A Method for Using Neurofeedback to Guide Mental Imagery for Improving Motor Skill

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***Abstract*— Mental imagery (MI) is gaining attention as a strategy towards endogenous brain stimulation for improving motor skill. Neurofeedback (NF) is commonly used to guide MI in order to activate the relevant brain networks. The current study investigates an individualized EEG-based method for NF through broad consideration of interactions between different brain networks. We selected the change in brain functional connectivity (FC) as an objective neurophysiological measure of change in motor skill during a longitudinal physical training (PT) program. Digital tracing tasks were developed for skill training and the spatial error in tracing was used to gauge the change in skill. We used partial least squares algorithms to find the most robust contributing networks towards correlation between the resting state FC and the acquired motor skill. We used the network with the largest margin for increasing FC as the candidate for NF training while experimenting with MI during a neurofeedback training program. The participant was informed of the changes in instantaneous FC through real-time audio feedback to help guide the MI. We showed over 20% reduction in tracing error through neurofeedback training alone, without any additional PT. We also showed retention of improvement in skill for several days after the completion of neurofeedback training. Our proposed methodology shows promise for a highly individualized approach towards improvement in motor skill. Given that EEG is an accessible health and wellness technology, such a method could provide a practical complementary option towards personalized therapeutic strategies to improve motor function.**

***Index Terms*— Functional connectivity, partial least squares, mental imagery, neurofeedback, EEG, motor skill.**

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Board of Simon Fraser University.

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I. Introduction

MOTOR function assessment is an integral part of development, planning, and implementation of training strategies to improve skill. Assessments have historically been based on measures of behavior that are evaluated through execution of specific physical tasks and are generally exposed to different degrees of subjectivity and dependence on expertise and availability of qualified examiners [1], [2], [3]. This has motivated a widespread interest in identification and utilization of physiological measures that can provide an objective and accurate measure of change in motor function [4], [5], [6], [7]. Selection of these objective measures should be guided by pragmatic considerations with respect to cost, availability, portability, ease of use, and duration of individual assessments [8]. Brain functional connectivity (FC) measures have shown potential as objective measures for this purpose [9], [10], [11]. To meet the pragmatic requirements, focus has been increasingly shifted towards EEG based resting state analysis to reduce the duration and extent of assessments, moderate the capital and operational cost, and increase portability and ease of use [12], [13], [14], [15], [16], [17].

An inherent characteristic of EEG systems is their high temporal resolution, which makes them a viable modality when using coherence as a measure of FC between different brain areas [18], [19], [20]. In this context, coherence is determined by phase synchronization at specific frequencies, and EEG electrodes represent different brain areas. The enhanced computing power of current electronic devices has facilitated the real-time processing of coherence and the subsequent analysis of instantaneous FC [21]. This has presented an opportunity to not only monitor FC but also investigate the activities that might influence it in real-time. The effect of these influencing activities on related behavior such as motor skill may then be examined and if favorable, integrated into relevant training programs for improvement of function [22]. Brain FC may be influenced through external stimulation [23], [24] or endogenous stimulating activities. The latter is the concept behind operant conditioning through NF, where individuals try to self-regulate and control the desired brain activation through MI in a closed-loop process [25], [26], [27]. MI as a mechanism to influence behavior is particularly appealing due to its relatively low implementation risk.

Specific to motor function, prior work showed change in motor skill by influencing regional brain activities [28], [29], [30], [31], [32], [33]. In these studies, the focus was to regulate the sensorimotor rhythms (SMR) through MI, based on the hypothesis that modulating a specific band power over motor areas would influence the related motor behavior. NF on the instantaneous strength of SMR was used to inform the participants about the impact of their MI. However, studies using functional magnetic resonance imaging have shown that MI can result in overlapping activation of different brain areas [34]. It has therefore been argued that analysis of network interactions might be a more wholistic approach for NF implementation [25], [35], [36]. In a study with both healthy participants [37] and stroke survivors [38], the authors showed that an NF protocol based on increasing the global alpha-band FC with the primary motor cortex resulted in improvement in motor function.

These are significant findings and encouraging results in favor of using NF to facilitate an endogenous self stimulation of brain towards improving motor skill. The targeted frequency band and brain networks for FC analysis is not limited to alpha-band or motor areas. Prior study with healthy participants showed interaction between networks at both alpha and beta-band that included FC with prefrontal cortex for motor learning [39]. Involvement of different brain networks and synchronization frequencies along with differences across subjects due to age or existing capabilities, motivates an individualized approach towards NF training [40], [41]. We therefore investigated an NF training method based on individualized FC analysis between different brain networks at multiple frequencies.

