Reducing the Calibration Time in Somatosensory BCI by Using Tactile ERD

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***Abstract*—Objective: We propose a tactile-induced-oscillation approach to reduce the calibration time in somatosensory brain-computer interfaces (BCI). Methods: Based on the similarity between tactile induced event-related desynchronization (ERD) and imagined sensation induced ERD activation, we extensively evaluated BCI performance when using a conventional and a novel calibration strategy. In the conventional calibration, the tactile imagined data was used, while in the sensory calibration model sensory stimulation data was used. Subjects were required to sense the tactile stimulus when real tactile was applied to the left or right wrist and were required to perform imagined sensation tasks in the somatosensory BCI paradigm. Results: The sensory calibration led to a significantly better performance than the conventional calibration when tested on the same imagined sensation dataset ($F_{(1,19)}$=10.89, P=0.0038), with an average 5.1% improvement in accuracy. Moreover, the sensory calibration was 39.3% faster in reaching a performance level of above 70% accuracy. Conclusion: The proposed approach of using tactile ERD from the sensory cortex provides an effective way of reducing the calibration time in a somatosensory BCI system. Significance: The tactile stimulation would be specifically useful before BCI usage, avoiding excessive fatigue when the mental task is difficult to perform. The tactile ERD approach may find BCI applications for patients or users with preserved afferent pathways.**

***Index Terms*—Brain-computer interface (BCI), tactile event-related desynchronization (ERD), somatosensory BCI, imagined sensation.**

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I. Introduction

BRAIN-COMPUTER Interface (BCI) establishes a non-muscular channel for interaction between the external environment and the brain, by decoding the motor/sensory or cognitive intention from the ongoing or evoked brain activity [1]–[3]. By mentally performing motor imagery (MI) [4], [5], the motor intention can be detected from EEG signals by analyzing event-related (de)synchronization (ERD/ERS) [6], [7], or movement-related cortical potentials [8]. Contrary to BCI systems based on visual P300 and steady-state visual evoked potentials (SSVEP) [9], [10], the MI-based BCIs do not dependent on external stimuli [11]–[14]. The MI-based BCI has been shown to have a wide range of potential applications, such as wheelchair control [15], [16], helicopter navigation [17], [18], neuro-prostheses in patients suffering from a high-level spinal cord injury [19]–[21], and for motor function rehabilitation of stroke patients [22]–[25]. Complementary to MI-based BCIs, we have shown that a new BCI paradigm based on imagined sensation can increase the number of BCI modalities, and we have validated that imagination of tactile stimuli can be reliably classified from EEG signal, which has been defined as SAO (somatosensory attentional orientation) [26]–[30]. In the proposed somatosensory BCI system, we have shown that real tactile stimulation on a subject's wrists can help to train the subject to perform the imagined sensation task [31], and can provide a way to train the BCI system before the online decoding on the imagined SAO task [32].

Both imagined movement and imagined sensation are covert mental tasks, which are inherently internal and difficult to observe and measure when no external cue is applied. This causes a wide range of performance variations [33], [34], with relatively poor performance even when training across weeks [35]–[37].

The quality and amount of the calibration data at the beginning of BCI usage is an important factor influencing BCI performance. Usually, it takes approximately 20 minutes to collect enough labeled training data for calibrating the classifier for SAO tasks. To reduce the calibration time and improve BCI performance, several approaches have been applied. Based on the similarity among subjects and sessions, transfer learning provides a potential approach to reduce the number of training trials and improve the system performance [38]. By exploring data from previous days or different subjects for compensating the lack of labeled data from the current user, a weighted transfer learning has been proposed to reduce the calibration effort with fewer trials than the conventional approach [39]. Moreover, domain adaptation is another potential way to further reduce the calibration effort by using advanced algorithms [40]. Besides from an algorithmic perspective, several experimental studies have shown new approaches to reduce the calibration effort. Based on the similarity of the EEG activation pattern between MI mental tasks and several other observable and controllable tasks, such as active/passive movement, and functional electrical stimulation [41]–[43], several calibration strategies have been developed and validated for MI task decoding. By using the data from different tasks other than MI itself, those new calibration strategies have shown to be beneficial in robot-assisted stroke rehabilitation [44], in a clinical population [45], for several specific users who cannot provide calibration data in conventional approaches [46]. Moreover, our previous studies showed that vibration-induced EEG signals can be utilized for setting up MI-based BCIs [47], and also for imagined somatosensory-based BCIs [32].

