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Investigation of appropriate fNIRS feature to evaluate cognitive load

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Functional near-infrared spectroscopy (fNIRS) allows researchers to noninvasively monitor cortical activity in a naturalistic environment, which is an advantage in a field of human well-being research to measure cognitive load in a daily-life situation. We investigated the appropriate features of fNIRS signals that best indicates the amount of cognitive load required for performing the multisensory-motor cognitive task. The features tested were (1) maximum amplitude relative to the baseline (MAX) and (2) cumulated amplitude (area under the curve (AUC)) of the normalized average fNIRS signals, and (3) beta value obtained by generalized linear modelling of the raw fNIRS signal using a block design (beta). Oxy-hemoglobin fNIRS features of AUC and beta showed better correspondence to the behavioral measure of cognitive load relative to that of MAX, suggesting that these two indices could be the suitable measure to evaluate cognitive load from fNIRS signals.

1. INTRODUCTION

Functional near-infrared spectroscopy (fNIRS) can measure cortical hemodynamic responses that reflect cognitive functions. The advantage of fNIRS is less constraint in a body posture and movement that enables noninvasive measurement of cortical activity in a state close to natural, daily-life environment. Utilizing these benefits, we have proposed to apply the fNIRS technology to evaluate the intensity of physical pain [Matsuda 2017a 2017b] and discomfort [Ono 2016], and cognitive load [Ono 2015] [Azman 2017].

Although the cortical origin of hemodynamic signal in fNIRS is well confirmed, the fNIRS signal is susceptible to external and/or internal artifacts such as probe displacement and systemic responses [Tak 2014]. Also the majority of commercial fNIRS systems uses continuous-wave NIRS, from which neither the absolute concentrations of oxy- and deoxy- hemoglobin (Oxy-Hb and Deoxy-Hb) nor the optical path length is obtained. Therefore the measured raw signals should appropriately be processed to determine the neuronal signals that represent the intensity of cognitive activity.

There are various fNIRS signal features that have been proposed to evaluate the intensity of cortical cognitive activity. Early studies used the concentration changes of hemoglobin oxygenation during the task period, and more sophisticated statistical approach of generalized linear model (GLM) was later introduced from its relevant field of functional magnetic resonance imaging (fMRI) [Tak 2014]. However, which feature is most appropriate for fNIRS analysis has not comparatively studied yet. We therefore investigated the most appropriate feature of fNIRS signals that represent cognitive load using the fNIRS data during the multisensory-motor cognitive task [Suzuki 2018]. We used dance video game (DVG) as a cognitive task since the cortical area required to integrate audio, visual, and proprioceptive information is well understood [Tachibana 2011][Ono 2014] and the cognitive load to perform the task can be quantitatively evaluated by the behavioral performance such as timing and response accuracies. We tested the fNIRS features of (1) maximum amplitude relative to the baseline (MAX) of the normalized average fNIRS signals [Matsuda 2017a 2017b], (2) cumulated amplitude (area under the curve (AUC)) of the normalized average fNIRS signals [Ono 2016] [Azman 2017], and (3) beta value obtained by GLM of the raw fNIRS signals using a block design (beta) [Ono 2015][Tak 2014]. The features were obtained in three different conditions with varied complexity of the task and compared with the behavioral performance.

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2. MATERIAL AND METHOD

2.1 Participants

We measured twelve healthy male adults, aged 21-25 years (mean and standard error 22.7 ± 0.3 years, all right-handed). The study was approved by the ethics committee of Meiji University, and all participants gave written informed consent to participate.

2.2 fNIRS measurement

We used OMM-3000 fNIRS systems (Shimadzu Co. Ltd., Kyoto, Japan). Optodes were arranged over the frontotemporal regions of both hemispheres of the participant with inter-optode distance of 3 cm for each source-detector pair. Oxy- and deoxy-hemoglobin concentration changes were measured with a sampling rate of 7.9 Hz. For the current study, we used fNIRS signals obtained from the left superior/middle temporal gyrus (S/MTG; Figure 1). S/MTG is involved in the comprehension of the rhythm [Liégeois-Chauvel 1998] and its activity duration correlates with the temporal accuracy of the responses in DVG play [Ono 2014]. Previous study has also shown that S/MTG activity depends on the cognitive aspect of the motor complexity but not on the exercise intensity [Tachibana 2011]. We used a 3D digitizer (PATRIOT, Polhemus, Colchester, VT) and obtained coordinates of all optode positions and the anatomical landmark positions (nasion, inion, auricles and Cz) of each participant immediately before data collection. Individual channel positions were normalized to the standard MNI coordinates using NIRS-SPM [Ye 2009] to confirm their anatomical location.

