Classification of mental tasks in the prefrontal cortex using fNIRS

Christian Herff, Dominic Heger, Felix Putze, Johannes Hennrich, Ole Fortmann and Tanja Schultz

Abstract— **Functional near infrared spectroscopy (fNIRS) is rapidly gaining interest in both the Neuroscience, as well as the Brain-Computer-Interface (BCI) community. Despite these efforts, most single-trial analysis of fNIRS data is focused on motor-imagery, or mental arithmetics. In this study, we investigate the suitability of different mental tasks, namely mental arithmetics, word generation and mental rotation for fNIRS based BCIs. We provide the first systematic comparison of classification accuracies achieved in a sample study. Data was collected from 10 subjects performing these three tasks.**
An optode template with 8 channels was chosen which covers the prefrontal cortex and only requires less than 3 minutes for setup. Two-class accuracies of up to 71% average across all subjects for mental arithmetics, 70% for word generation and 62% for mental rotation were achieved discriminating these tasks from a relax state.
We thus lay the foundation for fNIRS based BCI using additional mental strategies than motor imagery and mental arithmetics. The tasks were chosen in a way that they might be used for user state monitoring, as well.

I. INTRODUCTION

A. Motivation

Functional Near Infrared Spectroscopy (fNIRS) is a state-of-the-art non-invasive brain imaging technology based on hemodynamic responses to cortical activities. The effects that can be measured using fNIRS (see Section I-B) are the same ones observed with fMRI, the de facto standard in neuroimaging. Compared to fMRI, fNIRS is portable, cheap and does not confine the subjects. Measuring the very reliable hemodynamic responses and offering a very good spatial resolution, fNIRS has advantages over EEG, the standard in Brain-Computer-Interface (BCI) research, as well.
The paradigm used for BCI control can affect classification and recognition accuracies in EEG significantly [1]. Even though this has been studied in detail in EEG, there is, to the best of our knowledge, no systematic comparison of paradigms and the resulting accuracies for classification in fNIRS. To investigate the suitability of different mental tasks for BCI control and the discriminability of the tasks from relax and from each other, we conducted experiments with three mental tasks, namely mental arithmetics, word generation and mental rotation. An optode layout on the forehead, measuring hemodynamic responses in the prefrontal cortex, was used to allow for fast setup times.
Besides being useful in BCIs, the robust classification of these tasks might also enable user state monitoring, as we could classify which type of task is currently occupying the user. fNIRS could be used to classify user states, which are currently non observable. This might be useful in classroom settings, where it could help evaluate what type of problem, mathematical, language or orientation, the student is currently struggling with.
So far, motor imagery is the most popular paradigm for BCI research in EEG and has been published first for fNIRS based BCI, as well [2]. Accuracies achieved in these BCIs are usually good and motor imagery suits most users. However, setup of EEG caps is usually very time consuming. In fNIRS experiments, the identification of relevant areas for optode placement on the motor cortex is complex and cumbersome. To measure fNIRS signals, optodes require skin contact, a constraint often hard to meet on the motor cortex, where hair has to be moved aside under the optodes in a lengthy procedure. Our optode template, on the other hands, requires little anatomical knowledge and can be setup in less than three minutes.
Mental arithmetic [3], word generation [4] and mental rotation [5] have been shown to create hemodynamic responses in the prefrontal cortex, our area of interest. Mental arithmetic has been used successfully in single trial analysis of fNIRS data [6]. Ogata et al. have conducted first single trial experiments with different mental tasks in the prefrontal cortex [7]. However, in their study with only 10 trials per subject and task, they neither discriminate the tasks from one another nor compare classification accuracies.

