Age-Related Changes in Vibro-Tactile EEG Response and Its Implications in BCI Applications: A Comparison Between Older and Younger Populations

Mei Lin Chen, Dannie Fu, Jennifer Boger, and Ning Jiang, *Senior Member, IEEE*

***Abstract*—The rapid increase in the number of older adults around the world is accelerating research in applications to support age-related conditions, such as brain–computer interface (BCI) applications for post-stroke neurorehabilitation. The signal processing algorithms for electroencephalogram (EEG) and other physiological signals that are currently used in BCI have been developed on data from much younger populations. It is unclear how age-related changes may affect the EEG signal and therefore the use of BCI by older adults. This research investigated the EEG response to vibro-tactile stimulation from 11 younger (21.7±2.76 years old) and 11 older (72.0±8.07 years old) subjects. The results showed that: 1) the spatial patterns of cortical activation in older subjects were significantly different from those of younger subjects, with markedly reduced lateralization; 2) there is a general power reduction of the EEG measured from older subjects. The average left vs. right BCI performance accuracy of older subjects was 66.4±5.70%, 15.9% lower than that of the younger subjects (82.3±12.4%) and statistically significantly different (t(10)= −3.57, p= 0.005). Future research should further investigate age-differences that may exist in electrophysiology and take these into consideration when developing applications that target the older population.**

***Index Terms*—Aging, brain–computer interfaces, electroencephalogram (EEG), neuroplasticity, somatosensory, vibro-tactile stimulation.**

I. Introduction

THE global population of people over the age of 60 numbered 962 million in 2017, which was more than twice the 382 million older adults that there were in 1980 [1]. The number of older persons is expected to double again by 2050, when it is projected to reach nearly 2.1 billion [1]. Noncommunicable diseases, such as stroke, impose a significant burden on global health and is one of the leading causes of mortality and serious long-term disability [2], [3]. Globally in 2013, there were 6.5 million deaths from stroke, making it the second-leading cause of death behind ischemic heart disease [4]. 80% of stroke survivors are left with residual deficits in fine motor upper limb control [4], and further recovery after the first months post-stroke is often slow or non-existent [5]. Physical training techniques, such as constraint-induced movement therapy (CIMT) or bilateral arm training, have been shown to be useful strategies to improve motor function in chronic stroke patients [5]. However, these options are not applicable for patients with severe limb weakness because residual movements are required for therapeutic feedback [6], [7]. New approaches are needed to provide greater access to effective post-stroke rehabilitation. Brain-computer interfaces (BCIs; also known as brain-machine interfaces) are a promising approach for rehabilitation by either substituting for the loss of normal neuromuscular output or inducing activity-dependent brain-plasticity to restore normal brain function, both of which have been shown to support recovery [5], [8]–[11]. BCIs can be used regardless of the severity of the post-stroke paresis as it is dependent upon brain activity alone [12].

Much of the research in the field of non-invasive BCI stroke rehabilitation training leverage the brain's electroencephalogram (EEG) change in Sensory-Motor Rhythms (SMR) [9], [13]. SMR refers to the oscillatory activity observed in somatosensory and motor areas of the brain; activity in particular body parts causes a decrease in SMR activity in the respective sensorimotor cortex brain area, which is called the event-related desynchronization (ERD)[14]. SMR has been deemed a good fit for stroke rehabilitation because it is related to motor activity, accessible by EEG, and has a high signal-to-noise ratio [9], [15]. However, research to date has shown limited effectiveness with poor performance when it is applied in stroke rehabilitation [9], [16]. While this is in part a result of changes in brain function caused by stroke [17], normal aging may also play a significant

Manuscript received September 21, 2018; revised November 20, 2018 and December 29, 2018; accepted January 1, 2019. Date of publication March 12, 2019; date of current version April 8, 2019. This work was supported in part by the University of Waterloo's Starter Grant 203859, in part by Schlegel Research Chair funds, and in part by the Early Researcher Award from the Ministry of Research, Innovation and Science of Ontario under Grant ER17-13-183. *(Corresponding author: Ning Jiang.)*

M. L. Chen and D. Fu are with the Department of Systems Design Engineering, University of Waterloo, Waterloo, ON N2L 3G1, Canada (e-mail: mlchen@uwaterloo.ca; d24fu@edu.uwaterloo.ca).

J. Boger is with the Intelligent Technologies for Wellness and Independent Living (ITWIL) Lab, University of Waterloo, Waterloo, ON N2L 3G1, Canada, and also with the Research Institute for Aging, Waterloo, ON N2J 0E2, Canada (e-mail: jboger@uwaterloo.ca).