ERD/ERS is not only correlated with real/imagined movement and real sensory stimulus processing [48]–[51], but also with the imagined sensation, which was explored in somatosensory BCIs [26]. We have previously validated that tactile-induced oscillatory dynamics provide a novel approach to enhancing tactile BCI performance [52]–[54], by using the tactile ERD. Here, we hypothesized that the tactile ERD can be a potential approach to help to reduce the calibration effort by using fewer trials or training time required in the calibration phase before the actual usage of the BCI system and can also provide a more accurate approach than the conventional calibration strategy.

II. Methodology

A. Subjects

Twenty healthy BCI-naïve subjects participated in the experiments (eight females, all right-handed, average age 23.5±1.8 years). The study was approved by the Ethics Committee of Zhejiang University, Hangzhou, China, and the University of Waterloo, Waterloo, Canada. All participants signed an informed consent form before participation.

B. EEG Recording and Somatosensory Stimulation

EEG signals were recorded using g.Nautilus wireless EEG system (g.tec, Austria) with 32 electrodes, which were placed according to the extended 10/20 system. The ground electrode was located on the forehead and the reference electrode on the right earlobe. The sampling rate of the system was set at 250 Hz.

Linear resonant actuators (10 mm, C10-100, Precision Microdrives Ltd., typical normalized amplitude 1.4 G) were used for vibrotactile stimulation and were applied to the left and right wrists. The stimulation device produced a 27 Hz sine wave modulated with a 175 Hz sine carrier wave, which is in the frequency range of activating mechanical receptors of the Pacinian and Meissner corpuscles [55]. The vibration amplitude was adjusted individually such that the subjects were comfortable with perceiving the vibration.

C. Experimental Protocol

As shown in Fig. 1, the sensory cortex was activated by real tactile stimulation or by imagined tactile sensation. During the sensory stimulation (SS) period, the subjects were required to feel the tactile stimuli on the wrist. SS-L or SS-R corresponds to the condition when only the left or right wrist was tactile stimulated. For the imagined sensation (SAO task), there was no tactile stimulus during the task period, and the subjects were required to shift and maintain their somatosensory attention on the wrist and imagine the sensation (before the experiment, the subjects were exposed to the actual vibration beforehand to know how it 'feels' and can thus replicate this feeling during the imagined task). The subjects were required to perform two SAO blocks designated as the conventional calibration dataset, then two SS blocks as the sensory calibration dataset, and finally two SAO blocks as the common testing dataset. There were 40 trials for each block, with 20 for the left task and 20 for the right task. The subjects were seated on a comfortable armchair, with both forearms and hands resting on the armrests. The subjects were instructed to limit their eye, facial, and arm movements. The subjects were required to take self-controlled and sufficient rest (0.5$\sim$1 min) between every two blocks. The procedure of the SAO and SS blocks was as follows:

1) SAO Block: At the beginning of each trial ($T = 0$ s), a white fixation symbol ("+") appeared in the center of the screen. At $T = 2$ s, a 200 ms vibration pulse stimulated both hands to alert the user of the impending task. At $T = 3$ s, a red left or right cue was randomly presented and lasted for 1.5 s, with a left-arrow informing the subjects to perform the SAO-L task and a right-arrow for the SAO-R task. The imagined SAO task lasted for 5 s (the fixation symbol disappeared at $T = 8$ s). Next, a 1.5 s relaxation period was followed. Finally, the next trial started after a random time between 0 to 2 s.

2) SS Block: The timing structure of the trial was the same as the SAO block. At $T = 3$ s, the subjects were required to feel the tactile stimulus when the vibrotactile was applied to the left or right wrist. The sensation task lasted also for 5 s.

