The First Biannual
Neuroadaptive Technology Conference

NEUROADAPTIVE TECHNOLOGY NAT '17

CONFERENCE PROGRAMME

July 19 – July 21, 2017,
Berlin, Germany

The First Biannual
Neuroadaptive Technology Conference

Conference Programme

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Neuroadaptive Technology Conference
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Preface

Dear reader,

Neuroadaptive Technology concerns the use of measures from the brain and central nervous system to adapt a technological device to its user. In 2016, we decided that it was time to organise a series of biannual conferences on this topic, as many different fields of research included the use of neurophysiological and psychophysiological signals to improve human-technology interaction, but there was no regular event that served the research community by exclusively devoting itself to this topic.

With this programme, we are happy to welcome you to the first results of this endeavour: the first biannual Neuroadaptive Technology Conference, NAT'17.

NAT'17 is intended to serve as a hub and a conduit, exploring the emergence of this nascent technology and connecting all relevant fields of research, both technical and societal; for instance, we specifically emphasize issues related to privacy and ethics associated with neuroadaptive technology in the current programme. With NAT'17 being the first of the series, we will also announce the creation of a scientific society devoted to research on Neuroadaptive Technology. This society will facilitate communications within our research community and strengthen connections between researchers who are interested in neuroadaptive technology as well as to other scientific organisations and related conferences.

At NAT'17 we are bringing together around 100 researchers from 6 continents and from the scientific areas of: Brain-Computer Interfaces, Physiological Computing, Neuroergonomics, Human-Computer Interaction, Applied Neuroscience, Robotics, Affective Computing, Neurofeedback, Autonomous Technology, Gaming, Wearable Sensors, Machine Learning and Neuroethics.

This programme includes abstracts describing research contributions from all these fields. Keynote addresses are listed first, given by five excellent researchers representing fields strongly related to neuroadaptive technology. Oral presentations from the 12 sessions, in order of presentation, are listed next. Finally, in alphabetical order, this programme contains the abstracts of the poster presentations. An alphabetical list of all authors is included at the end of this programme. Authors who presented at NAT'17 are highlighted in boldface. We also have a Young Visionaries session devoted to those emerging scientists who are interested in the field of Neuroadaptive Technology whilst working on their first scientific graduation.

If you are a participant of NAT'17, we hope that you enjoy the conference and will support this development by becoming an active member of the society. If you did not participate, we hope that you appreciate our approach and that the programme of this inaugural meeting will excite your interest in research related to neuroadaptive technology. Either way, we hope to see you at NAT'19, which will be organized in 2019 by the Society for Neuroadaptive Technology. Next year, in 2018, the second Neuroergonomics conference will take place at Drexel University in the United States of America. If you are interested in NAT'17, we can highly recommend this conference as well.

In between the conferences, throughout the year, you will find interesting information about research, the society, and NAT conferences at the website: neuroadaptive.org. Members of the society will also have the chance to watch videos of all talks given at NAT'17 there.

With best regards,

Thorsten O. Zander	Stephen Fairclough
TU Berlin, Germany	LJMU, UK

DAY 1 – 19th July

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8. Designing And Understanding Convolutional Networks For Decoding Executed Movements From EEG, Schirrmeister, *Robin Tibor*

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11. Measuring Cognitive Conflict In Virtual Reality, *Singh, Avinash Kumar*

12. Neurophysiological Correlates Of Efficient Learning In The Neurofeedback Paradigm, *Minkov, Vasiliy*

13. User Identification From FNIRS Brain Data Using Deep Learning, *McDonald, Denisa*

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Foyer??