N. Jiang is with the Engineering Bionics Lab, University of Waterloo, Waterloo, ON N2L 3G1, Canada (e-mail: ning.jiang@uwaterloo.ca).

Digital Object Identifier 10.1109/TNSRE.2019.2890968

role. Thus, it is important that we understand the impacts healthy aging has on neuroelectrophysiology if we are to create effective BCI applications for older adults, such as BCI-based stroke rehabilitation.

Healthy aging is often accompanied by changes in the brain that include declines in processing speed, working memory, long-term memory, inhibitory functions, brain structure size, and white matter integrity [18]. The impacts of aging are a complex interaction of genetics, biology, and environmental factors [19]. PET and fMRI studies report that compared to younger adults, older adults show recruitment of brain regions with reduced lateralization [20], displaying relative overactivation of additional brains regions that are not activated by younger adults when performing the same tasks [21]. Often, this additional activated region is the same site that is activated in younger adults but in the opposite hemisphere [22]. This pattern of reduced asymmetry in older adults has been referred to as Hemispheric Asymmetry Reduction in Older Adults (HAROLD) [22]. More generally, this age-related overactivation is thought of as compensatory, and termed the compensation-related utilization of neural circuits hypothesis (CRUNCH) [21].

The average age of BCI stroke rehabilitation clinical studies stroke populations is above 55 years [9], while the fundamental algorithms for leveraging SMR as the BMI methodology have been developed using younger adults and have not been validated in a senior population [14], [15], [23]. The change in the location of activation in the brain to be more bilateral throughout the aging process begs the question of whether if this fundamentally challenges the basis of stroke rehabilitation strategies that use SMR and signal enhancement methods based on spatial information (such as the use of common spatial pattern and Laplacian filtering) [24]. To this end, a recent study reported a significant reduction of SMR lateralization during covert and overt motor tasks in healthy senior population, comparing with healthy young [25].

In this study, we investigated if the SMR induced by vibro-tactile stimulation would also exhibit such a difference between the two healthy populations. The primary motivation for using the vibro-tactile task paradigm, rather than the more commonly used motor tasks in BCI research, is to provide a foundation for future stroke rehabilitation techniques. Tactile feedback is often used in stroke rehabilitation where the therapist will provide gentle touch-based stimulation to the targeted muscle group. Whole-body vibration (WBV) training has attracted attention in both clinical and research, for it has significant therapeutic effects on balance, muscle strength, and mobility in older adults, although the optimal WBV protocol has yet to be determined.

As WBV have shown clinical effects, we are using the vibro-tactile task paradigm to further investigate a targeted approach to stroke rehabilitation, specifically through the application of vibration as well as incorporating brain-computer interface to provide a close-loop connection in neurorehabilitation. A secondary reason for our using the haptic vibro-tactile task paradigm is for the consistency in application. The expression of motor imagery [2] can be variable especially in naïve participants, hence applying a consistent intervention can better help to systematically isolate age as the factor that's being investigated. This provides that vibro-tactile stimulation is an optimal tactic for exploring age-related brain activation.

II. Methods

A. Participants

Participants were 11 older adults (over 55 years; 8 female) and 11 younger adults (18–25 years; 6 female). All participants were BCI naïve, right-handed, had normal or corrected vision, with no reports of psychiatric or neurological disorders, vascular diseases, use of psychiatric drugs, or any drugs affecting the central nervous system. All subjects provided informed consent prior to participation. This study was approved by the Office of Research Ethics of the University of Waterloo, Waterloo, Canada (ORE# 21401).

B. EEG Recording & Mechanical Somatosensory Stimulation

EEG signals were recorded using a 32-channel wireless g.Nautilus EEG system (g.tec, Austria). Electrodes were placed according to the extended 10/20 system. The reference electrode was located on the right earlobe, and the ground electrode was located on the forehead. A hardware notch filter at 60 Hz was used, and signals were digitally sampled at 250 Hz.

