Motor Imagery Observed by fNIRS

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***Abstract*—Motor imagery (MI) is expected to activate brain areas related to motor functions, yet, the brain is constantly active to some extent leading to difficulties in differentiating MI from supposedly non-motor tasks. In this study, we use functional near-infrared spectroscopy (fNIRS) to offer an objective and spatially precise measurement of brain activity during MI. The fNIRS findings of this study using our MI-based exercise framework with 15 healthy subjects indicate that casual imagination and especially relaxation do not induce an intense motor brain activation compared to active MI performance. Furthermore, dynamic visual cues for MI appear to enhance brain activation around the motor brain areas of the majority of subjects and MI training helps some subjects to activate their motor cortex. Future research may refer to our framework to validate the competence of stroke patients in MI-based motor rehabilitation.**

***Index Terms*—motor imagery, fNIRS, brain, activation, neuroplasticity**

I. Introduction

Motor imagery (MI) is the ability to mentally perform a movement [1]. MI primarily activates the brain areas responsible for motor processes and hence, can be a useful tool for motor recovery by triggering neuroplasticity. MI is particularly valuable when it comes to motor disabilities as MI does not require physical movement. MI is however, often a difficult task to perform well and requires practice [2]. Dynamic visual cues are often applied to assist MI by inducing an illusion of real movement that matches the MI task [1].

Despite the potential benefits of MI, there are limited studies that explicitly investigate the level of engagement of subjects during MI [2]. As the human mind is often unconsciously stimulated and there is no consensus on the essential neural substrates of MI compared to other motor processes, further research regarding the nature of MI is required [2]. Furthermore, the American Guidelines for Adult Stroke Rehabilitation and Recovery classify MI only as a reasonable adjunct to upper extremity and hemispatial neglect rehabilitation, with some conflicting evidence from multiple randomised clinical trials or meta-analyses [3]. To enable the study of the efficacy of MI, the ability to measure the activity in the brain during MI is required. Functional near-infrared spectroscopy (fNIRS) is a non-invasive and portable neuroimaging technique for studying cerebral oxygentation and haemodynamics [4]. fNIRS is more portable than fMRI; thus, fNIRS is relatively more accessible and compatible with experiments involving action observation via a computer display [1]. fNIRS also provides a higher spatial resolution than EEG; hence, fNIRS is ideal for locating brain activation induced by MI which is associated with a higher concentration of oxygenated haemoglobin [4].

In this paper we present a fNIRS study of brain activities across the whole scalp during MI and compare the results to that of relaxation and casual imagination. This aims to reinforce the validity of actively using MI to activate the motor cortex. Furthermore, our findings from 15 healthy subjects indicate that MI effectiveness could be influenced by training and the level of fatigue. Visual aids assist most subjects to perform MI. These results offer a basis for evaluating the practicality of MI in stroke rehabilitation in the future.

II. Experimental Protocol

The experimental protocol was approved by Shantou University, China in accordance with the Helsinki Declaration and all subjects provided written consent before the experiment. 15 healthy subjects participated in the study, 6 male and 9 female with age range 19 to 23 years (M=20.4, SD=1.2).

A. fNIRS Data Collection

fNIRS data were collected using a LIGHTNIRS system (Shimadzu Corporation, Japan) consisting of 8 source-detector pairs with a sampling rate of 4.44 Hz. The device simultaneously measures three different wavelengths of light at 780 nm, 830 nm and 805 nm allowing changes in deoxygenated, oxygenated and total haemoglobin concentration to be calculated. To cover the whole scalp, 14 fNIRS channels were used each

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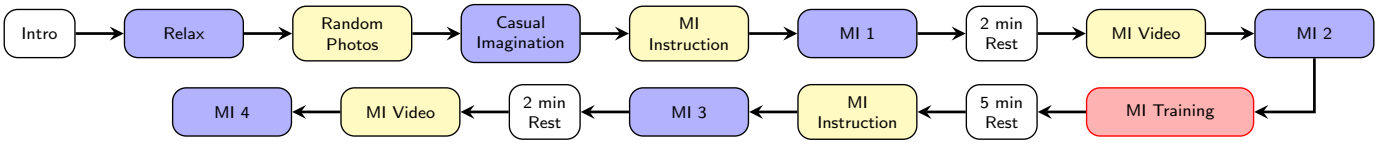

Fig. 1: Flowchart showing the voice-over video experiment sequence and 6 related 20-second tasks performed by participants.