B. Functional Near Infrared Spectroscopy

Light in the near infrared range of the electromagnetic spectrum (620 nm - 1000 nm) disperses through most biological tissues like bones and skin. Hemoglobin, the oxygen-carrying part of blood, on the other hand absorbs near infrared light. As changes in blood oxygenation in cortical areas are triggered by neural activity, hemoglobin levels change with neural activation. fNIRS makes use of this effect to measure cortical activity by shining near infrared light into the subject's head with light-sources and measuring the light intensities transmitted through the head with detector-optodes. For a source-detector pair with distance l, the measurement position is located in the middle between the two in a depth of approximately $l/2$ and is denoted as a channel. Oxygenated hemoglobin (*HbO*) and deoxygenated hemoglobin (*HbR*) have different light absorption characteristics (with absorption coefficients α_{HbO} and α_{HbR}) and thus their concentration changes (denoted as ΔHbO ΔHbR) can be calculated from the changes in light intensities (ΔOD) using the modified Beer-Lambert law [8]:

$$\Delta HbO = \frac{\Delta OD}{b \cdot l \cdot \alpha_{HbO}}, \qquad \Delta HbR = \frac{\Delta OD}{b \cdot l \cdot \alpha_{HbR}},$$

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where b is the length of the photon path between sources and detectors, along which the light travels.

A typical hemodynamic response to cortical activity rises

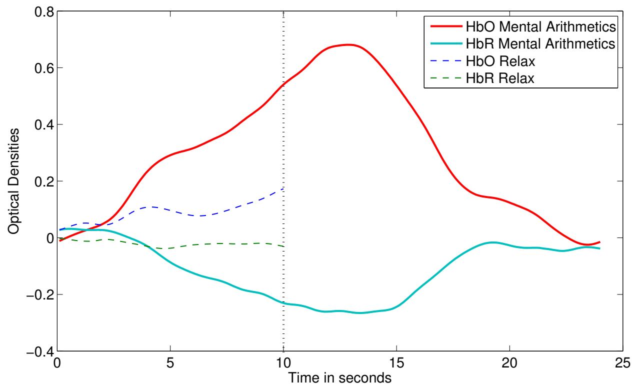


Fig. 1. Average hemodynamic response of subject 4 in channel 7 performing mental arithmetics (solid lines) and relax tasks (dashed lines). The dotted line indicates end of mental task.

during activity for *HbO* and returns to baseline after the end of the activation. *HbR* levels should respond inverted, i.e. decrease upon activity and rise back to baseline in rest periods. Figure 1 shows an average hemodynamic response of subject 4 to mental arithmetics and the return to baseline when resting. The Figure also illustrates that *HbO* and *HbR* do not change significantly during the averaged relax trial.

II. MATERIAL AND METHODS

A. Experimental Setup

To measure the hemodynamic responses in the prefrontal cortex, we used an Oxymon Mark III by Artinis Medical Systems. Four transmitter optodes, transmitting at two wavelength of 765 nm and 856 nm each, and 4 receiver optodes were placed on the subjects' foreheads. Transmitter and receiver optodes were placed 3.5 cm apart. In this setup, every receiver optode was measuring light intensities from two transmitter optodes resulting in a total of 8 channels of ΔHbO and ΔHbR data. Figure 2 illustrates our optode setup. An experienced assistant needs less than three minutes to fix the optode holder to the subject's forehead while assuring high data quality. Data was sampled at 10 Hz.

The experiment consisted of three different tasks the subjects

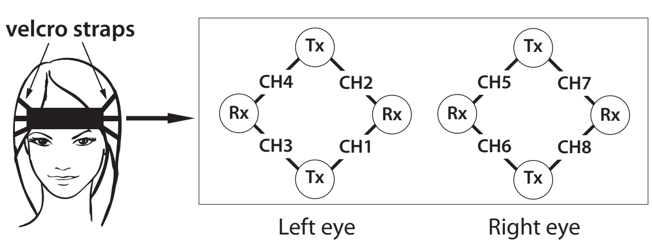


Fig. 2. Optode placement on subject's head. Transmitter optodes are labelled Tx. Receiver optodes are marked Rx.

had to process during trials. These were:

- **Mental Arithmetics (MA):** The subjects were asked to repeatedly subtract a given minuend between 7 and 19 (10 excluded) starting with a given number between 501 and 999.
- **Word Generation (WG):** The subjects were asked to imagine words starting with a given letter.
- **Mental Rotation (MR):** The subjects were asked to visualize rotating the shown 3D object around the x-axis.