Mechanical vibration stimulation was applied to the dorsal side of left and right wrists using wrist bands with linear resonance actuators (type C10–100, Precision Microdrivers Ltd.) sewn inside. Each of the actuator produced a 27 Hz sine wave for both wrists, modulated with a 175 Hz sine carrier wave. Different from stead-state somatosensory evoked potential (SSSEP) [26], where the vibration frequency is the frequency of interest in EEG, the vibration frequency used in this study is not within the effective bandwidth of EEG. Therefore, the sampling rate of EEG is not limited by the vibration frequency in this case. The normalized amplitude of the vibration was 1.4G. The two vibration stimulators were connected to and driven by a Sound Blaster E5, a high-resolution USB DAC Amplifier (Creative Inc). The vibration magnitude was adjusted for each subject between the range of maximum amplitude (11.3 μm) and half maximum amplitude at the resonant frequency. The optimal amplitude was adjusted based on feedback from the subjects, such that they could comfortably and clearly feel the vibration. The vibration frequency and the procedure of determining the vibration frequency and stimulation level was consistent with earlier BCI studies such as [26]–[29].

C. Experiment Setup & Paradigm

EEG signals were recorded from the subjects before, during, and after stimulation. The subjects were seated in an armchair with their forearms and hands relaxed on the armrest. They faced a computer monitor placed approximately 2m away at eye level. Prior to EEG recording, subjects were shown their EEG in real time on the computer screen to demonstrate how

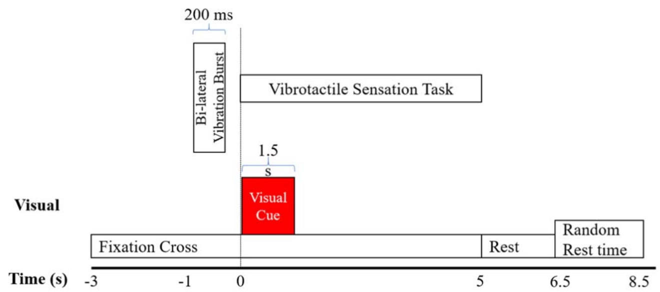

Fig. 1. Experimental protocol for a single trial.

to avoid motor artifacts caused by eye blinks, jaw clenching, and body movements. Subjects were asked to limit these physical movements during the EEG recording.

The experimental session consisted of two runs of continuous EEG recording. In each run, the subject performed 40 trials for a total of 80 trials. In each trial, subjects were visually prompted to perceive the feelings on their left or right wrist while a simultaneous vibration was applied to the respective wrist. The sequence of events in each trial is illustrated in Figure 1 and described in detail below. At −3s (the start of each trial), a white fixation cross ("+") appeared at the center of the dark screen and it lasts throughout the entire trial until rest. At −1s, subjects received a 175 Hz vibration burst lasting 0.2s on the median tendon of both wrists simultaneously, with equal intensity as a prompt for the task to follow. At 0s, either left or right wrist vibro-tactile stimulation would be applied, accompanied by a left or right pointing red visual cue superimposed the white cross. The vibro-tactile stimulation lasted for 5s, while the visual cue lasted for 1.5s. At 5s, the unilateral vibro-tactile stimulator stopped, and the white cross on the screen disappeared. A rest time of 1.5s was given, followed by an additional random rest time of 0 to 2s to prevent subject habituation. Each run contained 20 trials of both left and right task applied in random order. A 2–4 min rest was given between runs. The unilateral stimulation is to induce as clear as possible contra-lateral response.

D. Data Preprocessing & Signal Decomposition

Offline signal processing was performed and the EEG data was manually corrected for artifacts using EEGLAB toolbox prior to analyzing event related spectral perturbations (ERSP) and Event related desynchronization (ERD) / event related synchronization (ERS) [30]. Artifacts were removed in two steps: 1) trials containing non-ocular artifacts (i.e. large drifts, electrode spikes, saturation) were removed; 2) independent component analysis (ICA) was used to remove ocular artifact components from the remaining epochs [30]–[32].

E. Event-Related Spectral Perturbations (ERSP)

ERSP visualizes the mean change in spectral power relative to a baseline [33]. The baseline reference interval for ERSP calculation was taken from −2 to −1.2s, which is the 0.8s interval prior to the onset of the bilateral vibration burst. Each spectral transform of individual response epochs is normalized by dividing by their respective mean baseline spectra [34]. After performing the artifact removal mentioned above, Small-Laplacian (nearest-neighbor) filtering was applied to the EEG as a high-pass spatial filter to accentuates localized activity and reduces more diffused activity [35]. The ERSP at channels C3 and C4 were calculated after small Laplacian filter was applied, to visualize right and left stimulation, respectively. The resulting ERSP visualizes the mental processes and cortical responses to left or right vibro-tactile stimulation.