To this end, we explored a longitudinal PT program involving a computer-based tracing task. Tracing error was used as an objective measure of motor skill. The goal of PT was to reduce the tracing error. Spontaneous FC was estimated from coherence measures [20] using resting state EEG data collected as part of the PT program. Partial Least Square (PLS) algorithms [12], [42] were employed to select EEG electrode-pairs (channels) and frequency bands that correlated with changes in motor skill. PLS is a multivariate statistical method that uses singular value decomposition to project the covariance of input variables onto the latent space for correlation analysis. Bootstrap resampling is used to identify the most robust input variables towards correlation. Predictive models are generated through iterative deflation of the input data and generation of regression models that use the selected input variables (channels) from bootstrap analysis [42]. We used the channels from regression models to provide a real-time audio feedback on the instantaneous FC measures during MI sessions. The feedback was used by the participant to guide volitional control of the connectivity indices with the goal of improving motor skill without execution of additional PT.

II. Methods

A. Study Design

1) Workflow: Fig. 1 shows the experimental workflow for data collection and analysis. We balanced the requirements of quality data collection with the participant engagement and optimal performance. The latter was an important condition with respect to NF, as task demands have direct impact on the success of MI (e.g., attention/distraction). The different repetition numbers during successive stages of this study were selected to address practical training requirement that balanced the trade-off between optimal learning and fatigue.

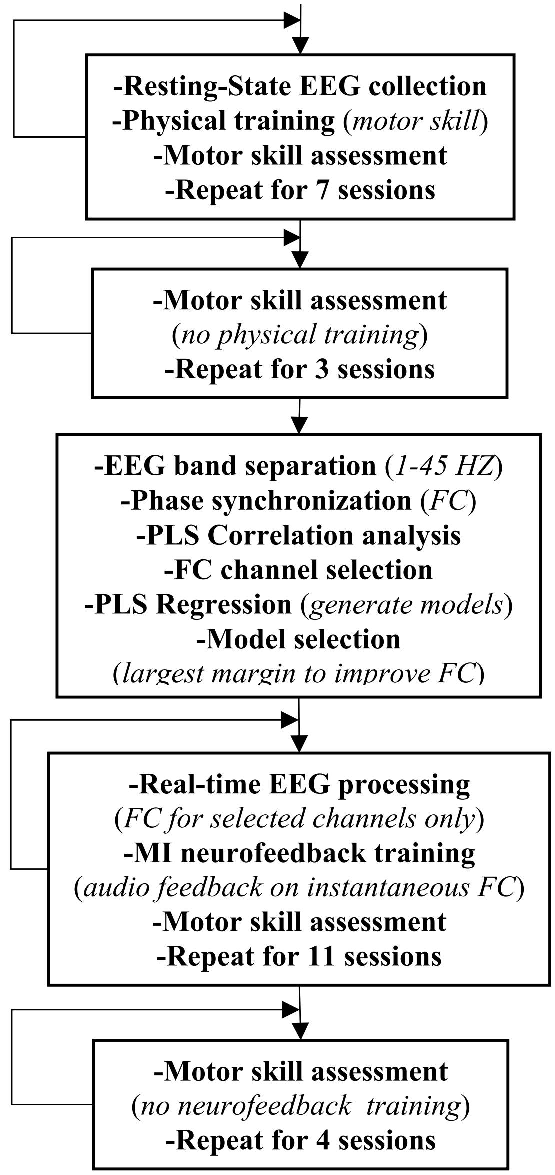

Fig. 1. Experimental workflow for data collection and analysis.

2) Setup: We used a 32-electrode dry-EEG cap (g.SAHARA, g.tec medical engineering, Austria) operating at a sampling rate of 250 Hz for data acquisition. We used a standard 10-20 montage with the reference electrode on the right mastoid and the ground electrode on the left mastoid.

Python 3.7 was used to create elliptical track patterns on a computer screen as depicted in the inset of Fig. 2. Participant was asked to use the computer mouse to trace the track section between the vertices identified by the green and red dots, respectively. The active track was selected randomly as explained later in the protocol. Distance between opposing tips of the track pattern was arranged to be approximately 35 cm of

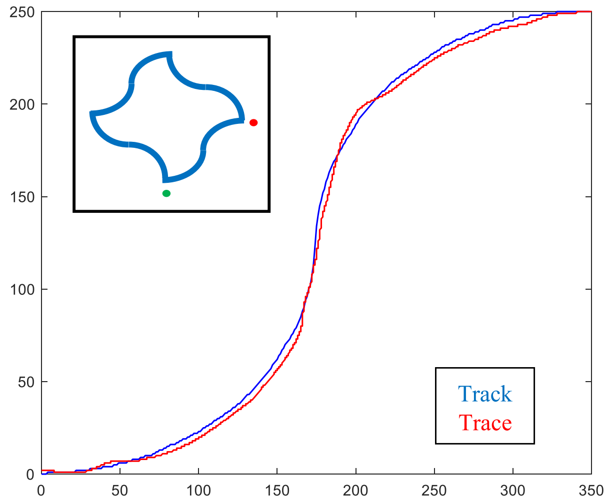

Fig. 2. Participant's tracing trajectory over a track section. The position-error is the total area between the trace (red) and track (blue) section. The inset at the top-left corner shows the complete track pattern. The green and red dots identify the active track to be traced. Axes are in units of screen pixels.