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Pim Haselager „Neuroethics“

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16:00 - 16:30 — **Summary of Each Session** — Main Room

16:30 - 17:00 — **Best Talk and Best Poster Award** — Main Room

17:00 - 17:30 — **Goodbye and Final Coffee** — Foyer

Keynote Lectures

Robert Jacob

Implicit User Interfaces

Room: Main Room
Time: 09:30 – 10:30
Day: 1

ABSTRACT

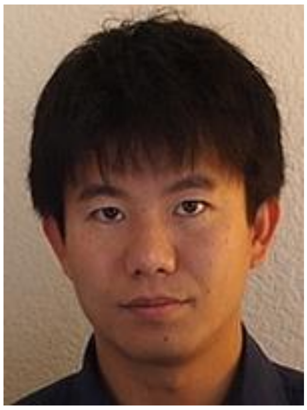
Implicit user interfaces obtain information from their users passively, typically in addition to mouse, keyboard, or other explicit inputs. They fit into the emerging trends of physiological computing and affective computing. Our work focuses on using brain input for this purpose, measured through functional near-infrared spectroscopy (fNIRS), as a way of increasing the narrow communication bandwidth between human and computer. Most previous brain-computer interfaces have been designed for people with severe motor disabilities and use explicit signals as the primary input; but these are too slow and inaccurate for wider use. Instead, we use brain measurement to obtain more information about the user and their context directly and without asking additional effort from them. We have obtained good results in a number of systems we created, as measured by objective task performance metrics. I will discuss our work on brain-computer interfaces and the more general area of implicit interaction.

BIOGRAPHY

Robert Jacob is a Professor of Computer Science at Tufts University, where his research interests are new interaction modes and techniques and user interface software; his current work focuses on implicit brain-computer interfaces. He has been a visiting professor at the University College London Interaction Centre, Universite Paris-Sud, and the MIT Media Laboratory. Before coming to Tufts, he was in the Human-Computer Interaction Lab at the Naval Research Laboratory. He received his Ph.D. from Johns Hopkins University, and he is a member of the editorial board for the journal Human-Computer Interaction and a founding member for ACM Transactions on Computer-Human Interaction. He has served as Vice-President of ACM SIGCHI, Papers Co-Chair of the CHI and UIST conferences, and General Co-Chair of UIST and TEI. He was elected as a member of the ACM CHI Academy in 2007 and as an ACM Fellow in 2016.

Makoto Miyakoshi

Computational Neuroscience of Human EEG



Room: Main Room
Time: 13:30 – 14:30
Day: 1

Title: I see a solution.

ABSTRACT

In this keynote lecture, I will talk about three topics: future, present, and the past of EEG research. In the first part, I will talk about the future of EEG research including Brain-Computer Interface using EEG/electrocorticogram (ECoG). I show my preliminary observation that dimension reduction using principal component analysis to keep 95% of original data variance produced 9/256 dimensions for EEG and 78/137 for ECoG. Based on this observation, I introduce Makoto's pessimism -- a suspicion that the true number of degrees of freedom of EEG data may be severely limited. The possible reason for this limitation is the anatomy and cytoarchitecture of EEG generation. Makoto's pessimism also seems to explain the reason why independent component analysis (ICA) on scalp-recorded EEG data always generates only 10-20 good effective brain sources regardless the number of scalp channels (from 32 to 256 channels, preliminary observation). If Makoto's pessimism is true, the possibility of future BCI using scalp-recorded EEG would have a fundamental limitation because the complexity of mental dynamics cannot be represented in such low dimensional data, though using ECoG should be much more promising.

In the second part, I will talk about the present of EEG research. I will first briefly introduce a demonstration of cutting-edge studies using the state-of-the-art signal processing and statistical methods including ICA and subsequent information flow analysis using Multivariate Autoregressive (MVAR) modeling. Next, I will discuss the vacancy of the ground truth in EEG research. For example, functional MRI has been considered as producing 'an X-ray of the experimental effect of interest' (according to the SPM website). This has been possible because for MR imaging, a phantom for calibration serves as a ground truth. However, in the history of EEG research, there has never been such an explicit ground truth available. Because of the lack of ground truth, there is circularity between assumptions of analyses and interpretation of the results. There is also an issue of relativism across the models due to lack of the ground truth, which produces incommensurability in comparing multiple studies with different models (e.g. linear vs. non-linear). I will discuss that we tend to compensate the lack of the ground truth by using 'fancy' signal processing and eye-indulging visualizations. I will discuss the distinction between science and engineering, and argue it is important to consider whether a given method for EEG analysis allows us to get closer to the ground truth of EEG. I name the current EEG research scene as adolesc-i-ence because it is immature but with full of possibility.