F. Event-Related Desynchronization/ Synchronization (Erd/S)

ERD and ERS are respectively defined as the percentage of EEG power decrease or power increase with respect to a baseline reference. Average ERD/ERS displays the activation and deactivation of brain regions. It is calculated in a defined frequency band in relation to a baseline reference interval [36]. The baseline reference interval for the ERD/ERS calculation was taken from −2 to −1.2s, which is the 0.8s period prior to the onset of the bilateral vibration burst. Similar to ERSP calculation, the Small-Laplacian (nearest-neighbor) was applied to the EEG after artifact rejection. The statistical significance of the ERD/ERS was verified by applying a t-percentile bootstrap statistic to calculate confidence intervals with a significance level of $\alpha = 0.05$.

The quantification of ERD/ERS was calculated in following three steps: 1) Bandpass small Laplacian filtered signals between alpha-beta (8–26 Hz) frequency band; 2) Band power calculation, and 3) Epoch averaging to obtain grand average ERD/ERS. ERD/ERS topoplots sample points were plotted after averaged over the specified time intervals.

G. Feature Extraction (Common Spatial Filter)

A fourth-order Butterworth filter was applied to the raw EEG signals prior to further spatial filtering. In this study, common spatial pattern (CSP) is used prior to the classification of EEG epochs into either 'left' or 'right' classes. Mathematically, CSP is performed by simultaneous diagonalization of the covariance matrices of the data from two classes (left or right in the current study) [37].

The kth trial of the EEG signal before CSP filtering is represented as E_k with dimensions $C \times N$, where C is the number of EEG channels and N is the number of sample points of the trial. The normalized spatial covariance of the EEG can be obtained from

$$C_k = \frac{E_k E_k^{'}}{trace(E_k E_k^{'})} \tag{1}$$

where k is the trial index and $'$ denotes the transpose operator and trace(x) is the sum of the diagonal elements of x [37]. For each of the two classes to be separated, let the spatial covariance

$$\in\in C_l = \sum_{kS_l} C_k C_r = \sum_{kS_r} C_k \tag{2}$$

where S_l and S_r are the two index sets for the two separate classes, left and right, respectively.

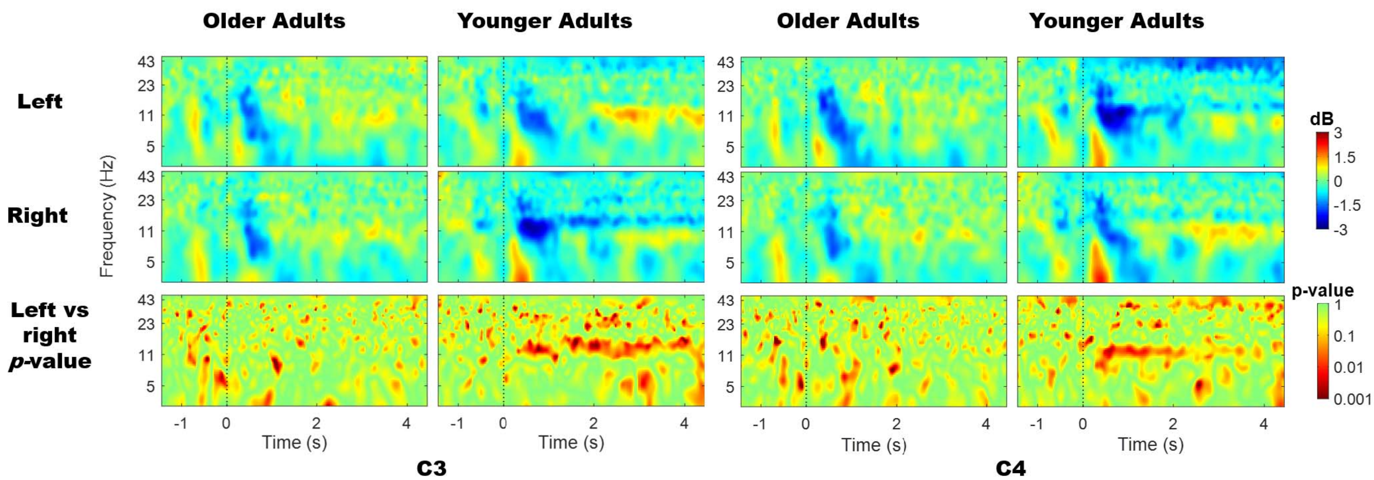

Fig. 2. Average ERSP for all younger and older participants, before and during vibro-tactile stimulation (which lasted between 0–5s), during Left-side stimulation (top row) and Right-side stimulation (middle row). The ERSPs of channels C3 and C4 are on the left and right panel, respectively. The bottom row is the map for the statistical tests (p-values of pair-wise t-test) comparing Left and Right in each column, where darker color indicates smaller p-value. The clear discriminative power of the ERSPs of the Younger Adult group is visible following the unilateral stimuli (t=0) and is most concentrated in the frequency band between 8 and 26 Hz. This is confirmed by the statistical tests. In contrast, no such clear discriminative pattern can be found for the Older Adults group.