mouse travel across the torso (x-axis: left to right) and 25 cm away from the torso (y-axis: top to bottom). The rational was to deliver large physical movements that engaged multiple arm joints without the need to involve the torso. Motor skill was measured in terms of position error between the track and the participant's tracing trajectory, as well as the time taken to complete the corresponding tracing task. Position error for each tracing task was quantified as the area, in pixels, between the active track and tracing trajectory as shown in Fig. 2.

3) Participant: A healthy right-handed 61-year-old female volunteered in order to test the methodological feasibility for this study. The participant had no known neurological or physically limiting conditions, and no implants. The Research Ethics Board of Simon Fraser University approved the protocol for this study, and the participant signed an informed written consent form.

4) Protocol: The participant completed a longitudinal PT program that included 7 training sessions, limited to a single session per day. Each session consisted of 8 tracing trials with the right hand followed by 90 tracing trials with the left hand. A trial was defined as a tracing task over a track section, where the specific track and direction of tracing was randomly selected by the program. The rational behind using the left (non dominant) hand for tracing was to induce motor learning effect [11], [43], [44] thereby increasing the potential for larger changes in FC during a short PT program. Data for the right hand were collected but not used in this study. We collected 5 minutes of pre- and post-PT resting state EEG data in each session. Each session lasted approximately 50 minutes.

The protocol for assessment of motor skill was like that of PT but limited to only 30 tracing trials for the left hand. We carried out three motor assessments over three consecutive days after the end of PT program to obtain a baseline for skill level before the start of the NFT program. Three assessments were the minimum number of samples needed to determine a trend and measurements' deviation around that trend. Our goal was to minimize the number of sessions before NFT to reduce the potential for fatigue in our participant. We also carried out four motor assessments over four days after the completion of the NFT program to test for retention of the acquired skill. We had planned to obtain more than the minimum samples after the NFT program, but the participant could only partake in 4.

NFT started after the completion of the PT program. EEG data were acquired at 1-second intervals and processed in real-time to calculate the instantaneous FC measures and generate the subsequent audio feedback. Volume of the audio feedback was proportional to the magnitude of the FC measures. Each NFT session lasted 5 minutes. Depending on the participants level of fatigue, we carried out at least two sessions, and at most, five sessions in each day of the NFT program. There were a few minutes break between each session to document the participant's recollection of MI in the preceding session and the strategy, if any, for the next session. We also collected 5 minutes of resting-state EEG data before the start, and after the end of all NFT sessions in each day.

B. Measure of Motor Skill

We evaluated two measures of performance indicators, namely the accumulated position error during each tracing task, and the product of the accumulated position error and the time taken to complete the corresponding track (position-time error). The latter brought the tracing speed into consideration. Position error was calculated from the total area between the track and tracing trajectory (Fig. 2) and converted to spatial units of squared centimeter (cm^2) based on an approximate conversion factor of 0.25 mm^2 per square pixel. Position-time error was in units of cm^2 seconds.

We generated three separate measures of motor skill for each session. 1) A single value corresponding to the median error of all 90 tracing trials, referred to as single-median option. 2) Median error of the first 30 trials to represent the tracing performance before PT, and 3) that of the last 30 trials for performance after PT, referred to as dual-median option. The process was carried out for both position and position-time errors. These were used to evaluate four distinct FC corelates of motor skill as explained in the signal processing section.

For assessments of motor skill associated with NFT, a single set of 30 tracing trials was carried out before the NFT sessions and another 30 tracing trials after the completion of all NFT sessions on that day. Motor skill before and after NFT was quantified by the median of the respective tracing errors. We also used 30 tracing trials for each skill assessment after the completion of PT and NFT programs.

C. Signal Processing and Analysis

1) EEG Preprocessing: Recorded resting state EEG data were imported into MATLAB-7.8.0 (MathWorks Inc) for signal processing and analysis during the PT program. We applied a frontend bandpass filter of 1-45 Hz using a finite impulse response digital filter. The filtered data was then visually inspected in EEG-Lab V14.1.2 to select a 2-minute continuous section with minimal amount of interference from muscular activities. The frequency range was further divided into five canonical bands of Delta (1-4 Hz), Theta (4–8 Hz), Alpha (8–15 Hz), Beta (15–30 Hz) and Gamma (30–45 Hz), each with three additional sub-bands of low, medium, and high frequencies. This was the design criteria for the 15 distinct Morlet-wavelet filters with center frequencies that were approximately one bandwidth apart [45]. We used coherence between EEG electrode pairs (channels) at each of the 15 frequencies as a measure of functional connectivity at that frequency and evaluated the instantaneous coherence through Phase Lag Index (PLI) algorithms [45].