Trials were presented to the subjects on a screen for 10 seconds in a random order. After every trial of one of the three tasks, the subjects had to rest for 15 seconds to ensure that hemoglobin levels could return to baseline levels. None of the tasks required any input by the user assuring that there are no systematic motion artifacts in our data. We recorded 30 trials of each task for every subject. A total of 30 relax trials were inserted randomly after resting periods to gather data during a mental relax state without prior activation. The subjects continued to rest motionlessly in these intervals and did not receive specific instructions. In total, we collected 120 trials per subject. Longer pauses of 5 minutes were included after each 15 minute block in which the subjects could drink and talk to the experiment supervisor. This resulted in a total recording time of 52.5 minutes per subject. In total, we recorded 10 right handed subjects (3 female) with a mean age of 23 and a mean Edinburgh handedness score [9] of 83. All subjects were informed prior to the experiment and gave written consent.

B. Signal Preprocessing

To remove heartbeat artifacts and long period shifts from the 8 channels of ΔHbO and ΔHbR data, we bandpass filtered the signals from 0.01 Hz to 0.6 Hz using elliptic IIR filter with filter order 6. Subsequently, linear trends were removed in 5 minute blocks using linear detrending.

In an excellent comparison of movement artifact reduction techniques for fNIRS, Cooper et. al. [10] suggest the wavelet denoising technique as the most reliable to remove movement artifacts from fNIRS data. We applied the wavelet artifact removal technique suggested in [11] to our signals. For this procedure, the ΔHbO and ΔHbR data $y(t)$ of every channel is transformed using the general wavelet transformation:

$$y(t) = \sum_k c_{j_0 k}\phi_{j_0 k}(t) + \sum_{j=j_0}^{\infty}\sum_k d_{jk}\psi_{jk}(t)$$

with $c_{j_0 k}$ and d_{jk} being the approximation and detail coefficients and $\phi_{jk}(t)$ and $\psi_{jk}(t)$ being scaling and wavelet functions. The parameter j represents the dilation, with j_0 being the coarsest scale in the decomposition, k is the translation parameter. Assuming a normal distribution of wavelet coefficients, we can easily estimate the probability of coefficients higher than a given coefficient. Hemodynamic signals should have a smooth probability distribution and very low variance. Based on these observations, one can remove artifacts by removing wavelet coefficients with probabilities smaller than a cutoff threshold α. We used a threshold of 10 times the interquartile distance. As none of our tasks contain any systematic movement and since our subjects were sitting relatively still, we applied a very low threshold to filter only the most unlikely wavelet coefficients. After preprocessing, trials were extracted based on the experiment timing. Each 10 second trial was baseline normalized by subtracting the mean of the 5 seconds prior to the trial. A label corresponding to one of the 3 tasks or relax was assigned to each of the trials. We did not include the resting periods directly after each trial, in which hemoglobin levels returned to baseline, nor the long pauses of 5 minutes in our analysis.

C. Feature Extraction

Feature extraction for single trial fNIRS analysis usually uses simple features based on a typical hemodynamic response. Rising and falling trends in the trials are often extracted by subtracting the mean μ of the first half of the trials from the mean of the second half of the trial [12], [13]. We extend on this idea, by looking for the largest increase and decrease between the mean of two adjacent frames of size *fs*. As beginning and end of the hemodynamic response vary between subjects and even trials, we extract both decrease and increase. These features are denoted as $f^{\uparrow}_{t,c}$ and $f^{\downarrow}_{t,c}$, respectively.