The projection matrix W is obtained from the augmented generalized Eigen-decomposition, $(C_l + C_r)W = \lambda C_r W$. The rows of W are spatial filters; the column of W^{-1} are spatial patterns. The filtered signals $Z_k = WE_k$ is uncorrelated between each of the kth trials. The feature vectors for classification were obtained by taking the log variance of the first three and last three rows of the spatially filtered signal Z_k, as these correspond to the three largest eigenvalues for one class and three smallest eigenvalues for the opposite class [37]. These retained CSP components (rows) were then used as inputs to linear discriminative analysis (LDA) for classification.

H. Offline Classification

The raw EEG data was used for analyzing BCI classification accuracy to simulate the performance from online BCI. Therefore, no artifact removal was done for the analysis on BCI performance. The data set of each subject was divided into a training and testing set. The training set was used to obtain the CSP components and the parameters of the LDA classifier, which were then used to classify the testing set. This training/testing procedure was repeated 10 times with different random partitions into training and testing sets through $10\times$ cross validation [37].

The EEG data from 0 to 2s was used from each epoch for classification accuracy calculation. No trials were discarded to simulate online classification accuracy. There was high inter-subject variation for discriminative frequency bands, hence smaller sub-frequency bands were used in the subsequent analysis: theta (θ, 6–8 Hz), low alpha ($\alpha-$, 8–10 Hz), alpha (α, 8–13 Hz), upper alpha ($\alpha+$, 10–13 Hz), low beta ($\beta-$, 13–20 Hz), beta (β, 13–26 Hz), upper beta ($\beta+$, 20–26 Hz), alpha-beta ($\alpha\beta$, 8–26 Hz), and gamma (η, 30–70 Hz). $10\times$ cross validation was performed for all sub-frequency band to evaluate BCI performance, and the frequency band that resulted with the highest classification accuracy was individually selected for each subject.

I. Statistics

The pair-wise $t-$test was used to test between statistical difference between the ERSPs from the left-hand and right-hand. ERD/ERS data was averaged over segments of 0.2s and the difference between left and right stimulation was analyzed via an independent-sample $t-$test with Bonferroni correction for each segment. The above tests were performed using EEGLab [30]. An independent-samples t-test was also used to compare BCI performance accuracies between younger and older adult populations. Our null hypotheses are that there is no difference between C3 and C4 in each of the tasks performed and that there is no difference between younger and older adults in BCI classification accuracy. The significance level of all tests were set at $\alpha = 0.05$.

III. Results

The age of the older (72.0±8.07 years old) and younger (21.7±2.76 years old) adult populations were significantly different ($t = 21.8$, $p < 0.001$). The number of years of education of the younger (16.2±3.0 years) and older (4.8±2.67 years) adults were not significantly different ($t = -1.25$, $p = 0.226$).

A. Event-Related Spectral Perturbation (Ersp)

A comparison of the older and younger adults' ERSP at small-Laplace filtered C3 and C4 channels is shown in Figure 2. For younger subjects, upon the onset of unilateral vibration stimulation (on either the left or right hand at 0s), a prominent bilateral desynchronization is observed in the alpha-beta frequency band (8–26 Hz) for approximately 0.5s,

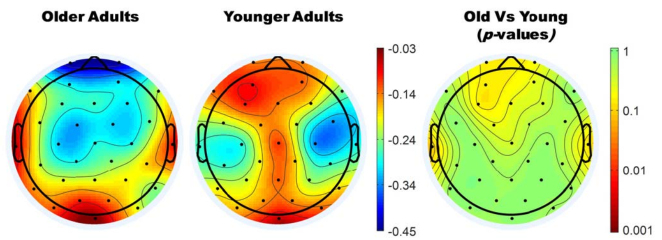

Fig. 3. ERD/ERS (8–26 Hz) topography averaged over −0.4 to −0.1s in response to the 200 ms bilateral stimulation at −1s. The two topographies on the left depict the mean of the averaged ERD/ERS from −0.4 to −0.1s for all older and younger adult subjects, respectively. The right-most topography is the p-values of the pair-wise t-test.

