frequency band with highest classification accuracy was selected.

RESULTS

The age of the two groups were significantly different (old: 72.0±8.07; young: 21.7±2.76 years-old with t=21.8, p<0.001). The number of years of education of the two group were not significantly different (old: 16.2±3.0; young: 14.8±2.67 with t=-1.25, p=0.226).

BCI classification accuracy is reported in Table 1. The average left vs. right BCI performance is 64.5±7.75% for older adults, and 85.3±14.1% for younger adults. The two results are statistically different (t(20) =-4.3, p<0.001).

DISCUSSION

Our BCI classification results (Table 1) suggest there is an age-related change in healthy older adults which resulted in a significant difference in BCI classification accuracy. We noticed that five out of the eleven younger adults had their highest classification accuracy in the upper alpha frequency band, while in the older adults there was no particular frequency band that consistently yielded the highest performance.

The reason behind our findings may be explained by physical and cognitive changes in the brain, as well as physiological changes to the body as a whole. Structurally, the brain reduces non-uniformly in volume as one ages [23]. The areas that are being activated in the current experiment (by the left or right vibro-tactile stimulation) is the somatosensory cortex. These structures or accompanying structures have been affected by the process of natural aging. Cognitively, aging causes a decrease in processing speed, working and long-term memory, as well as functional inhibition [1]. This multitude of factors that accompany aging may contribute to the decreased BCI performance seen in the results.

A recent study by Volosyak et al. [24] also investigated the age-related difference in BCI performance. They examining the accuracy and speed of a steady-state visual evoked potential (SSVEP)-based BCI spelling application, showing older adults have a significantly lower information transfer rate compared to younger adults [24]. Volosyak et al. attributed their results to smaller SSVEP amplitudes for older adults as well as slower reaction time and learning ability [24]. Our findings concur with their findings such that we also found a decreased BCI performance in the older adult population.

Other factors that might have played into this difference include changes in scalp thickness [25], [26] and skin sensitivity from mechanoreceptor loss [27], [28]. From our experiments, we noticed that it took a notable longer time to set up the EEG electrodes for the older adults due to an increased scalp impedance. We recommend taking this into account in future works.

Limitations to our research include alternative uncontrollable lifestyle and habits such as physical and cognitive exercise, which may have an effect on EEG [29].

CONCLUSION

In summary, there is strong evidence that age-related changes affect the classification accuracy of the current BCI algorithms, such as CSP. This suggests future work should further investigate the reason(s) for such effect, to provide appropriate measures to complement age-related differences in physiology and electrophysiology in BCI applications intended for older adults.

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