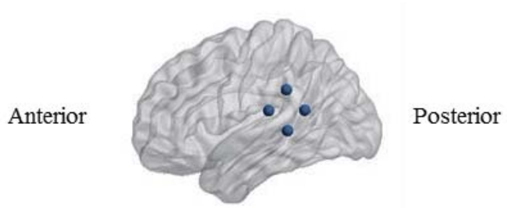

Figure 1. fNIRS channel layout. The mean channel positions across all participants of the current region of interest (S/MTG) were shown as blue dots on the normalized brain. Channel positions were visualized with the BrainNet Viewer (http://www.nitrc.org/projects/bnv/) [Xia 2013].

2.3 Experiment design

We prepared a DVG task (Figure 2) using an open source software StepMania software version 3.9. DVG is similar to the commercial game Dance Dance Revolution (Konami Corporation, Tokyo, Japan). In this experiment, we used 4 arrows, which were up, down, right and left. The participant had to press arrow buttons on the game controller with their finger or on the dance pad with their foot at the right timing which are indicated as visual cues (arrows) on the screen and by the background music. For hand-played condition, participants were instructed not to hold the game controller in hands but press the button of the controller that was fixed on the table.

Figure 2 illustrates the experimental design. All participants performed DVG three times with different appendage conditions (dominant hand (DF), foot (F) and non-dominant hand (NH)) in a random order. Generally, the foot-played condition is more difficult than hand-played condition since participants require more cognitive load to make foot movement to the appropriate direction while maintaining their trunk position, which is much larger and unfamiliar movement compared to hand movement. However our region of interest was located in the multisensory integration area of S/MTG, not in the primary motor area, therefore the recorded fNIRS signals is hypothesized to represent neuronal activities required for cognitive process of multimodal integration.

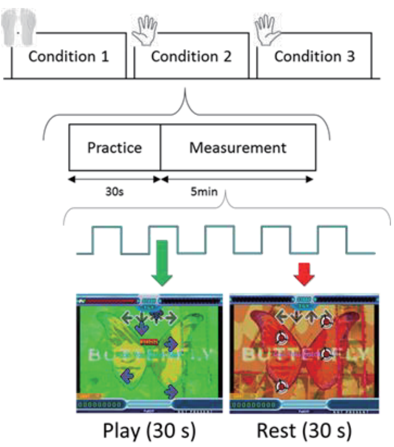

Figure 2. Experiment design. All participants performed DVG three times with different appendage conditions (dominant hand (DF), foot (F) and non-dominant hand (NH)) in a random order.

A single measurement is consisted of 30 s of playing DVG and 30 s of rest alternately 5 times.

The fNIRS measurement of each condition was always preceded by 30 s of practice with the corresponding appendage. A single measurement is consisted of 30 s of playing DVG and 30 s of rest alternately 5 times. A song entitled 'Butterfly' (recorded by SMILE.dk) used as the background music with total of 240 visual cues. The performance of DVG was determined by the number of correct arrow cues that were responded in accurate timing (those being responded within ± 22.5 ms from the exact timing). All participants answered a questionnaire on which appendage was the most difficult in this experiment after the fNIRS recording.

2.4 Data analysis

Oxy-Hb and Deoxy-Hb data in the left S/MTG were analyzed to determine the features of MAX, AUC and beta as neuronal activity indices. One among 4 channels, which was localized most closely at S/MTG, was selected for each participant.

The MAX and AUC were obtained as follows. Change in hemoglobin concentration signals were first averaged with the task onset and smoothed using the moving average filter (25 point, 5 times). The averaged data was then baseline corrected so that the signal amplitude of task onset was set to zero. Lastly, the averaged signals were normalized by dividing the averaged data by the standard deviation of those during the 10 s before the task onset. The averaged hemodynamic responses were manually examined for systemic and/or facial muscle artifact [Schecklmann 2017][Zhang 2016]. The data were regarded as contaminated with systemic and/or muscle artifact and removed from further analysis if both Oxy-Hb and Deoxy-Hb responses continuously deflected to the same direction (either increasing or decreasing) for 10 s from the beginning of the task. Two datasets were excluded with this criterion.