followed by a sustained contralateral desynchronization centered in the high-alpha frequency band (10–14 Hz). However, for older subjects only the bilateral desynchronization was present; the latter sustained contralateral desynchronization seen in younger subjects was absent. Another observation is the ipsilateral synchronization in the alpha frequency band (7.5–12.5 Hz) that is present in both the younger and older subjects, appearing approximately from 2 to 4s. However, this is much more prominent in the younger adults than in the older adults. The statistical test (bottom row of Figure 2) showed that in the older adult group, no clear pattern existed for the region with statistically significant lateralization. In the contrary, for the younger adult group, regions of significant lateralization clustered temporally from 0.5s to 4s following the cue, and within the frequency band of 8–26 Hz, which was used to determine the optimal frequency band to investigate for ERD/S.

B. Event-Related Desynchronization/ Synchronization (Erd/S)

The ERD/ERS was plotted within the alpha-beta (8–26 Hz) frequency because this band is shown to contain the most discriminative information from the ERSP analysis above (Figure 2). The ERD/ERS topoplots in response to the 200 ms bilateral stimulation at −1s (on both left and right wrist) was averaged over −0.4 to −0.1s (Figure 3). The desynchronization at channels C3 and C4 are visually more pronounced in younger adults, compared with older adults. Specifically, in the younger adults, there appears to be desynchronization centered around the central-parietal region and parietal lobe at channels CP1, CP2 and PZ. In the older adults, this desynchronization is not as clear. However, pair-wised t-test did not detect any statistically significant difference between the two groups (the right-most plot of Figure 3).

For the ERD/S in response to the sustained vibro-tactile stimulation from 0 to 5s, a distinct contralateral oscillatory desynchronization was observed for younger adults but was absent for older adults (Figure 4(a)), where C3 and C4 signal were processed with small Laplacian filter. For younger adults, the desynchronization of the channel associated with the respective wrist being stimulated (C4 for left hand, C3 for right hand) would reach more than 150% power decrease compared to baseline and remain more than 100% until approximately 1.5s. At the end of the 5-s epoch, the ERD would still be approximately 50% below the baseline. The ipsilateral side also had clear desynchronization, but were not as pronounced as the contralateral side, neither in magnitude and nor in duration. This contrast resulted in statistical difference between the two channels over a large portion of the post-stimulation period (0 to 5 s), as indicated by the vertical shaded areas in the right panel of Figure 4(a). On the other hand, for older participants, while ERD/S was observed in all cases, the magnitude was markedly smaller than those of the younger one, maximized approximately 100% below baseline. More importantly, no clear lateralization between the contralateral and ipsilateral side was observed, as indicated by the lack of regions with statistical difference (few shaded areas in the left panel of Figure 4(a)). In summary, the lateralization pattern of ERD/S is distinct and significantly different in the younger adults but not at all in the older adults. The mean of ERD/S across the scalp over the period from 0.25 to 1s is displayed as topographs in Figure 4(b). The desynchronization of C3 and C4 are distinctly less prominent and diffused in the older adults compared to the younger adults. This observation is further confirmed by the pair-wise statistical test, shown as topographies (the bottom row of Figure 4b).

C. BCI Classification Accuracy

Figure 5 compares the offline BCI classification performance for the vibro-tactile sensation task for individual older adults and younger adult subjects, respectively. The optimal frequency band was selected for each subject to maximize the classification accuracy obtained through a 10× cross-validation procedure. An independent-samples t-test was conducted to compare BCI performance in younger adults and older adults. The average left vs. right BCI performance accuracy of older subjects was 66.4±5.70%, 15.9% lower than that of the younger subjects (82.3±12.4%) and statistically significantly different ($t(10) = -3.57$, $p = 0.005$).

IV. Discussion

Our results showed that age-related electrophysiological changes in healthy older adults significantly affected SMR characteristics in EEG. Such changes have critical implications for BCI applications such as BCI-based stroke rehabilitation, which target at older population but are currently developed and validated with much younger population. The significant reduction in activation power spectrum in older adults (the ERD/ERS pre-cue shown in Figure 3 and the ERD/ERS post-cue in Figure 4) indicates older adult EEG signals are more susceptible to noise and interferences than EEG from younger adults. More importantly, SMR in older adults demonstrated a statistically significant reduced lateralization, seen through ERSP (last row in Figure 2) and ERD/S (Panel B of Figure 4) in the somatosensory cortex in response to vibro-tactile stimulation, compared to younger adults. These visibly different characters in EEG resulted in a significantly lower BCI classification accuracy for the older adults (Figure 5). For 5 out of 11 of the younger adults, the frequency α^+ band yielded the highest classification result,