D. ERD/ERS and Time-Frequency Decomposition

ERD/ERS is defined as the percentage of the band power decrease/increase in a defined frequency range in relation to a reference period [43]. ERD/ERS was calculated as the change

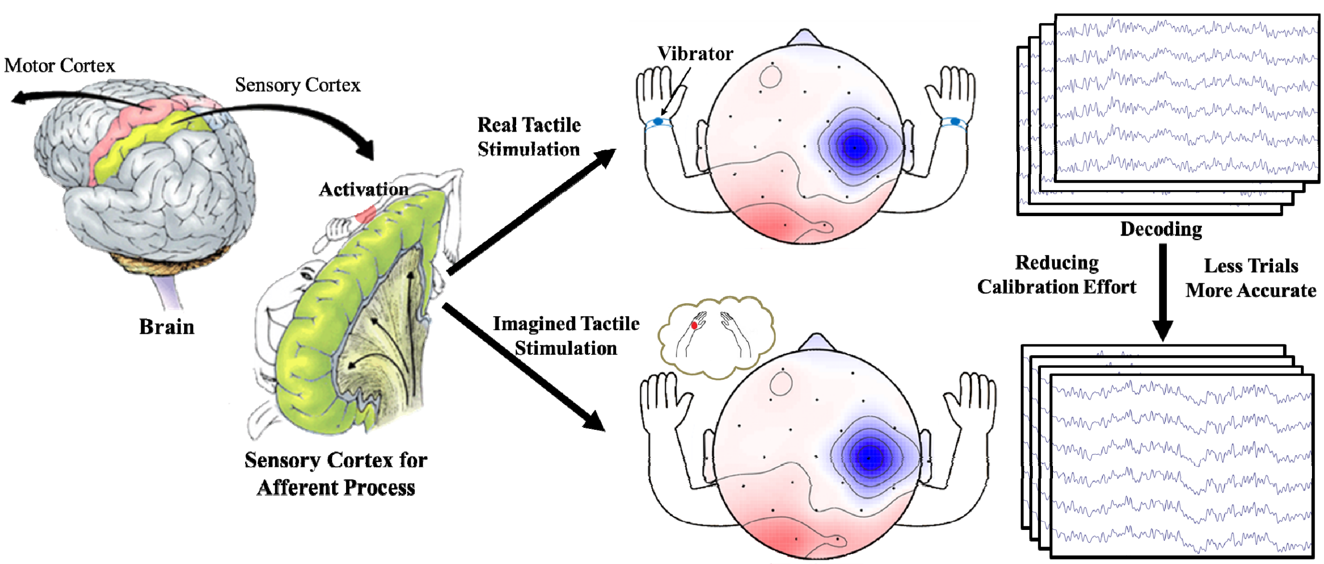

Fig. 1. Graphic illustration of the reducing calibration effort by using tactile ERD. Note: real tactile stimulus was delivered to subject wrist for producing tactile induced ERD activation; in imagined task, subjects were instructed to shift and maintain the somatosensory attention on the left or right hand, and to imagine sensation even when there were no tactile stimuli.

in power within the alpha-beta band (8 Hz - 26 Hz). The baseline interval was between T = 1 s and T = 1.8 s. The ERD/ERS difference was defined as the difference between the ERD/ERS of the C3 channel (left hemisphere) and that of the C4 channel (right hemisphere).

The EEGLAB toolbox was used to correct artifacts [56]. The trials with head/body movement artifacts were excluded from the analysis of ERD/ERS. The Fieldtrip toolbox was used to perform time-frequency decomposition analysis [57]. This was calculated every 0.2 s with a hanning tapper, convoluted with a modified sinusoid basis with 7 cycles at each frequency point to achieve proper time and frequency resolution [57]. The R^2 index is the squared Pearson-correlation coefficient between the feature and class label [58], [59], and was used to show the EEG channels that are important for the classification of the corresponding mental tasks.

E. Algorithms and Performance Evaluation

Spatial filters were calculated by the Common Spatial Pattern (CSP) algorithm, which was used to reduce the number of channels and enhance the feature discrimination between different tasks [60], [61]. Mathematically the CSP is realized by simultaneous diagonalization of the covariance matrices for the two classes. The log variance of the first and last three components of the spatially filtered signals was chosen as feature vectors, and linear discriminative analysis (LDA) was utilized for classification. Before the CSP spatial filtering, a 4th-order Butterworth filter (8 Hz – 26 Hz) was applied. EEG signals were epoched between T = 4 s to T = 7 s. In the sensory calibration model, the trials in the SS blocks were used to train the classification model; while in the conventional calibration model, the trials in the first two SAO blocks were used. The last two SAO blocks were used as the common testing dataset to evaluate the calibration models. For the number of trials used for calibration, we randomly selected the required number of trials, and this process was repeated 40 times and the performance on the SAO testing dataset was averaged.