To calculate beta value from GLM analysis we used raw fNIRS data. The beta value is obtained by solving the following equation of GLM by minimizing the square of error $\varepsilon(t)$:

$$y(t) = \beta \cdot x(t) + \varepsilon(t)$$

where $y(t)$ is raw fNIRS data and $x(t)$ is a regressor matrix consisted of vectors of regressor functions. The regressor matrix was consisted of a block-design model function derived by hemodynamic response function (HRF) [Tak 2014], baseline offset, and baseline drift components. The coefficient for the block-design model in β was determined as the beta value representing the intensity of the fNIRS signal that changed along with task. The model function was derived using spm_hrf.m function implemented in SPM8 toolbox and obtained the beta value at each condition of each subject.

To investigate the difference in hemodynamic activity among different appendages for motor output, we first compared the fNIRS features across DH, F, and NH by Friedman test as Shapiro-Wilk test failed to confirm the normality of the data. Post-hoc multiple comparison was performed by Wilcoxon signed-rank test with Bonferroni correction. Behavioral performance was compared between conditions using repeated measures analysis of variance (ANOVA) with post-hoc multiple comparison using paired t-test with Bonferroni correction due to the normality of the data.

3. RESULTS

Table 1 shows the mean behavioral performance of DVG task among three appendage conditions. There was a significant difference in the performance among appendages (repeated measures ANOVA: $F = 22.00$, $p < 0.01$). DVG play with foot resulted in the worst performance compared to dominant and non-dominant hands (paired t-test with Bonferroni correction: F and DH: $p < 0.01$, F and NH: $p < 0.01$) but there was no difference in the performance between DH and NH ($p = 0.50$). The performance scores were in accordance with the result of the questionnaire in which all participants answered that DVG played with foot was the most difficult.

Figure 3 shows the typical raw waveform of fNIRS measurement. Model functions of GLM (black solid and dotted lines) well approximated the raw data (P value for linear approximation was below 0.001 for all data). Figure 4 shows the typical waveform of event-related average hemodynamic responses. The area shaded with pink is AUC of Oxy-Hb activity. The time-course of both raw and averaged hemodynamic signals showed task-related increases in Oxy-Hb and decreases in Deoxy-Hb, showing a cortical activity pattern [Scholkmann 2013]. In each data, the opposite polarity of Oxy-Hb and Deoxy-Hb deflection was confirmed. Figure 5 show the results of mean MAX, AUC and beta values of different conditions. Although the behavioral performance showed statistically significant differences between hand- and foot- played conditions, the mean MAX value of Oxy-Hb data failed to capture the significant difference between these conditions (Friedman test: $\chi^2 = 5.60$, $p = 0.061$). On the other hand, the mean AUC and beta values of Oxy-Hb data showed significantly different values among appendages (Friedman test: $\chi^2 = 7.80$ and 9.50, $p = 0.020$ and 0.009 in AUC and beta, respectively).

Post hoc multiple comparison was performed for AUC and beta features by Wilcoxon signed-rank test with Bonferroni correction. Statistically significant difference was confirmed between foot-played and dominant-hand conditions in both AUC and beta features (AUC: $p = 0.021$, beta: $p = 0.009$). The temporal activity was larger when DVG played by foot relative to hand.

We did not find any statistically significant conditional differences in any of these fNIRS features using the Deoxy-Hb signals.

Table 1. Mean behavioral performance of participants in hand- and foot- played DVG task. The performance was represented as percentage of temporally accurate responses. The asterisk indicates that the value is significantly larger than foot-played condition ($p < 0.05$).

Appendage condition	Percentage of temporally accurate responses
DH	49.4 *
NH	46.6 *
F	36.1

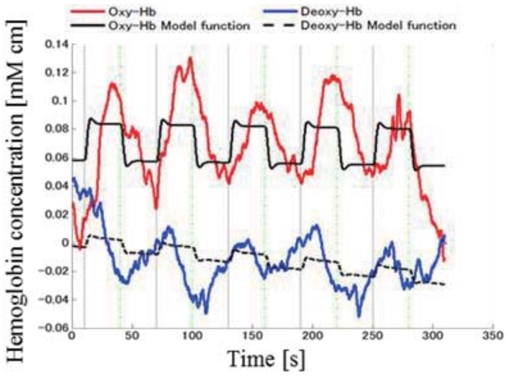

Figure 3. The typical raw fNIRS waveform (Participant 10 on foot-played condition). The dotted vertical lines indicate task start (black) and end (green).