In the third part, I will talk about the past of EEG research. I will refer to a brief history that EEG has been used as psychologists' tool to serve a box model. I will introduce the concept of viewing the role of a scientific experiment to be a one-bit information generator, i.e., a device to give a yes or no answer to a Popperian hypothesis. This is a scientifically valid point of view, but I criticize it as a Popperian Defense that justifies not taking advantage of advanced

engineering methods available today, one that is keeping the majority of EEG researchers within an evolutionary cul-de-sac. I will introduce ICA as a promising approach for analyzing EEG, will explain its nature, and will discuss how it relates to the ground truth of EEG -- its specific strengths as well as weaknesses. In a concluding remark, I will claim that for EEG research to progress from its current status as adolesc-i-ence, it is necessary to think how EEG could become more like an X-ray of the (electrical) brain, and how to overcome the Popperian Defense by demonstrating an advantage for science (rather than for engineering). I will also claim that anatomical studies on morphology of neurons and axons as well as their connections and projections should be re-visited since they are a part of ground truth of EEG.

BIOGRAPHY

Makoto Miyakoshi is an associate project scientist of Swartz Center for Computational Neuroscience (SCCN), Institute for Neural Computation, University of California San Diego. He received Bachelor's degree in Philosophy in Waseda University in 2003, Master's degree and PhD in Psychology in Nagoya University in 2005 and 2011. He received fellowship from Japan Society for the Promotion of Science (JSPS) during 2005-2008 and 2011-2013 with which he visited SCCN director Scott Makeig, and later he became Scott's post-doc in 2011. In parallel with analyzing clinical EEG data in collaboration with clinical researchers of schizophrenia, epilepsy, and post-stroke motor rehabilitation using TMS, he has been working on optimizing workflows and algorithm of EEG preprocess pipeline using independent component analysis (ICA). He also makes contribution to user community of EEGLAB, which is the most widely used free, open-source EEG analysis library developed by SCCN, by developing extensions, answering questions to the mailing list, and publishing information in SCCN websites.

Surjo Soekadar
Applied Neurotechnology

Room: Main Room
Time: 09:00 – 10:00
Day: 2

Title: Towards clinical applications of neuroadaptive brain-computer interfaces

ABSTRACT

Today, five out of ten diseases worldwide resulting in long-term disability are related to the central nervous system. Due to the immense complexity and inter-individual variability of the human brain there are still no effective treatment options for many serious neurological and psychiatric disorders such as stroke, major depression, schizophrenia or dementia. Recent advancements in sensor technology and computational capacities resulted in the development of brain-computer interfaces (BCIs) that translate electric, magnetic or metabolic brain activity into control signals of external devices, robots or machines. Moreover, novel transcranial magnetic and electric brain stimulation (TMS/TES) systems were developed allowing for direct modulation of brain activity. However, current BCIs are limited by the low information extraction rate constraining fluent direct brain-computer interaction. Furthermore, as simultaneous assessment of brain oscillations during TES was regarded unfeasible due to stimulation artefacts, current TES systems can only deliver "open-loop" stimulation unrelated to the underlying dynamic brain states resulting in highly variable TES effects.

The key-note lecture will describe how combing both techniques into a neuroadaptive BCI might overcome these limitations and lead to new and more effective treatments strategies for neurological and psychiatric disorders. Besides addressing the feasibility of assessing brain oscillations during TES, the lecture will also provide an overview of how BCIs can be taken out of the lab, e.g. to restore activities of daily living after quadriplegia and improve motor function after stroke. The next steps towards the development and application of neuradaptive BCIs will be depicted, and possible neuroethical dimensions discussed.

BIOGRAPHY

Dr. Surjo R. Soekadar, MD, is head of the Applied Neurotechnology Laboratory at the University Hospital of Tübingen. From 2009-2012, he was fellow at the Human Cortical Physiology and Stroke Neurorehabilititation Section (HCPS) at the NIH, USA. His research interests include cortical plasticity in the context of brain-machine interface (BMI) applications, non-invasive brain stimulation and neural mechanisms of learning and memory. He developed the first paradigms that combine BMI with transcranial electric stimulation (TES), and demonstrated full restoration of independent daily living activities, such as eating and drinking, across quadriplegic patients who used a hybrid brain/neural hand-exoskeleton outside the laboratory. He is member of board of several NGO's dealing with improving health care in developing countries and served as resource specialist at the Salzburg Global Seminar. Surjo

Soekadar was co-chair of the 2013 and 2015 International Workshops on Clinical Brain-Machine Interface Systems. He received various prizes such as the NIH-DFG Research Career Transition Award (2009), the NIH Fellows' Award for Research Excellence (2011), the international BCI Research Award 2012 (together with Niels Birbaumer) and the Biomag 2014 Young Investigator Award.