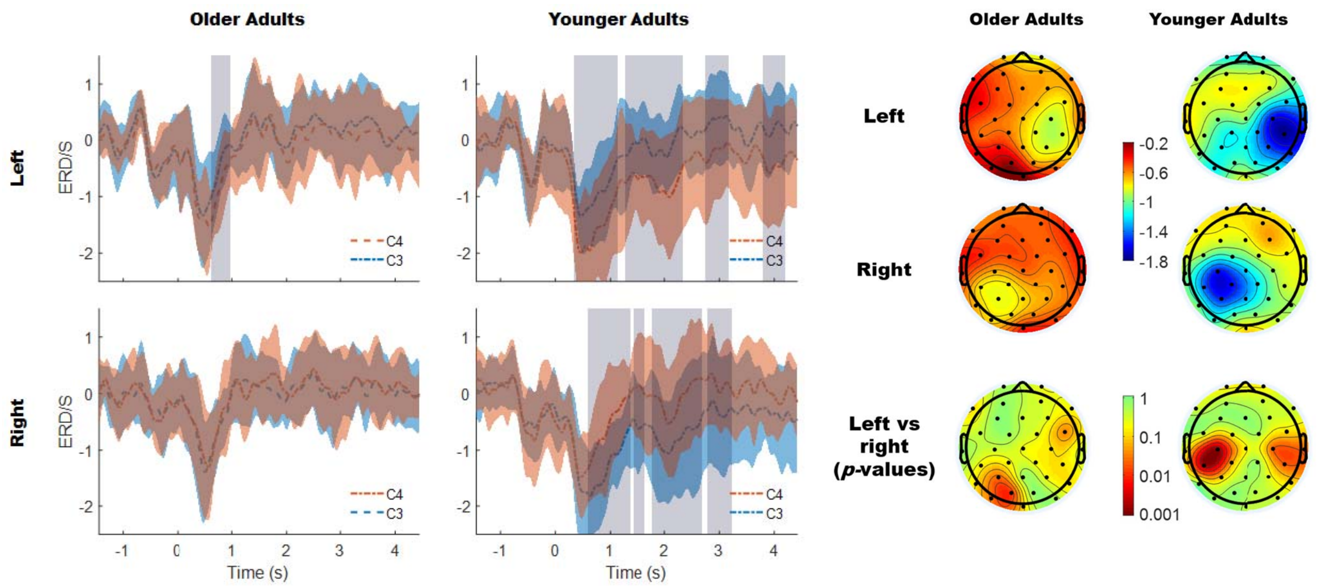

Fig. 4. Comparison of average ERD/ERS of younger and older participants in the alpha-beta frequency band (8–26 Hz). a) denotes the ERD/ERS change for channels C3 and C4 over time; the center dashed line shows the averaged ERD/ERS while the shading around the dash line indicates averaged ERD/ERS±SD. The vertical shaded areas superimposing the graph indicate regions of significant difference (averaged over intervals of 0.2s) between the two channels ($p<0.05$, with Bonferroni correction); b) displays the ERD/ERS averaged over the interval 0.25 to 1s as a topography, as well as the topographies of the p-values of the pair-wise t-tests between the Left and Right stimulus.

while that in the older adults is more wide-spread. These results are in agreement with the findings in [25], where such a significant reduction of ERD/S lateralization induced by motor tasks (covert and overt) was observed in an older adult population. However, the generally weaker and shorter duration of ERD/S induced by somatosensory stimulation in senior population was not observed in the motor tasks induced ERD/S reported in [25], indicating somatosensory ERD/S is more susceptible to noise than motor-tasks induced ERD/S for seniors.

A recent study on SSVEP-based BCI by Volosyak *et al.* [38] investigated the age-associated difference in BCI performance by examining the accuracy and speed of SSVEP-based BCI spelling application. The results showed that older adults had a significantly lower information transfer rate compared to younger adults [38]. Volosyak et al. [38] attributed their results to smaller SSVEP amplitudes for older adults as well as slower reaction time and learning ability. Different from [38], we demonstrated the significant reduction of lateralization in ERD/ERS is likely the key reason for the observed reduction of BCI algorithm performance.