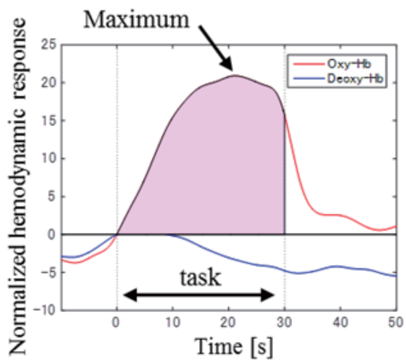

Figure 4. The typical event-related average hemodynamic responses (Participant 5 on foot-played condition). The dotted black vertical lines indicate task period. The area painted with pink shows AUC.

4. DISCUSSION

We investigated three types of fNIRS features during cognitive task to investigate the appropriate signal feature representing the amount of cognitive load. We used DVG as a cognitive task because the behavioral score of the DVG can be approximate the cognitive load required to perform the task.

The behavioral performance showed that DVG played with foot is more difficult than that played with hand. This indicates that the DVG played with foot need a higher cognitive load than with hand.

The mean AUC and beta values with foot-played condition were significantly larger than those with dominant hand-played condition. The increased fNIRS activity corresponds to the requirement of more cognitive activity to perform the task, which resulted in the lower behavioral score. However, there was no significant difference between hand and foot conditions in fNIRS features when we used mean MAX values. Previous study showed that S/MTG is necessary for motor output at the correct timing that required audiovisual integration [Suzuki 2017]. Another research reported that MTG becomes active when a person with limited ability of beat perception tried to perceive rhythm [Grahn 2009]. It is suggested that both AUC and beta values obtained from GLM analysis could be used for evaluating cognitive load. Although more data analysis using different data set is required, the higher statistical confidence in beta values suggests the superior ability to detect cognitive load over AUC.

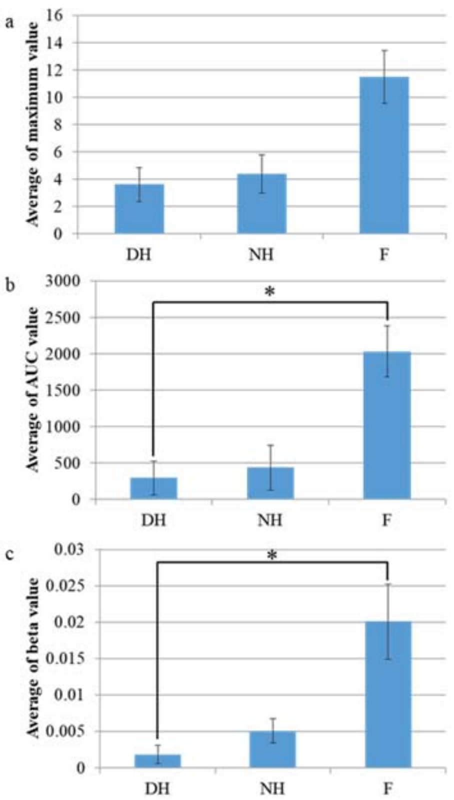

Figure 5. Average MAX (a), AUC (b), and beta (c) values in S/MTG. Error bars show standard error. Asterisk shows statistically significant difference ($p < 0.05$, Wilcoxon signed-rank test with Bonferroni correction).

In the current analysis, Deoxy-Hb signals failed to show significant difference between conditions in all analysis methods. Although its lower signal-to-noise ratio, there are reports showing the superiority of Deoxy-Hb signals in the sense of robustness of the signals against global systemic responses [Zhang 2016]. Since we observed a slight time delay in the Deoxy-Hb waveforms relative to Oxy-Hb ones (Figure 3), there may be a necessity to change the time window and/or modify the model function to be analyzed which matches with Deoxy-Hb signals to obtain meaningful features.

5. ACKNOWLEDGMENT

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