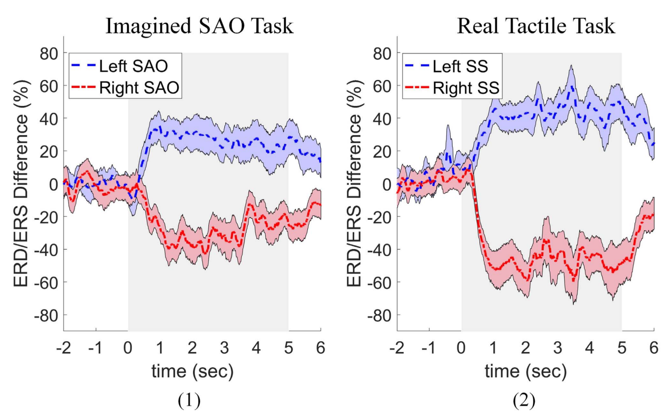

Fig. 2. Grand-averaged ERD/ERS difference within alpha beta frequency band (8 Hz - 26 Hz), with (1) corresponds to Imaged SAO task and (2) corresponds to Real Tactile Task. Note: The blue-dash line corresponds to left hand task and the red dash-dotted line corresponds to right hand task. The grey background corresponds to the task period, and the upper and lower curves indicate standard error. Time 0s corresponds to the time when the cue appeared (The 3rd second from the beginning of the trial).

F. Statistics

One-way ANOVA with repeated measures was used to analyze performance differences among different calibration models (with $p = 0.05$). Whenever the main effect was found to be significant, multiple comparisons with Bonferroni correction were used for post-hoc comparison.

III. Results

A. Tactile ERD and SAO Mental Task

Fig. 2 illustrates the ERD/ERS difference between the imagined SAO task and the real tactile task, indicating the similarity

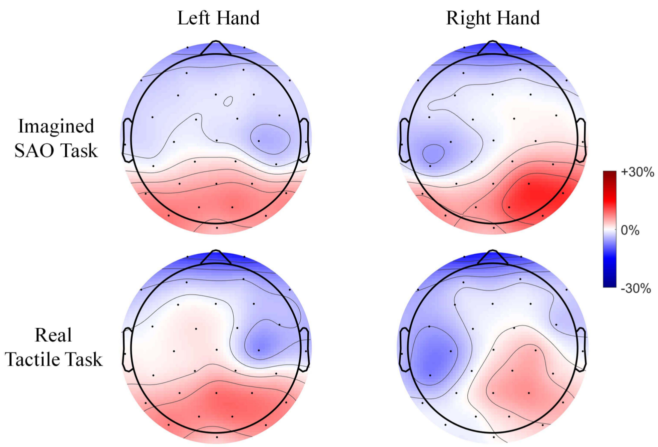

Fig. 3. Grand-averaged ERD/ERS topographic distribution within alpha-beta band (8 Hz - 26 Hz) within task period. The top row corresponds to Imagined SAO task, the bottom row corresponds to Real Tactile Task; The left column corresponds to left hand task while the right column corresponds to right hand task.

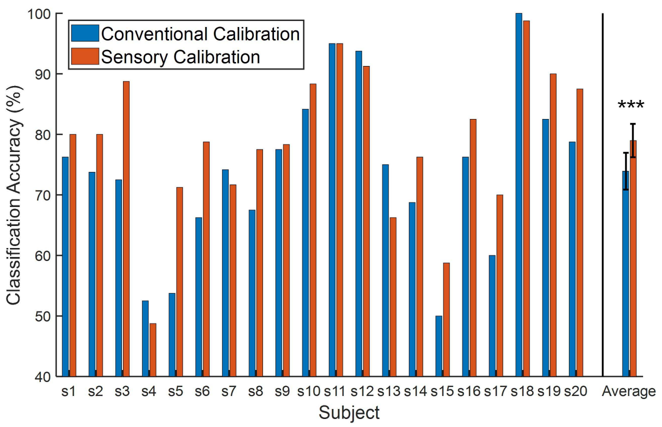

Fig. 4. The classification accuracy across subjects by using different calibration strategies, which were tested on the same testing dataset. The blue bar corresponds to conventional calibration model; the red bar corresponds to the sensory calibration model. The stars indicate significant different with p<0.01.

of induced activity between them, and the left and right-hand tasks were different. Moreover, Fig. 3 illustrates the spatial distribution of the ERD/ERS within the task period across different tasks, indicating the spatial similarity between the imagined SAO task and the real tactile task, and diverse spatial patterns between left and right-hand tasks.

