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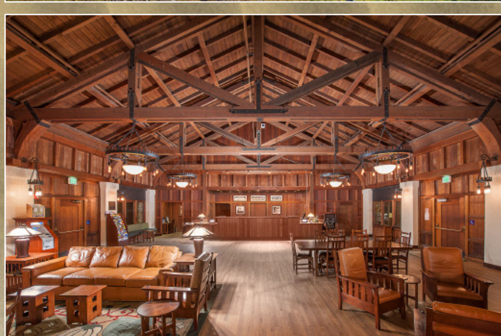
Abstract Book



BCIs: Not Getting Lost in Translation

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classifier. Then the user had to copy 8 words containing a total of 37 characters. After completing both sessions, the user rated the difficulty of each paradigm and indicated which one they preferred. For character prediction, the EEG data was first pre-processed and then windowed from 0 to 500ms to capture the ERPs of each visual stimuli. PCA was used for dimensional reduction and regularized discriminant analysis (RDA) for feature extraction. A maximum a-posteriori (MAP) classifier combined the EEG features with a 6-gram language model and predicted users' intended target. Results: 100% accuracy was achieved when predicting each character for most of the participants in both paradigms. This is because multiple repetitions were used for prediction. To better compare both paradigms, we compared the AUCs for single-trial ERP detection obtained after 10-fold crossvalidation as shown in the figure. An average of 0.88 was achieved for both paradigms. The figure also compares the rating of difficulty given by each user. Overall, users found the deterministic paradigm easier. Discussion: Similar results were obtained for both paradigms. Some users performed slightly better with the oddball paradigm, whereas others performed better with the deterministic. Statistical analysis does not show significant differences in performance between the two paradigms. However, most of the users preferred the deterministic paradigm and found it easier as the highlighting of each row or column is predictable. Significance: In this study we have shown that the widely used matrix-based spellers are not ultimately dependent on an oddball paradigm. A deterministic paradigm can be used instead. This paradigm is easier to use according to our participants, potentially causing less fatigue and making it more suitable for long usage. Although, this needs further investigation, we think it has potential to be used with people with disabilities. Acknowledge: Our work is supported by NSF (IIS-1149570, CNS-1544895, IIS-1717654), NIDLRR (90RE5017-02-01), and NIH (R01DC009834). References: [1] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brainpotentials", 1988, DOI:10.1016/0013-4694(88)90149-6. [2] M. Akcakaya et al., "Noninvasive brain-computer interfaces for augmentative and alternative communication", 2014, DOI:10.1109/RBME.2013.2295097. [3] U. Orhan et al., "Rsvp keyboard: An eeg based typing interface", 2012, DOI:10.1109/ICASSP.2012.6287966. [4] M. Moghadamfalahi et al., "Language-model assisted brain computer interface for typing: A comparison of matrix and rapid serial visual presentation" 2015, DOI:10.1109/TNSRE.2015.2411574.

2-C-17 Semiautomatic physiologically-driven feature selection improves the usability of a brain computer interface system in post-stroke motor rehabilitation

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Introduction: Sensorimotor Brain-Computer Interface (BCI) systems can be beneficial for post-stroke functional motor recovery. In a randomized controlled clinical trial, it was demonstrated that an electroencephalogram (EEG)-based BCI-assisted Motor Imagery (MI) training improved the outcome of motor rehabilitation of the upper limbs with functional and neurophysiological relevant benefits in subacute stroke patients [1]. In this context, the reinforcement of a specific EEG pattern elicited by correct MI required that expert neurophysiologists with knowledge of BCI technology identified the optimal control features for each single patient. As such, this procedure is highly dependent on the operator and is currently restricted to researchers with experience in the BCI field and specific neurophysiological knowledge. To overcome these limitations, we developed a semiautomatic method to select control features that by combining both physiological and statistical approaches could ultimately increase the usability of BCI technology and thus, foster its use in clinical routine. Here, we present a preliminary validation of performance accuracy based on a comparison between classification performances obtained using BCI control features selected by expert professional users (manual procedure) and those obtained by semiautomatic method (guided procedure). Material, Methods and Results: EEG dataset previously acquired from 13 first ever, unilateral, subacute stroke patients [1] were analysed to compare manual vs guided procedure in terms of classification performance. In [1] all patients were trained to perform motor imagination of the affected hand movements. EEG data from the initial screening session [1], collected from 61 electrodes according to an extension of the 10-20 International System, were analysed to identify the control features. For the performance evaluation step, EEG data collected in the first training session [2] were considered. EEG data (sampled at 200 Hz) were re-referenced to the common average reference and divided into epochs of 1 second. Spectral features (spectral amplitude at each bin for each EEG channel) were extracted using the Maximum Entropy Method (2 Hz resolution). Two types of features selection were considered: i) the manual selection in which expert professional users (neurophysiologist, BCI researchers) identified the control features and assigned them weights based on visual inspection of the EEG pattern as in [1]; ii) the guided selection in which experts imposed some constraints(e.g., topographical, that is involving only the stroke hemisphere) and the semiautomatic method which was implemented as a stepwise regression algorithm would then operate the feature selection and the weight evaluation. For each procedure, the linear combination of the selected features and weights was the score value used for the offline performance assessment evaluated by means of the Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) curve. A paired-samples t-test was applied to compare AUC values relative to manual vs guided procedure (statistical significance threshold $p < 0.05$). Figure 1 shows for each dataset and each procedure the AUC values. No significant differences were found between two procedures ($p=0.13$). Discussion: The improvement of the BCI system's reliability is substantially based on an optimization of BCI system control features. When dealing with BCI application in post-stroke rehabilitation to promote motor function recovery (and plasticity related phenomena) control feature selection requires specific knowledge and expertise. The application of a guided procedure based on a method that combines both physiological and statistical feature selection approaches on real data sets showed performances comparable to those obtained with manual procedure. This suggests that it is feasible to successfully support the professional end-users such as therapist/clinicians who are not necessarily expert in BCI field, in the EEG feature selection yet according to evidence-based rehabilitation principles. Significance: The provision of BCI control feature selection with the semiautomatic physiologically-driven method allows for the reproducibility of the selection (and thus, reliability) and facilitates it, promoting the transferability of BCI technology to post-stroke rehabilitation routine. References: [1] Pichiorri et al., Ann Neur 2015 [2] Morone et al., Arch Phys Med Rehabil 2015

2-C-18 Post-stroke rehabilitation training with a Brain-Computer Interface: Clinical and neuropsychological study

Guzel Aziatskaya[1], Roman Lyukmanov[1], Olesya Mokienko[1], Nataliya Varako[1], Alexander Frolov[2], Lyudmila