2) Motor Skill Correlates: With the 32 electrode EEG, coherence had to be evaluated for each of the 496 non-directional channels. The individual coherence samples from each channel were averaged over a one-second non-overlapping epoch, resulting in 120 coherence measures in each of the 15 frequency bands. We used the maximum coherence in each band as an index of FC at the corresponding center frequency, resulting in an array of 7,440 indices for PLS analysis [40]. We used single-median tracing performance for correlation analysis between FC indices from both the pre- and post-PT EEG data separately. For the dual-median option, we used the pre-PT tracing performance (median of the first 30 trials) for correlation analysis with FC indices from pre-PT EEG data, and post-PT tracing performance (median of the last 30 trials) for correlation analysis with FC indices from post-PT EEG data.

3) PLS Overview and Analysis: PLS-Correlation (PLSC) was used to identify the channels and frequency bands that exhibited correlation between FC and motor skill [42]. Bootstrap resampling was employed to compute the standard error of the saliences associated with each connectivity channel. This was done to limit the number of channels for regression analysis, thereby reducing the potential for overfitting [40]. PLS-Regression (PLSR) was used to generate models for estimating motor skill from FC. Analysis was restricted to the reduced channel count from the bootstrap stage. Leave-one-out cross-validation was used to evaluate the model's estimation performance (R^2). Number of channels in the regression model was further reduced (generalized) iteratively while maintaining the statistical power above 0.8.

We screened for promising channels and frequencies by selecting those with strong correlation ($p < 0.05$) with each of the single- and dual-median tracing performances using PLSC analysis. We carried out 50 iterations of the correlation analysis to identify the channels that were present in at least 80% of the repetitions, and at the same level of robustness. We then used PLSR to generate a model for estimating the tracing performance from the FC indices of the identified channels. The error in estimation was quantified by root-mean-square-error (RMSE) using leave-one-out cross-validation over the seven PT sessions. The RMSE was presented as a percentage of the average tracing error obtained from each of the single- and dual-median options. This allowed for comparison between models for position or position-time tracing performances.

4) Neurofeedback Training Program: EEG data during NFT program were acquired at one-second intervals and processed in real-time using C++ programming under Microsoft Visual

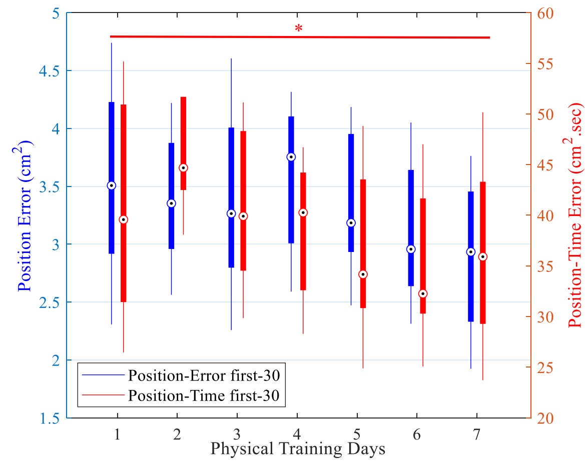

Fig. 3. Longitudinal tracing performance during physical training in terms of position error (blue bars), and product of position error and time (red bars). The bullseye indicates the median value. Corresponding results from all 90 and last 30 trials were similar in nature and were excluded for the sake of clarity. (∗) indicates significant ($p < 0.05$) change in tracing performance.

Studio 2019 environment. Coherence was only evaluated for the channels and frequency bands that were identified through PLSR analysis during the PT program. The instantaneous coherence measures were averaged over the one-second epoch for each channel and subtracted from a baseline threshold separately. The threshold was selected from the minimum FC index at each of the channels in the regression model. The resulting data were then used to adjust the volume of an audio feedback. The participant was advised to finetune their metal imagery with the goal of increasing the volume of the audio feedback.

III. Results

A. Physical Training

The participant completed seven tracing sessions as part of the PT program. Tracing was done with the left hand and repeated for 90 trials over randomly selected track sections and directions of movement. Fig. 3 shows the resulting position error (blue bars) and position-time error (red bars) for the first 30 tracing trials during the seven sessions of the PT program. The results for the last 30 and all 90 tracing trials were similar in nature and were omitted for the sake of clarity and space. Note that the position-time error has two degrees of freedom, where a change in its value without a corresponding change in position error is also an indication of change in skill due to the tracing speed. The red asterisk indicates significant ($p < 0.05$) change in position-time performance over the PT program. Statistical analysis of the change in motor skill is explained later in this section.