Tim Mullen

Ubiquitous Neurotechnology in the Cloud

Room: Main Room
Time: 13:00 – 14:00
Day: 2

Title: Into The Wild: When Neurotechnology Escapes the Lab and Other Adventures in Translation

ABSTRACT

In this talk, I will discuss and demonstrate efforts at Qusp to reduce the barrier for translation of neurotechnology beyond the laboratory and into ubiquitous, real-world applications. Throughout the talk, I will address several opportunities for translational neurotechnology and "real-world" brain-computer interfacing. These include emerging sensors and systems for pervasive measurement and interpretation of brain and body signals during everyday activities; signal processing and machine learning for adaptive brain/behavioral state identification and closed-loop feedback in complex, noisy environments; infrastructure and methods for large-scale multi-study analysis ("Big EEG") facilitating generalizable knowledge discovery and modeling across heterogeneous data; emerging industry standards for multi-modal data storage, organization, and interoperability; and a cloud-based, scalable middleware platform enabling diverse industry applications which build on validated scientific research and methods, facilitating the widespread integration of brain and body sensing into everyday life.

BIOGRAPHY

Dr. Tim Mullen (Qusp Neurotechnologies founder & CEO/CSO; Qusp Labs Director) holds degrees in computer science and computational and cognitive neuroscience with dual B.A.s from UC Berkeley and M.S. and Ph.D degrees from the UC San Diego Dept. of Cognitive Science and Institute for Neural Computation. At Xerox PARC he developed patented applications of wearable brain-computer interface (BCI) technology. He has advanced widely used software for neuronal data analysis and prediction (EEGLAB, BCILAB, SIFT, MPT), and led high-profile mobile brain imaging projects such as the "Glass Brain". Prior academic awards included the UCSD Chancellor's Dissertation Medal, IEEE best paper awards, Glushko, San Diego, and Swartz Fellowships, and UC Berkeley highest honors. His scientific publications focus on the use of machine learning and adaptive system identification techniques to infer cognitive and emotional states and to detect neuronal pathologies. He is a frequent speaker at international conferences and workshops, and his work has been highlighted in numerous print and TV media including BBC World, Discovery Science, and Wired, and before the US Congress. He is also a musician and artist whose work in audiovisual new media, exploring real-time interactions between the brain and body and external environments, has been presented nationally and internationally. He is a Creative Director for San Diego classical arts organization Mainly Mozart. There he serves as founding director of the annual Mozart & the Mind festival, a series of concerts, presentations, and interactive media and neurotechnology exhibitions exploring the impact of music on our brains, health, and lives. His hobbies include SCUBA diving, motorcycling, writing music, trans-global travel, and hanging out with his wife and cat in San Diego.

Pim Haselager
Neuroethics

Room: Main Room
Time: 09:00 – 10:00
Day: 3

Title: Sense of agency and responsibility in neuroadapted action

ABSTRACT

The distinction between something I do and something that happens to me is generally clear, but not always an easy one to make. Increasingly we are embedded in environments full of artificial ‘helpers’ that actively contribute to the translation of human (sub)conscious intentions into action. Neuroadaptive technology has the potential to create fascinating cases of mediated action where the question ‘who did that?’ will make sense individually and societally. I will examine some of such cases and discuss their potential ethical, legal or societal consequences.