In typical hemodynamic responses, ΔHbO and ΔHbR are strongly negatively correlated [14] with changes more pronounced in the ΔHbO data. To reduce the size of the feature space, we only extracted features for ΔHbO and did not include the mostly redundant ΔHbR data. In total, we extract two features for every trial t in every channel c in the following manner:

$$f^{\uparrow}_{t,c} = \max_{i \in [fs, len(t)-fs]} (\mu(\Delta HbO^{t}_{c,i:i+fs}) - \mu(\Delta HbO^{t}_{c,i-fs:i}))$$

$$f^{\downarrow}_{t,c} = \max_{i \in [fs, len(t)-fs]} (\mu(\Delta HbO^{t}_{c,i-fs:i}) - \mu(\Delta HbO^{t}_{c,i:i+fs}))$$

We chose a framesize of 3.5 seconds in this study.

In total, we thus extracted 16 features for each of the 120 trials.

D. Evaluation

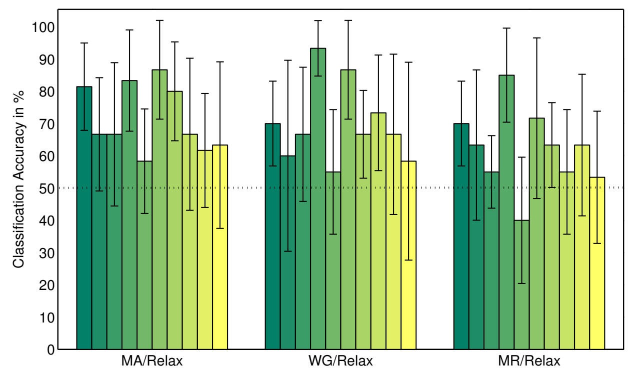
To judge the suitability of the different mental tasks for fNIRS based BCI or user state monitoring, we evaluated our system using a 10-fold cross-validation approach. We divided the data into 10 equally sized folds and trained a Linear Discriminant Analysis (LDA) classifier on the features of 9 of these folds and tested on the features of the remaining fold. This was repeated 10 times in a round-robin manner.

We evaluated classification accuracies of all mental tasks (MA, WG, MR) against relax and of the mental tasks against each other.

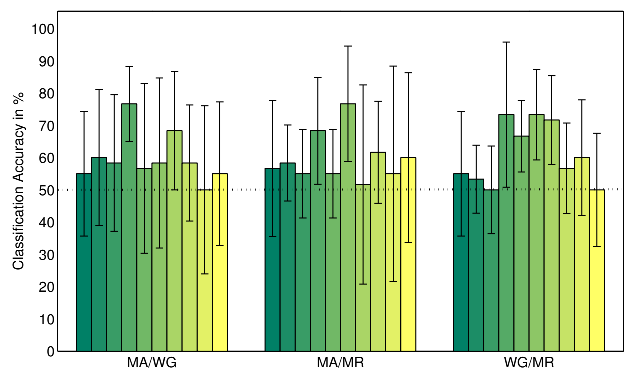
III. RESULTS

Figure 3 illustrates the differences in average hemodynamic responses which serve as basis for our classification. Decreases and increases in ΔHbO occur in different channels and at different points in time for the different mental tasks, leading to earlier returns to baseline and different amplitude of hemodynamic responses. Our extracted features $f^{\uparrow}_{t,c}$ and $f^{\downarrow}_{t,c}$ make use of this fact and allow us to distinguish reliably between the tasks and the relax state.

A complete overview of all classification results is presented in Figure 4. Part (a) depicts classification results of the three



(a)



b)

Fig. 4. Classification results of all 10 subjects for experiments against relax (a) and against each other (b). Each bar represents one subject in one experiment. Whiskers indicate standard deviations. Dotted line denotes naive classification rate.

tasks (MA, WG, MR) against relax for all 10 participants. Classifying mental arithmetics from relax worked with an average of 71% accuracy. This result is comparable to that achieved in [15]. Differentiating between word generation and relax yielded 70% average accuracy. Accuracies for mental rotation were lower with an average of 62%. There was no significant difference in the classification performance of mental arithmetics and word generation, as tested by a Wilcoxon rank-sum test ($p = 0.4280$), but both were significantly better than mental rotation ($p < 0.01$). All three tasks could be discriminated from the relax state significantly better than naïve classification ($p < 0.01$). These results show that all three mental tasks are effective paradigms for fNIRS based BCI or user state monitoring, but word generation and mental arithmetics work more reliably than mental rotation.