B. PLSC Analysis

FC indices from 496 EEG channels at 15 center frequencies for each of the pre- and post-PT data were separately used in correlation analysis with each of the position (Pos-only) and position-time (Pos-time) assessments of motor skill. Each skill assessment was quantified through a single- or dual-median

TABLE I

RESULTS OF PLS ANALYSIS FOR FC INDICES FROM EEG DATA COLLECTED BEFORE (PRE-PT) AND AFTER (POST-PT) PHYSICAL TRAINING. INPUT DATA CONSISTED OF 496 EEG CHANNELS AT 15 CENTER FREQUENCIES, USING SINGLE- OR DUAL-MEDIAN ASSESSMENTS FOR POSITION (POS-ONLY) OR POSITION-TIME (POS-TIME) TRACING ERRORS. ONLY FOUR COMBINATIONS (OPTION-A TO D) MET OUR SCREENING CRITERION FOR STRONG CORRELATION ($p < 0.05$ UNCORRECTED), SHOWN IN DESCENDING ORDER OF COEFFICIENTS (CORR. COEFF.). CHANNELS REPRESENT THE FINAL NUMBER OF PREDICTORS USED IN THE REGRESSION MODEL FROM PLSR ANALYSIS. R^2 IS THE COEFFICIENT OF DETERMINATION. MODEL PERFORMANCE IS DETERMINED BY THE RATIO OF RMSE OVER THE AVERAGE TRACING ERRORS FROM ALL 7 PT SESSIONS

Input				PLSC Results		PLSR Results		
Option	EEG	Freq. Band (center)	Tracing Performance	*p-value*	Corr. Coeff.	Channels	R^2	RMSE (%)
A	Pre-PT	Beta-Med (21 Hz)	Single-median Pos-only	0.008	0.999	4	0.879	3.04
B	Pre-PT	Beta-Low (16 Hz)	Dual-median Pos-time	0.019	0.999	4	0.945	2.51
C	Post-PT	Beta-Low (16 Hz)	Single-median Pos-only	0.001	0.998	4	0.908	2.81
D	Post-PT	Beta-Low (16 Hz)	Dual-median Pos-only	0.020	0.998	4	0.974	2.13

TABLE II

ELECTRODE-PAIRS FOR EACH CHANNEL IN TABLE I

	Negative Regression Coefficients		Positive Regression Coefficients	
Option	Channel-1	Channel-2	Channel-3	Channel-4
A	AF3 - P4	FC1 - T7	F8 - PO8	C3 - OZ
B	PZ - PO7	FC5 - P7	FZ - F4	AF3 - FC2
C	FC2 - C4	CP1 - PO8	FC1 - PO3	F4 - T7
D	F4 - FC1	CP1 - PO8	T8 - PZ	C4 - PO8

approach. The latter was represented by the median of the first and last 30 tracing trials and were used in conjunction with the pre- and post-PT EEG data, respectively. This resulted in four separate PLSC analysis for each of the pre- and post-PT EEG data. Table I shows the results of the PLSC analysis that generated promising correlations ($p < 0.05$ uncorrected), and Table II shows the corresponding Electrode-Pairs for each channel. We used bootstrapping to identify the most robust channels and center frequencies that contributed towards the correlation with tracing performance [40]. PLSR analysis was constrained to these channels and frequencies as described in the next section.

C. PLSR Analysis

We generated a separate regression model for each of the entries in Table I. Predictors of the models were limited to the most robust channels and frequencies that were identified from PLSC analysis. Regression coefficients in each model represented the contribution from the identified channels (predictors) at the specific frequency sub-band towards valuation of the tracing performance (behavior) from FC indices (objective measures). We used leave-one-out cross-validation to quantify the RMSE in estimating tracing performance. Estimation error was represented as the ratio of the RMSE and the average of all 7 tracing performances. The small number of behavior samples had an unfavorable impact on the statistical power of our regression analysis. To counter the effects of the small sample size, we reduced the number of predictors to achieve a statistical power of 0.8 at $\alpha = 0.05$ and R^2 of the respective regression model. This was done by removing the predictor with the lowest regression coefficient and generating a new model through iterative PLSR analysis. Our rational for this approach was the argument that these channels would have less impact on the overall estimation error compared to those with higher regression coefficients. PLSR columns in Table I show the results of this iterative process with the final number of channel counts and corresponding RMSE ratio. The statistical power for Option-D was well above 0.8, but we could only achieve a power of 0.78 for Option-B as we reduced the number of channels to 4 and less. The R^2 for options A and C were too low and became worse for lower number of channels, resulting in a best-case power of 0.57 and lower. We therefore excluded options A and C and only focused on Option-B and D for neurofeedback training.