B. Performance for Different Calibration Strategies

Fig. 4 shows the classification performance of each subject by using conventional calibration and sensory calibration strategies. One-way ANOVA with repeated-measure showed that there was a significant difference between the conventional calibration and sensory calibration ($F_{(1,19)}$=10.89, P=0.0038), with 73.9%±13.6% for the conventional calibration model and 79.0%±12.3% for the sensory calibration model. Moreover, the grand-averaged R^2 distribution (Fig. 5), indicates a similarity between the imagined SAO task and the tactile sensation task across the different frequency bands, while in general the SS task exhibited higher R^2 in the upper alpha band than the

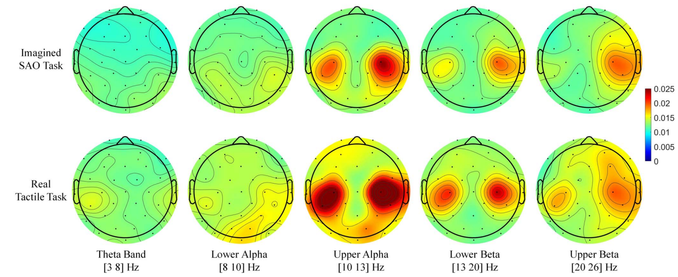

Fig. 5. The grand-averaged R^2 distribution across different frequency band and between imagined SAO task and real tactile Task. The upper row corresponds to imagined SAO task, and the bottom row corresponds to real tactile task. Different columns correspond to different frequency band.

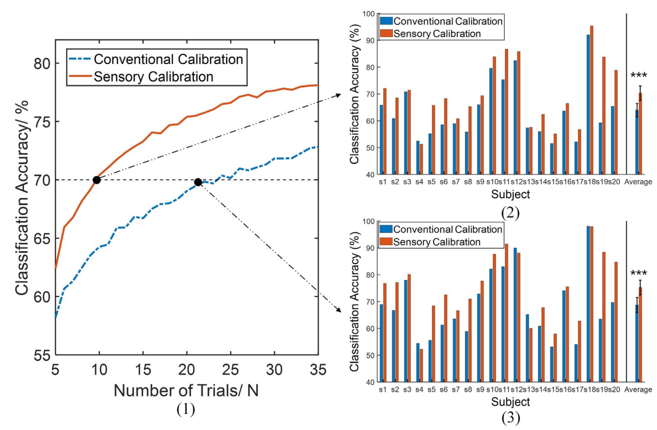

Fig. 6. Performance of the calibration models by using different number of trials. (1) The averaged classification accuracy of different calibration models by gradually increasing number of trials for model training. Note: Number of Trials represents the trial number of each class. (2) The performance of models across subjects when 10 left and 10 right trials were randomly selected, at the time when averaged performance of sensory calibration surpasses 70%. (3) The performance of models across subjects when 20 left and 20 right trials were randomly selected, at the time when averaged performance of conventional calibration reaches 70%. The stars indicate significant difference with P < 0.01.

SAO task. Both tasks exhibited lower R^2 in the lower alpha band than the upper alpha band.

C. Reducing the Calibration Effort by Using Tactile ERD

Fig. 6 shows the performance difference between the two calibration strategies when a different number of trials were utilized for calibration training. Higher performance is attained by using sensory calibration when the same number of trials were used for the calibration. In the case when 10 left and 10 right trials were selected for training, the performance of sensory calibration was significantly higher than that of conventional calibration ($F_{(1,19)}$=23.46, P=0.0001); in the case when 20 left and 20 right trials were used for training, the performance of the sensory calibration was also consistently higher than that of the conventional calibration (F(1,19)=17.69, P=0.0005). When setting 70% accuracy for each subject and each calibration strategy, the sensory calibration strategy could reduce the time by 39.3%±23.9% on average.

IV. Discussion

We showed that the time required for calibration as well as the accuracy of a somatosensory BCI can be significantly improved by implementing a novel calibration strategy based on tactile vibration. Testing was performed on a relatively large number of subjects, and the performance even when the training data was reduced by 39.3% remained significantly greater (on average, 5.1% increase in accuracy) compared to conventional calibration. The conventional strategy requires data of the training and testing set to be from the same or very similar tasks. Conversely, the approach proposed here allows the inclusion of data from quite different tasks for the training data. In the current study, this was comprised of data from real tactile stimulation and testing data from the imagined task. The SAO is a purely mental task, which is inherently internal and difficult to be monitored by others, however, the vibrotactile stimulation is external and can be precisely applied when needed. Thereby, the training data from SS is easier to obtain and more consistent as compared to SAO. In practice, the tactile-induced-oscillation approach would be specifically useful before BCI usage, avoiding excessive fatigue when the mental task is difficult to perform.