Classification results among the three different tasks are shown in part (b) of Figure 4. Mental arithmetics was

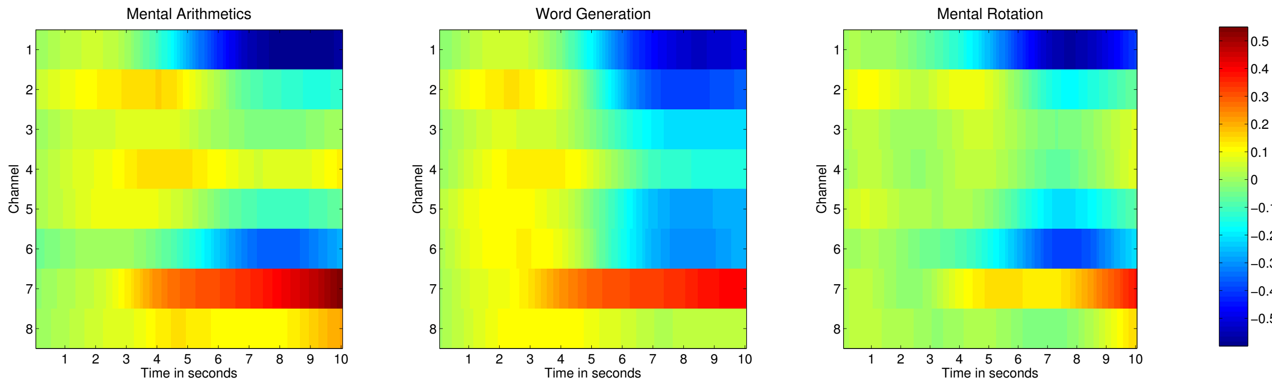


Fig. 3. Average hemodynamic responses in *HbO* of subject 4 during all tasks.

discriminated from word generation with an average performance of 60%. The LDA classifier achieved 60% between mental arithmetics and mental rotation. Word generation and mental rotation yielded an average result of 61%. Results for discrimination between the three different tasks were significantly better than naïve classification ($p < 0.01$), as well. The fact that all these experiments yield significant results shows that fNIRS based BCIs with multiple tasks is feasible and might reach results comparable to 4-class systems in EEG [16]. Table I summarizes our findings with average results and standard deviations across all 10 folds of all 10 subjects.

TABLE I

AVERAGE CLASSIFICATION RESULTS AND STANDARD DEVIATIONS ACROSS SUBJECTS IN %. RESULTS MARKED WITH * ARE SIGNIFICANTLY BETTER THAN NAIVE CLASSIFICATION.

	MA	WG	MR	MA/WG	MA/MR	WG/MR
Acc.	71*	70*	62*	60*	60*	61*
Std.	10.3	12.1	12.2	7.6	7.5	9.5

IV. CONCLUSION

In a study with 10 subjects, we have shown that fNIRS signals in response to three different mental tasks can be reliably discriminated both from a relax state and from each other. The optode template we used supplied us with good measurements of hemodynamic responses in relevant parts of the prefrontal cortex and can be set up quickly. We thus present the first systematic comparison of classification accuracies of the mental tasks mental arithmetics, word generation and mental rotation and prove that all tasks are suitable for fNIRS based BCI. All of these tasks have been of prior interest to the neuroscientific community, but have never been evaluated in single-trial analysis with fNIRS.
Classification accuracies and hemodynamic patterns lay the foundation for fNIRS based BCI using different mental tasks than the established motor imagery paradigm and might be used for state monitoring.