Our findings may be explained by changes in the physical structure of the brain including cognition, neurology, and biochemistry, as well as physical features in the body. Structurally, the brain undergoes an age-related volume reduction that non-uniformly affects the majority of brain regions [39]. The greatest shrinkage is usually in the caudate, cerebellum, frontal cortex, insula, anterior cingulate gyrus, superior temporal gyrus, and inferior parietal lobule [39], [40]. The areas being activated in this task (left or right-hand stimulation) is the somatosensory cortex; its structure may be affected by the natural aging of the brain. Cognitively, it is established that aging causes a decrease in processing speed, working memory capacity, inhibitory functions, and long-term memory [18]. Thus, while changes in the brain because of the stroke likely play a significant role, physiological changes brought about by normal aging may be a contributing factor to the poor performance of BCI algorithms for stroke survivors.

Our results agree with the CRUNCH hypothesis proposed by Reuter-Lorenz and Cappell [21] and HAROLD theory proposed by Cabeza [22], both of which suggest a compensatory account of neural circuits that results in a more symmetrical activation in the senior's brain compared to younger adults. This can be observed in our results in the ERSP as well as ERD/ERS (Figures 2–4). This is a crucial aspect as the change in the locality and strength of activation can significantly alter BCI classification accuracy (as seen in Figure 5), especially when relying on spatial information from CSP and Laplacian filters.

Other factors that may have played a role in the observed differences include scalp thickness [41], [42] and skin sensitivity due to mechanoreceptor loss [43], [44], and there may well be others. In our research, we noted it takes a noticeably longer time to set up the EEG electrodes and noticed an increased scalp impedance for the older adults. We speculate this to be due to a difference in scalp thickness or dryness, and we recommend that this be taken into account for future research and application designs involving older adults. We accounted for the differing skin sensitivity as much as possible by adjusting the stimulation intensity such that all participants perceived a similar level of calibrating all vibration sensation.

Since many EEG processing algorithms for BCI, particularly those based on sensory or motor dynamics, are based on exploiting the lateralization of SMR (e.g., CSP and Laplacian methods), our finding that the classification accuracy in elderly is significantly lower than the younger population by 15.9%

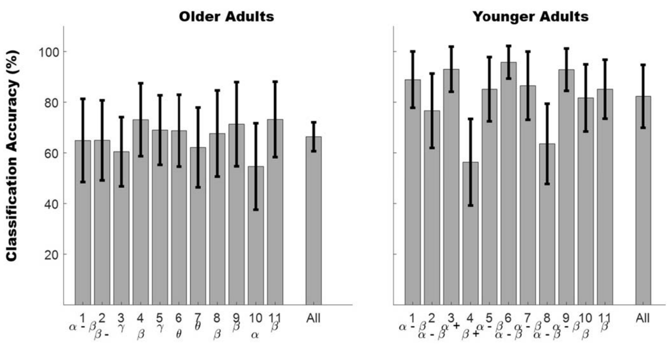

Fig. 5. BCI classification performance accuracy for younger and older adults. Error bars indicate one standard deviation. The right-most bar is the mean and standard deviation across the respective group. For each participant, the frequency band that yielded the highest classification result is shown below the x-axis.

indicates that normal aging results in a detrimental impact on the performance of these classification methods. Our research suggests that alternative algorithms and approaches, which are less dependent on lateralization, need to be developed for BCI applications targeting at older adults such as BCI-based stroke rehabilitation. User training will also play an important role. Zich *et al.* [25] showed that online neurofeedback can enhance lateralization acutely and such training can be combined with non-invasive brain stimulation in improving efficiency [45].

Limitations of our research include factors out of our control, including individual lifestyle and habits such as physical and cognitive exercise, social status and life experience that may influence EEG [46]. Moreover, participants were relatively healthy from a small sample size. We also only investigated somatosensory related SMR in our study, while a combination of sensory and motor tasks will likely be more powerful to practical applications such as stroke rehabilitation. Future work should include a greater diversity of older adults over longer periods of time to investigate variability due to population differences and changes over time.

V. Conclusion

The primary findings of our study are that aging appears to cause a substantial EEG power reduction and diminished cortical lateralization of the somatosensory cortex. This resulted in a lower BCI performance accuracy in classification based on spatial activation information. Future BCI research targeting applications with older adult populations should further investigate the impact of age and develop appropriate measures to accommodate age-related differences in EEG. Neurofeedback training methods to increase lateralization, as well as algorithms that does not only depend on EEG lateralization, should be investigated.

Data Availability

The data that support the findings of this study are available from the corresponding author upon request.

Acknowledgment

The authors would like to thank all the participants for their contribution to this study. They would also like to thank Maxwell Ng for providing valuable insights for this paper.

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