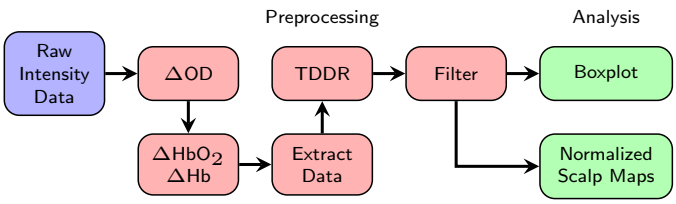

Fig. 2: fNIRS data processing pipeline.

with a source and a detector separated by 3 cm. The channels approximately correspond to EEG channels: Fz, AF4h, AF3h, Fpz, C1, FC3, CP3, C5, PO1, PO2, C2, CP4, FC4 and C6.

B. Experimental Design

The subjects were seated comfortably in front of a screen on which was shown a voice-over video to instruct subjects throughout the experiment. Fig. 1 illustrates the timeline of these instructions and the 6 tasks the subjects were asked to perform. All tasks were 20 seconds in duration and performed with their eyes closed. In brief after the introduction of the experiment, the subjects was asked to relax ($relax$). Next random scenery photos were displayed after which the subjects imagined whatever they chose ($casual$). Following this the subjects were instructed by both audio and text to imagine reaching with both hands for a cup of water on the table in front of them and bringing it towards their mouth (MI_1). After a 2-minute rest and then a video showing the same task, the MI was repeated (MI_2). Finally, the subjects underwent MI training involving an explanation of MI in the first-person perspective which they practiced 5 times, followed by a 5-minute rest. The first-person perspective was chosen as it is the most effective form of MI for activating the motor region of the brain [2]. The subjects then repeated the MI task twice more after the MI training (MI_3 & MI_4). An after session survey was conducted based on item 3 (External Visual), item 7 (Kinaesthetic) and item 11 (Internal Visual) of the motor imagery questionnaire 3 (MIQ-3) [5].

III. Data Preprocessing

The ΔHbO_2 data corresponding to the tasks specified by the experimental timeline as shown in Fig. 1 are extracted.

The fNIRS data processing pipeline used in this study is shown in Fig 2. The LIGHTNIRS system automatically converts the raw light intensity data to changes in optical density (ΔOD_λ), and then to changes in oxygenated and dexoygenated haemoglobin concentration (ΔHbO_2 and ΔHb) in units of $mM \cdot cm$ using the following formula [6]:

$$\begin{bmatrix} \Delta HbO_2 \\ \Delta Hb \end{bmatrix} = \begin{bmatrix} -1.489 & 0.597 & 1.485 \\ 1.855 & -0.239 & -1.095 \end{bmatrix} \begin{bmatrix} \Delta OD_{780} \\ \Delta OD_{805} \\ \Delta OD_{830} \end{bmatrix}. \quad (1)$$

Motion of the subject causes artifacts in the signal, which are much larger than that of non-motion noise [7]. To correct for these the temporal derivative distribution repair (TDDR) is applied. TDDR is effective at removing spikes and baseline shifts while not requiring any tuning parameters [7]. First, a 3rd order low-pass Butterworth filter with a cut-off frequency of 0.5 Hz is applied to extract the low frequency signal for correction. The corrected signal is then obtained as the sum of the corrected centred low frequency signal, the uncorrected high frequency signal and the mean of the original signal.

Following TDDR any physiological noise is removed by filtering. A 6th order Butterworth filter was chosen for the flat frequency response in the passband. First a low-pass filter with an upper bound of 0.9 Hz is applied to minimise heart rate noise [4]. Then two band-stop filters with stop-band ranges [0.07 0.13] Hz and [0.2 0.4] Hz are applied to remove the Mayer waves and respiratory frequency noises respectively [4].

IV. Data Analysis

An objective of this study is to verify whether MI is distinguishable from casual imagination and relaxation by comparing the activity across the whole brain during different experimental tasks. To compare the effects of the different tasks the changes in haemoglobin concentration reflected by the preprocessed ΔHbO_2 data were used in the analysis. As the brain may unintentionally be active even during relaxation no task in this experiment is assumed to be a baseline [1], [2].

As the aim of MI is to stimulate the motor cortex, the average ΔHbO_2 during each of the 6 different experimental tasks in this study was respectively calculated across all channels and samples of the motor cortex. Statistical significance between each pair of tasks was computed using the Python package statannotations [8]. The Wilcoxon signed-rank test is non-parametric, thus, ideal for comparing two conditions for the same subjects without assuming normality of samples [9].