REFERENCES

[1] E VC Friedrich, R Scherer, and C Neuper, "The effect of distinct mental strategies on classification performance for braincomputer interfaces," *International Journal of Psychophysiology*, vol. 84, no. 1, pp. 86 – 94, 2012.

[2] SM Coyle, TE Ward, and CM Markham, "Brain-computer interface using a simplified functional near-infrared spectroscopy system," *Journal of Neural Engineering*, vol. 4, no. 3, pp. 219, 2007.

[3] M Tanida, K Sakatani, R Takano, and K Tagai, "Relation between asymmetry of prefrontal cortex activities and the autonomic nervous system during a mental arithmetic task: near infrared spectroscopy study," *Neuroscience Letters*, vol. 369, no. 1, pp. 69 – 74, 2004.

[4] E Watanabe, A Maki, F Kawaguchi, K Takashiro, Y Yamashita, H Koizumi, and Y Mayanagi, "Non-invasive assessment of language dominance with near-infrared spectroscopic mapping," *Neuroscience Letters*, vol. 256, no. 1, pp. 49 – 52, 1998.

[5] N Shimoda, K Takeda, I Imai, J Kaneko, and H Kato, "Cerebral laterality differences in handedness: A mental rotation study with nirs," *Neuroscience Letters*, vol. 430, no. 1, pp. 43 – 47, 2008.

[6] KK Ang, C Guan, K Lee, JQ Lee, S Nioka, and B Chance, "A Brain-Computer Interface for Mental Arithmetic Task from Single-Trial Near-Infrared Spectroscopy Brain Signals," *Int. Conference on Pattern Recognition*, pp. 3764–3767, 2010.

[7] H Ogata, T Mukai, and T Yagi, "A study on the frontal cortex in cognitive tasks using near-infrared spectroscopy," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, aug. 2007, pp. 4731 –4734.

[8] A Sassaroli and S Fantini, "Comment on the modified beerlambert law for scattering media," *Physics in Medicine and Biology*, vol. 49, no. 14, pp. N255, 2004.

[9] RC Oldfield, "The assessment and analysis of handedness: The Edinburgh inventory," *Neuropsychologia*, vol. 9, pp. 97–113, 1971.

[10] R Cooper, J Selb, L Gagnon, D Phillip, H W Schytz, H K Iversen, M Ashina, and D A Boas, "A systematic comparison of motion artifact correction techniques for functional near-infrared spectroscopy," *Frontiers in Neuroscience*, vol. 6, no. 147, 2012.

[11] B Molavi and GA Dumont, "Wavelet based motion artifact removal for functional near infrared spectroscopy," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 31 2010-sept. 4 2010, pp. 5 –8.

[12] C Herff, F Putze, D Heger, C Guan, and T Schultz, "Speaking mode recognition from functional near infrared spectroscopy," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, 2012, pp. 1715 –1718.

[13] C Herff, D Heger, F Putze, C Guan, and T Schultz, "Cross-subject classification of speaking modes using fnirs," in *Neural Information Processing*, T Huang, Z Zeng, C Li, and C Leung, Eds., vol. 7664 of *Lecture Notes in Computer Science*, pp. 417–424. Springer Berlin Heidelberg, 2012.

[14] X Cui, S Bray, and AL Reiss, "Functional near infrared spectroscopy (NIRS) signal improvement based on negative correlation between oxygenated and deoxygenated hemoglobin dynamics," *NeuroImage*, vol. 49, no. 4, pp. 3039–46, Feb. 2010.

[15] S D Power, A Kushki, and T Chau, "Intersession consistency of single-trial classification of the prefrontal response to mental arithmetic and the no-control state by nirs," *PLoS ONE*, vol. 7, no. 7, pp. e37791, 07 2012.

[16] E VC Friedrich, R Scherer, and C Neuper, "Long-term evaluation of a 4-class imagery-based braincomputer interface," *Clinical Neurophysiology*, 2013.