BIOGRAPHY

Pim Haselager obtained master degrees in philosophy and psychology, and received his PhD in 1995 at the Free University of Amsterdam, the Netherlands. Currently he is associate professor and principal investigator (Theoretical Cognitive Science) at the Donders Institute for Brain, Cognition and Behaviour, at the Radboud University Nijmegen.
His research focuses on the implications of Cognitive neuroscience and Artificial Intelligence for human self-understanding. He investigates the ethical and societal implications of research in, and the ensuing technologies of, CNS and AI, such as Robotics, Brain-Computer Interfacing, and Deep Brain Stimulation. He is particularly interested in the integration of empirical work (i.e. experimentation, computational modeling, and robotics) with philosophical issues regarding knowledge, identity, agency, responsibility and intelligent behavior.
He has published in journals such as American Journal of Bioethics, Neuroethics, Journal of Cognitive Neuroscience and Journal of Social Robotics. He is vice-president of the European Association for Neuroscience and Law.

Neuroadaptive Technology: Concepts

Session AI

COGNITIVE PROBING FOR AUTOMATED NEUROADAPTATION

Laurens Ruben Krol , Thorsten Oliver Zander
Team PhyPA, Biological Psychology and Neuroergonomics, Technische Universität Berlin, Germany
E-mail address: {lrkrol, tzander}@gmail.com

ABSTRACT: The concept of *cognitive probing* is presented as a method for a computer system to autonomously gather information about a user's preferences. This is demonstrated using a form of cursor control.

INTRODUCTION

Neuroadaptive technology uses measures of its user's neurophysiological activity in order to enable and inform its own adaptation to that user [1]. As such, a goal-directed closed feedback loop can be created where the user state induces system adaptations, and system adaptations influence the user state [2]. Such a system must then also have a goal or "agenda" to guide its adaptations [3]. For example, adaptive automation systems increase automation levels when a user's workload is high and vice versa [4-5]. Their goal is to balance workload such that an optimal level of engagement is maintained. The logic to reach this goal, however, is generally pre-programmed: the adaptive responses to different levels of workload are fixed. Furthermore, the closed-loop adaptation limits the possibilities of adaptation to the information that is present within that loop—in this case, the one-dimensional measure of workload can only have a one-dimensional response of automation levels. *Cognitive probing* represents a way to a) automatically learn which adaptations are effective in which contexts with only limited prior logic, and b) go beyond closed-loop adaptation to *automated adaptation*: the automatically gathered information can be used by the system to act autonomously, outside of any ongoing control loop, in order to achieve or pursue any number of different goals. A cognitive probe is an adaptation initiated by the system in order to gauge the user's response to it. The responses to different adaptations are registered along with their contexts in a user model. With an increased number of context-probe-response samples, the model increasingly accurately describes various aspects of the user's (cognitive) behaviour, such as preferences and goals. It is these inferred, higher-level preferences and goals, finally, that form the basis of user-supportive adaptations—not merely the current context and neurophysiology.

MATERIALS AND METHODS

In a cursor control task, the cursor was autonomously controlled by the system. Probes consisted of cursor movements into random directions. Movements were restricted to a grid with up to eight possible directions. EEG was recorded from 19 participants passively observing these movements. The responses recorded from the EEG represented approval or rejection of the observed movement. This signal was automatically induced by the cursor movements and not consciously modulated. After a number of probes, the user model thus contained information concerning the preferred direction of movement. The system could now guide the cursor towards the correct direction. See [1] for details.

RESULTS

Figure 1 displays the average improvement in cursor performance. The system did not know where the user-intended target was, and the user did not know it had any influence on the system-controlled cursor. However, using automated neuroadaptation, the cursor effectively found its way to the target.

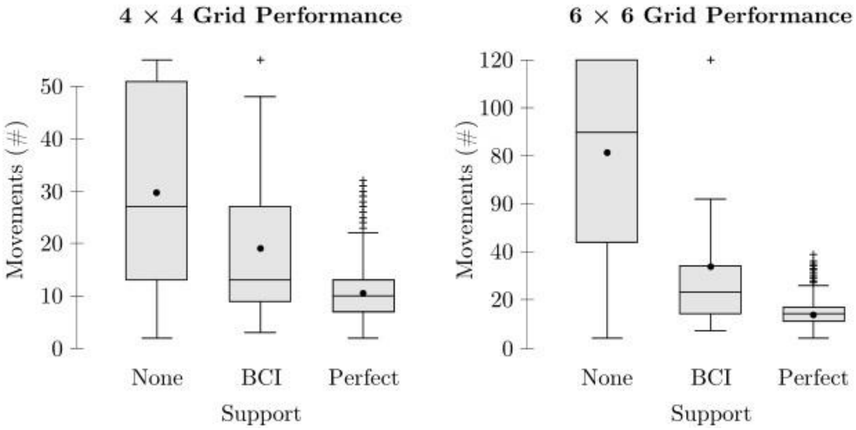


Figure 1: Cursor performance on two different grid sizes. ‘Random’ indicates cursor performance without neuroadaptation, ‘online’ with neuroadaptation, and ‘perfectly reinforced’ is the theoretically optimal performance given the constraints of the paradigm.