The intensity of brain activation is directly proportional to ΔHbO_2 [4]. To investigate the effects of the different tasks across the brain, the Python MNE library was used to produce scalp maps of the preprocessed ΔHbO_2 averaged over all samples within each channel for every subject [10]. Then, to allow the different tasks to be compared without intersubject variability, the average ΔHbO_2 of each subject

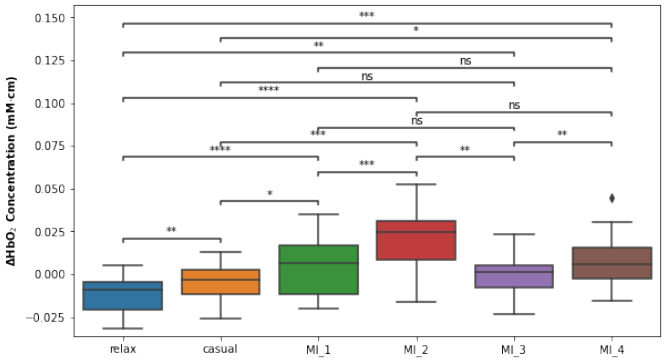

Fig. 3: Box plot of the average ΔHbO_2 over the motor cortex of 15 subjects, respectively, for each experimental task, with the Wilcoxon signed-rank test statistical significance. ns: $0.005 < p \leq 1.0$; *: $0.001 < p \leq 0.005$; **: $0.0001 < p \leq 0.001$; ***: $0.00001 < p \leq 0.0001$; ****: $p \leq 0.00001$.

was normalized with respect to the subject's own maximum and minimum ΔHbO_2 (respectively = 1 and -1) relative to all experimental tasks. However, some channels had low signal-to-noise ratio (S/N). This may be attributed to subjects' dense hair follicles and dark hair absorbing too much light [6]. Therefore only subjects having at least a channel with optimal S/N for each of the frontal, motor and occipital cortices were included to estimate an overall brain pattern via scalp maps.

V. Results & Discussion

Fig. 3 is a boxplot containing ΔHbO_2 averaged over the motor cortex from each of the 15 subjects for all experimental tasks. The average ΔHbO_2 of the 15 subjects for all MI tasks are higher overall than that of $relax$ and $casual$ with significant p-values. This indicates the efficacy of MI at activating the motor cortex. The null hypothesis that the ΔHbO_2 of $relax$ is the same as that of MI-based tasks is rejected. For 3 of the 4 MI tasks when comparing the ΔHbO_2 with $casual$ the p-values are statistically significant, rejecting that actively performing MI and casual imagination are the same.

Fig. 4 shows scalp maps of normalised ΔHbO_2 for subjects 1 to 5, 12, 14 and 15. All of the scalp maps show that the subject's brain is least active during $relax$ and most subjects have low brain activity during $casual$. Only subject 1 has a greater brain activity around the motor cortex during $casual$ than that of MI tasks; however, this could be a result of thinking visually of the random photos which had just been presented as Fig. 4(a) indicates an active occipital area during $casual$. Subjects 5, 12, 14 and 15 have higher brain activity around the frontal and motor areas during MI_2 which could indicate the assistance of watching the MI video instruction.

The effects of the MI training were mixed. For subjects 1 to 3 there was clear benefit from training when it came to successfully performing MI. Prior to training, MI_1 and MI_2 do not induce any greater brain activities than during $casual$ as illustrated by Figs. 4(a–c). However, after training, subjects 1 to 3's brains are more active during MI_4 compared with MI_2. This highlights that without understanding of MI, different types of imagery may be performed. Regardless of the cues presented in any form, untrained subjects are often unable to distinguish between a 1st and a 3rd person perspective MI, or the difference between visual imagery and MI [2]. Figs. 4(d–h) indicate MI training being less effective for subjects 4, 5, 12, 14 and 15, which could be due to post-MI fatigue. Subjects 4 and 12 in particular show brain activity during MI_3 and MI_4 comparable to that of $relax$ and $casual$, possibly caused by mental withdrawal from prolonged MI. The post-session survey reaffirms that subjects experience difficulty in kinaesthetic MI, that is, feeling their targeted muscles while attempting to perform MI. However, all MI tasks induce more intense brain activity than during $relax$ and $casual$ for subjects 2, 3, 5, 14 and 15 as shown in Fig. 4.