D. Neurofeedback Training

The regression models for estimating tracing error had both positive and negative coefficients. This meant that an increasing FC in channels with negative coefficients resulted in a reduction in tracing error, or an improvement in motor skill. Increasing FC in channels with positive coefficients had the opposite effect. We only provided feedback on FC of channels that were conducive towards a reduction in tracing error. The volume of the audio feedback was proportional to the increase in FC above a baseline threshold. We selected the baseline threshold to be the smallest FC index for the corresponding channel during the PT program. The indices of the channels with negative regression coefficients for Options B and D are shown in Fig. 4(a) and (b), respectively. Options A and C were not used for neurofeedback, due to their low statistical power of the regression model. Bearing in mind that the maximum value of an FC index is limited to 1, we looked for the regression model that provided the largest potential for increasing FC through neurofeedback. Option-B was the only model that

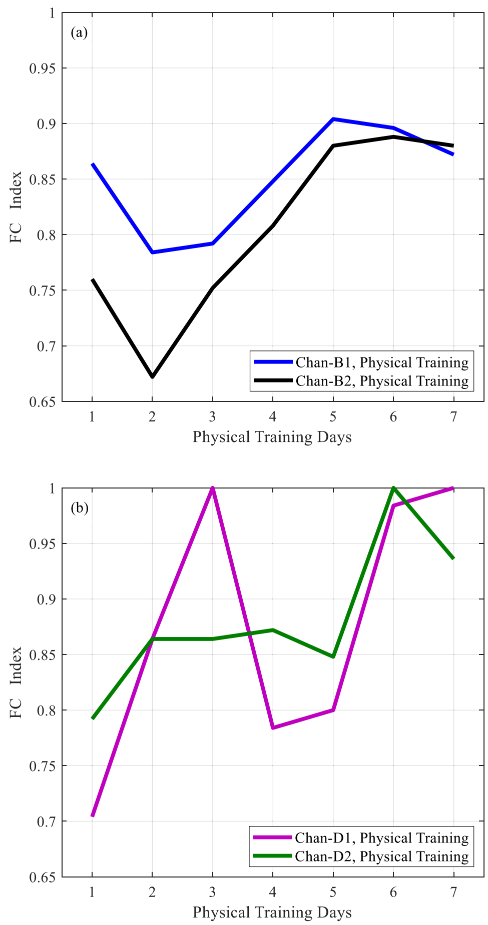

Fig. 4. FC indices for (a) EEG data from Option-B in Table I, and (b) those of Option-D. Only the two channels with negative regression coefficients are shown. These channels were selected for neurofeedback training. Option-B provided a larger potential margin for increasing FC indices as compared with option-D.

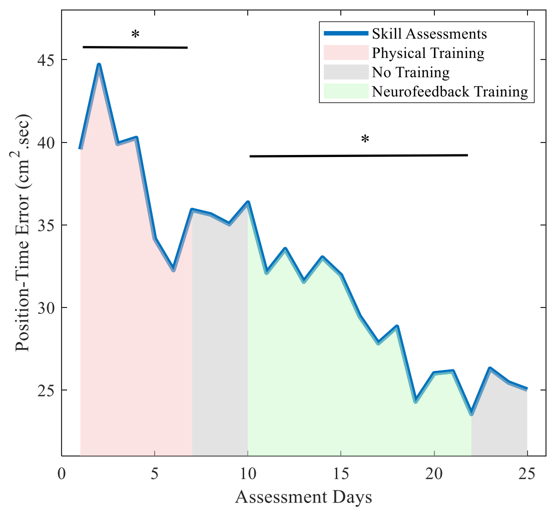

Fig. 5. Motor assessments for Option-B with Dual-median Position-time selection. (∗) indicates significant ($p < 0.05$) change in tracing performance.

showed an opportunity for the participant to increase the FC indices of both contributing channels (B1 and B2) by over 0.12 (∼14% of the last reading). Option-D was limited to 0.05 and only available for one contributing channel (D2).

We carried out three assessments of tracing performance between the end of PT and start of the NFT program. Motor skill assessments were also done for each of the eleven NFT days. After the completion of the NFT program, the participant went through an additional four tracing assessments to examine the short-term retention of acquired motor skill. Fig. 5 shows the results of all the motor skill assessments in terms of the tracing error specific to Option-B in Table I. Impact of guided MI on the resting state FC of selected channels during the NFT program is shown in Fig. 6. FC indices are from resting state EEG data collected before the NFT sessions. The corresponding FC indices during the PT program are also included in Fig. 6(dashed lines) to provide a reference for relative changes in individual FC indices.