There have been extensive studies on machine learning approaches to reduce the calibration effort before the actual BCI usage [62]. A regularization approach provides an effective way to construct the data model when the number of training data is small, and a regularized estimation of the covariance matrices can be obtained by shrinkage [63], [64]. By relying on user-to-user transfer, the data from other users or previous data from target users can be used to improve the calibration when a small amount of training data is available [65], [66]; by using semi-supervised learning, the decoding model is adaptively retrained as new EEG data become available and the unseen data are labeled according to the classifier output [67], [68]. Using a priori physiological information, such as by selecting the relevant channels or source regions, can also reduce the parameters to be estimated, thereby reducing the number of trials needed [69]. Artificial EEG data generation was also shown to be a promising approach to improve performance and reduce the calibration trials, by generating enough labeled data from already available limited numbers of labeled samples [62], [70]. Our approach is different from the algorithmic approaches but could provide new calibration data to novel algorithms. The combination of our sensory calibration with advanced training algorithms could further enhance BCI performance.

ERD/ERS dynamics can not only be induced by real/ imagined movement [4], [71], but also by sensory stimulation [51]. In the current study, the unilateral tactile sensation showed a decrease in power in the contralateral hemisphere, indicating activation of the somatosensory cortex. And this somatosensory ERD activation can be passively modulated by delivering stimuli to different body parts in a controllable way, such as the left and right wrist in this work. The tactile ERD provides a novel signal modality for tactile BCIs [52], [72], and can largely improve tactile BCI performance based on steady-state somatosensory evoked potentials (SSSEP) to repeated tactile stimuli [73]–[75], similar to SSVEP responses to repeated visual stimuli, reaching an average accuracy of 70.4% [76]. However, 80% of subjects showed an accuracy below 70% (4 out of 5 subjects). This BCI paradigm was reproduced by another similar study on SSSEP with more subjects involved in the evaluation, resulting in average performance of 58% over a group of 16 subjects [77]. By evaluating a larger number of 57 users, we have shown that tactile-ERD-based BCI was able to improve tactile BCI performance by around 10% [53], [54]. The present study further confirmed that the somatosensory cortex ERD activation can be induced by unilateral tactile stimulation, and showed a stable activation across subjects and a higher discriminative spatial pattern between left and right stimulation, as depicted in the R^2 distribution in Fig. 5. Moreover, the co-stimulation of both hands would induce co-activation of both left and right sensorimotor cortex [54], which can then be utilized to increase the output commands of the current BCI system. The benefit of the tactile ERD approach for reducing the calibration effort in multi-class BCI system would be worthy of future study.

The proposed approach was motivated and based on our previous work on MI calibration [47], in which vibration stimulation was introduced to facilitate MI training, and on imagined SAO calibration and training [31], [32], in which we showed the feasibility of using tactile stimuli for both calibration and training before BCI usage. In the current study, however, we further demonstrated how the proposed calibration strategy can facilitate reducing the calibration effort and improve the system performance on more users. The proposed methodology could have potential applications for patients with attention deficits, such as attention deficit hyperactivity disorde (ADHD), the controlable stimulus may be utilized to attract their attention, and after a short calibration time, the system can work as an independent BCI modality without external stimulus. In addition, for those stroke patients with motor impairment, while preserving sensory ability, the current approach may help their motor rehabilitation. Due to the mechanical property of LRA vibrators, the range of controllable parameters was limited. The induced ERD activation may correlate with the stimulation parameters, such as amplitude. In the future, an advanced piezo stimulation system (parameters can be fully controlled) should be utilized to evaluate the effect of the optimized parameters for further reducing the calibration effort.

V. Conclusion

In this study, we evaluated a tactile ERD strategy to reduce the calibration effort on somatosensory BCI based on imagined sensation. The proposed tactile ERD approach significantly improved the conventional approach by 5.1% and reduced calibration time by 39.3%. The current approach also provides novel domain data for transfer learning, which provides the potential to further advance the BCI performance.

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