CONCLUSION

We have demonstrated a system that automatically ‘probes’ for information in order to learn and adapt to its user’s preferences, without the users being aware of these preferences being transmitted

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ENDOWING THE MACHINE WITH ACTIVE INFERENCE: A GENERIC FRAMEWORK TO IMPLEMENT ADAPTIVE BCI

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ABSTRACT: Recent developments in computational neuroscience gave rise to an efficient generic framework to implement both optimal perceptual (Bayesian) inference and choice behaviour. This framework named Active Inference rests on minimizing free energy or surprise [3]. We suggest it could be used to implement efficient adaptive Brain-Computer Interfaces (BCIs). We briefly illustrate it on a simulated P300-speller task.

INTRODUCTION

BCIs still suffer from poor reliability which can be attributed to the highly variable, noisy and incomplete nature of brain signals that need to be interpreted online. However, this challenge is very similar to the one faced by Robotics, or by any Human-Computer Interfaces where an artificial agent has to implement perceptual abilities to interpret its environment and decide how to act optimally. BCI is quite challenging though, because it is also facing the lack of fundamental knowledge to define appropriate features. The precise mappings between the targeted user mental states or intentions and some specific features of brain activity remain unknown. This renders the BCI challenge very acute.
To overcome these limitations, several authors have highlighted the need for adaptive approaches able to cope with noisy brain signals [4, 5, 6, 7, 8]. However, many of these adaptive approaches do not explicit the relationship between the modulation of the brain signals and the factors related to both the task and the user. Yet, the Good Regulator theorem states that “*Every good regulator of a system must be a model of that system*” [1]. In BCI, the system to be regulated is the triplet: {user, task, signal processing pipeline}. Hence to implement an optimal adaptive BCI, this theorem prescribes to use an explicit model of that triplet. The signal processing pipeline is already part of the machine. The tricky part is thus to implement a model of the user and the BCI task.

METHODS

The Bayesian modelling framework is a powerful and generic one. A recent Bayesian approach has been proposed to cast human perception and action within a common - Active Inference - framework [2]. In Active Inference, the human brain makes use of a model of its environment, including the task to accomplish. We propose to endow the machine with Active Inference (see Fig. 1.a), hence with adaptive behaviour through optimized perceptual inference and action. We use a discrete formulation of that model, which we exemplify on a simulated P300-speller BCI. The model entails three main components (see Fig. 1.b): the data likelihood (prescribed by matrix A), that maps the model hidden states s_t to observations o_t at time t; the priors over hidden states (prescribed by matrix B), which formalize likely state transitions, given the control states (or actions) u_t of the machine; and the preferences or prior probabilities that a final outcome will be observed (prescribed by vector C). Finally, parameter γ defines the exploration-exploitation tradeoff for action selection. A, B, C and γ have to be specified beforehand by the BCI designer, so as to estimate s_t and u_t online, from o_t.