E. Statistical Analysis

We began our analysis by testing for the presence of a significant ($p < 0.05$) change in motor skill during each of the PT and NFT programs. We also investigated the manifestation of discernable structure in the way motor skill changed during the NFT program. Statistical analysis was done using version 4.2.1 of R (R Core Team, 2022).

We fit a simple linear regression model to the motor skill assessments during the PT program. The slope of this regression model was significantly different from 0 ($p = 0.048$) and indicated a decrease in mean tracing errors across PT sessions. Next, we fit a linear regression model to the motor assessments scores during the NFT program, which also showed a significant ($p = 8.5 \times 10^{-5}$) decrease in mean tracing errors. We also considered higher-order polynomial regression models using standard information criteria [46] and found that a linear fit was most appropriate.

We probed the motor assessment scores during the NFT program for a possible substantive change in the relationship between motor skill and NFT sessions. This was done to explore the presence of change-points in the regression models, indicating different phases in the way NFT influenced motor skill. Processing was done by performing a structural change analysis using the 'strucchange' package in R [47]. The three F-statistic based tests gave inconsistent conclusions (p-values: $\sup F = 0.064$, $\text{ave}F = 0.073$, $\exp F = 0.04$). Repeating this analysis using quadratic regression models gave similar results. We therefore concluded that there was insufficient evidence to suggest a structural change during the NFT program.

Using a two-sample T-test, we found a significant ($p = 7.19 \times 10^{-7}$) difference between the mean tracing performance in motor skill assessments before the start of the NFT program to that of post NFT assessments (Fig. 5). The 95% confidence interval reported that mean performance was lower by between 9.3 and 12.3 cm^{2}sec after the completion of the NFT program. To analyze the impact of the NFT on resting state FC, we used an exact permutation test to check if the mean FC index was increased in the channels that were the focus of MI (Fig. 6). Computation was done using the

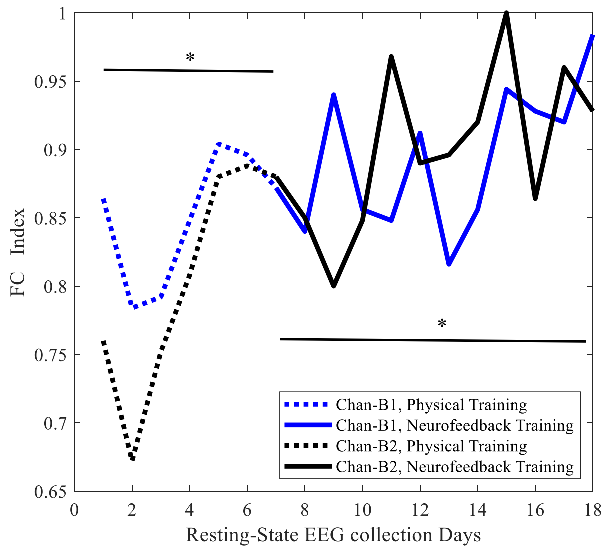

Fig. 6. Resting state FC indices in channels from Option-B. Processing was done on pre-training EEG data for both PT and NFT program. B1 and B2 are the channels with negative regression coefficients. Data from both PT (dashed lines) and NFT (solid lines) are included for comparison. ($*$) indicates significant ($p < 0.05$) change in FC indices.

'EnvStats' package in R [48]. A preliminary investigation did not find evidence of strong heteroscedasticity, and permutation tests found a significant increase in peak resting state FC of both channels (p = B1: 0.047, B2: 0.0016 with 31,824 permutations).

IV. Discussion

Prior research has characterized the relationship between MI, NF, and motor skill. Motor learning is associated with repetitive activation of relevant neural networks [49], with similar structures being involved for real and imagined actions [50]. This is the rational for using MI as an adjunct for acquisition of skill [51] and NF to guide the MI for activation of the relevant networks [52]. Our objective in this study was to investigate the causal effects of changing FC on motor skill based on individualized selection of brain networks and synchronization frequencies. We built on the results from a previous study [40] that showed encouraging performance in estimating motor function from connectivity measures based on global consideration of brain areas. To this end, we chose a longitudinal physical training program for an initial identification of EEG channels that exhibited strong correlation between their respective FC and the change in motor skill. The identified channels were then specifically targeted to induce a change in their connectivity indices. We selected MI as a non-invasive and pragmatic technique to influence FC and chose neurofeedback to guide the MI that had the highest impact on the FC indices of the identified channels. Our results showed over 20% improvement ($p = 7.19 \times 10^{-7}$) in motor skill at the end of the NFT program as compared with the skill assessment after PT. The results also indicated a retention of the motor skill that was measured through assessments spread over five days after the completion of the NFT program. This, however, needs to be better evaluated in future studies.A cursory look at the tracing performance during the NFT program (Fig. 5) seems to indicate an initial learning period of about five days that did not result in a major improvement in motor skill. Additional NFT sessions showed a gradual decrease in tracing error over the subsequent NFT days. But statistical analysis of this data pointed towards insufficient evidence for a structural change in the regression model during the NFT program. However, all three F-statistic tests exhibited p-values near our significance threshold ($p = 0.05$), suggesting that future research with a larger cohort may identify a more complicated relationship than a single linear model. Similar learning periods were observed in other neurofeedback studies, but the authors did not consider the observations conclusive [51]. Such a structural change in how motor performance improves would provide consequential information for future adoption of NFT as a complementary therapeutic activity. Knowing that there may be a learning period during which a major change in skill is not to be expected can help limit the discouraging psychological effects from lack of progress.