VI. Conclusions

As indicated by the normalised ΔHbO_2 scalp maps of Fig. 4 and the box plot of Fig. 3, for all 15 subjects in this study the motor brain areas may be activated by MI. Casual imagination generally does not activate the motor cortex as effectively as active MI performance. Moreover, all subjects show minimal activation in the motor cortex during $relax$ and $casual$ compared to MI tasks, illustrating that MI induces brain patterns distinctive from random thoughts. Although MI could be difficult for subjects who lack understanding of MI or experience fatigue, the brain patterns shown in Fig. 4 appear to be supportive of visual aids and MI training. We propose to use this work as a basis for future research on the quality of MI with appropriate training and visuals in rehabilitation.

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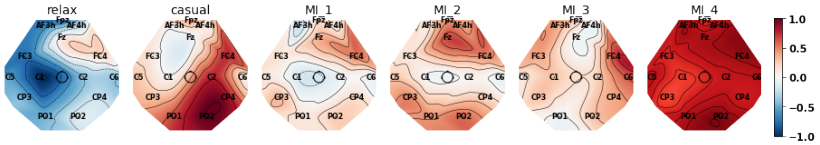
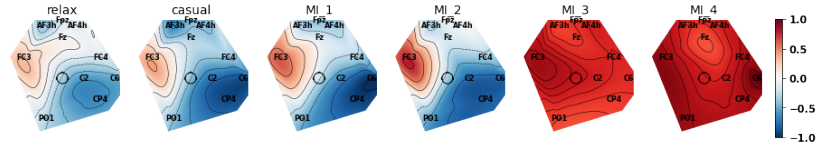


(a) Subject 1



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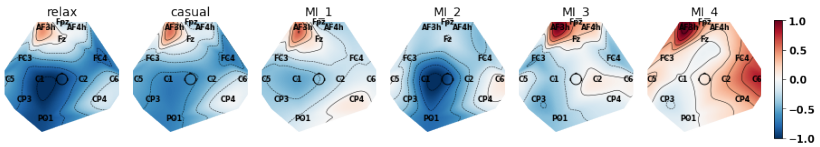

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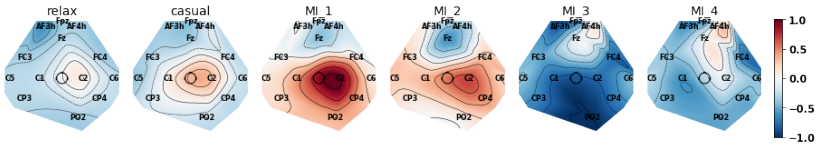
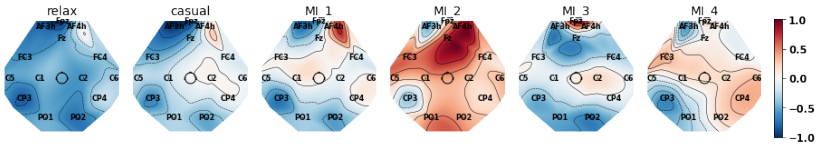


(d) Subject 4



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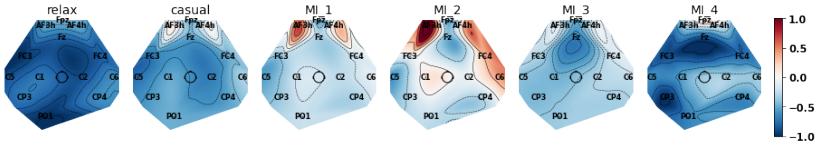

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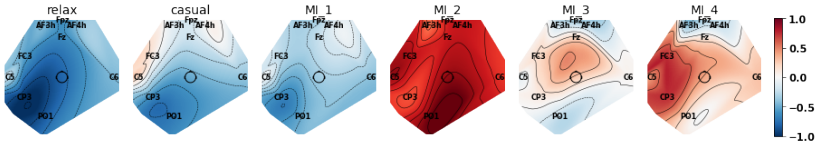

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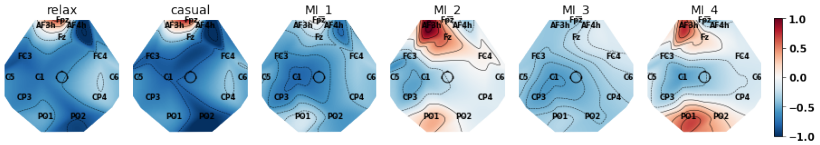

(h) Subject 15

Fig. 4: Scalp maps of ΔHbO_2 normalised relative to all experimental tasks (maximum $= 1$; minimum $= -1$). Only those subjects having at least one fNIRS channel with optimal signal-to-noise ratio for each of the frontal, motor and occipital areas are shown. Maps are oriented with the frontal area to the top of the page.