Our proposed approach is contingent on an initial PT program that triggers measurable change in motor function to enable the identification of contributing channels and synchronization frequencies. This may appear as an impediment towards the application of our methodology for individuals with limited ability to partake in the PT. In such cases, we believe that the alternative approach of neurofeedback on generalized areas of interest, such as global connectivity with motor areas, may be an appropriate strategy for inducing an initial level of improvement [38]. The latter would still require the collection of EEG data and assessment of motor function, which could then be used for subsequent PLS analysis and identification of relevant channels. A shift in strategy from a generalized to an individualized approach can then follow these initial intervention steps with the potential to expedite or possibly increase further improvements in function [41]. Concerning the clinical application of our proposed method, resting state EEG data can be collected without major hindrance during the initial therapeutic activities as the individuals improve their motor function. Individualized contributing channels and frequencies can then be identified and used for NF training as a complementary activity to the ongoing physical therapy.

In our design of the experiment, we used the error in tracing as a measure of motor skill. This represents an inverse relationship between the regression model and behavior, meaning that a decrease in tracing error signifies an improvement in skill. Consequently, increasing the FC in channels with negative regression coefficients resulted in a better tracing performance. This was equivalent in effect to decreasing FC in channels with positive regression coefficient. We could not, however, propose a mechanism to guide specific MI that would reduce the peak FC in a particular channel. We therefore focused on providing neurofeedback on channels with negative regression coefficients to help the participant identify the MI that resulted in an increase in FC. The model represented by Option-D (Table I) had the lowest RMSE in estimating the tracing performance and was therefore the preferred model for

NFT. But an examination of the maximum resting state FC in the channels with negative regression coefficients (Fig. 4(b)) showed a small margin for increasing FC. The latter represents a ceiling effect for our models and the reasoning behind the selection of our second candidate model, despite its lower performance in estimating skill (higher RMSE ratio). Option-B provided a better opportunity for inducing a larger range of change in FC (Fig. 4(a)). This ceiling effect might be a limiting factor for individuals without multiple options for predictive models. Future work in this area should investigate the proportion of participants that exhibit this limitation.

The positive regression coefficients in our model may imply a gradual development of specialized networks for efficient execution of motor tasks, thereby requiring a decreasing recruitment of those networks to perform the respective tasks [10], [53]. This represents an inherent dependence of our approach on the passage of time, where alternative networks start to contribute more towards further improvements in skill. A continuous development of alternative regression models as new data samples become available may be conducive towards indirect circumvention of the ceiling effect, by introducing new contributing channels with potentially larger margins for increasing FC. This dynamic evolution of predictive models may help extend further improvements in skill. It is important to clarify that we are not arguing for targeted brain stimulation through neurofeedback as a replacement for physical therapy or training. We instead propose our approach as a complimentary activity that could potentially enhance and finetune the efficacy of established intervention strategies. This study shows promise for individualized targeted endogenous brain stimulation that is optimized through the use of neurofeedback. We are hopeful that our results would encourage a more comprehensive study of this methodology with a sufficiently larger number of participants and under controlled experimental conditions. The objective would be to investigate the potential of individualized stimulation in expediting or possibly increasing the effect of MI, as compared with the conventional approach of mental practice that focuses on the SMR activities or generalized connectivity measures with motor areas only.

V. Conclusion

In this study, we investigated the effect of individualized approach towards improving motor skill through influencing FC in EEG channels that were not constrained to the motor areas. We selected coherence at specific synchronization frequencies between electrode pairs (channels) as a measure of FC and used peak resting state FC as an objective measure for estimating change in motor skill through PT. We applied PLSC analysis to detect the contributing channels and PLSR to generate a model for estimating change in motor skill. We then used MI as an endogenous brain stimulation mechanism to influence the FC in the contributing channels of the regression model. We provided real time feedback on the instantaneous FC in the identified channels to guide the MI in a way that was conducive towards improvement in skill. We showed over 20% improvement in motor skill through neurofeedback training alone, without any additional PT. We also showed retention of improvement in skill for several days after the completion of NF training.

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