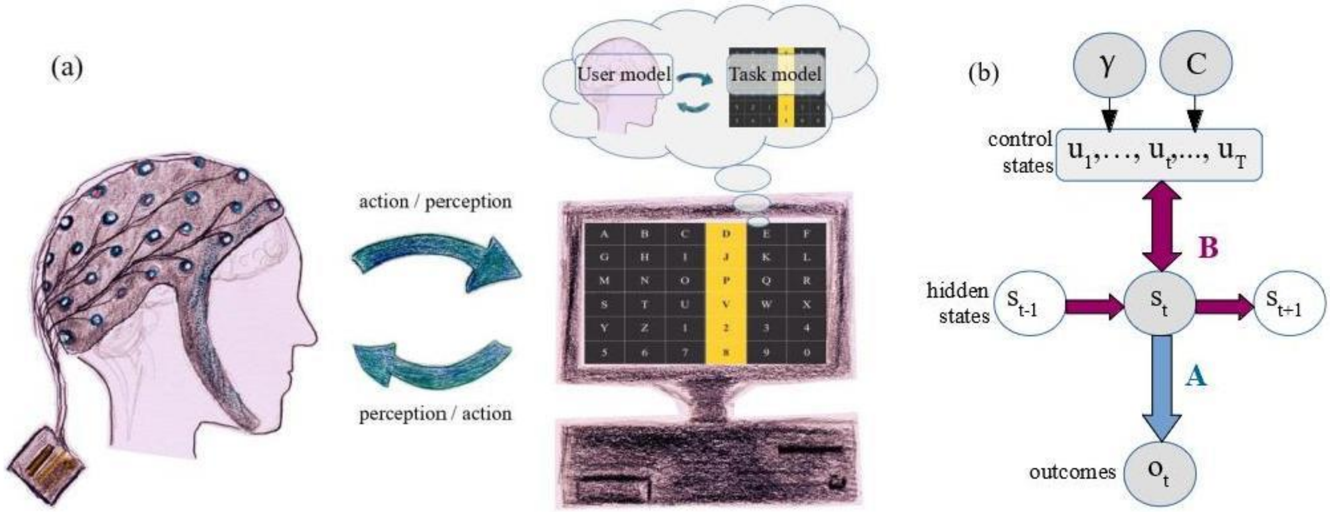

Figure 1: (a) BCI closed-loop where the machine is endowed with a model of the task and the user which subsumes its perception of EEG commands and prescribes its action; (b) Generic form of the (Bayesian) Markov Decision Process implementing Active Inference. (adapted from [2]).

RESULTS

With the P300-speller, time amounts to trials. Each trial t yields a single action u_t: "*flashing a group of items*" or "*sending the feedback of the chosen item*". Hidden state s_t refers to the user's state of mind one has to infer: "*I just saw my target flashing*", "*the flashed items did not contain my target*" or "*I saw a feedback and now change target*". This simple model already enables to implement two adaptive features: optimal stopping but also optimal flashing. The later refers to moving away from a pseudo-random sequence of flashes (method M1) by optimally choosing the group of items to flash next which best reveal the target (method M2). Comparing M1 and M2 on one hundred simulated spelled items, we could show that M2 is both more accurate (85.2% vs. 80.6%) and faster (15.8$\pm$6 vs. 20.1$\pm$9 flashes).

CONCLUSION

These preliminary results demonstrate the face validity of this new approach and further illustrate how it can easily provide additional and new adaptive behaviour, namely optimal flashing. Future work will consider real data while ensuring that the flashing sequence complies with the oddball paradigm.

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Session Name: AI-3

Room: R1
Session: Neuroadaptive Technology: Concepts
Time slot: 11:00 – 12:30
Day: 1

LEARNING FROM LABEL PROPORTIONS IN BCI -- A SYMBIOTIC DESIGN FOR STIMULUS PRESENTATION AND SIGNAL DECODING

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ABSTRACT: A brain-computer interface (BCI) translates neuronal signals into control commands. We propose a new design in which the stimulus presentation works together with the machine learning model to allow for an adaptive decoder that can learn from scratch without requiring any calibration session. This so-called learning from label proportions (LLP) based BCI was tested successfully in an online EEG study with 13 subjects. LLP is the first method for classification of unlabelled ERP signals with the theoretical guarantee to converge to a high-quality decoder.

INTRODUCTION

In BCI, the stimulus presentation and machine learning model are often regarded to be separate entities. Previous studies aimed at improving the signal-to-noise ratio of the data, e.g. by enhancing the saliency of the stimuli [1-4] or avoiding confusion between different stimuli [1, 5, 6]. Other approaches improved the machine learning model [7-10]. We introduce learning from label proportions (LLP) [11, 12] to the BCI community [13], a semi-supervised approach in which known proportions of different classes in different groups of the data are used to derive statistics about the individual classes. In BCI, this represents a synergistic approach where the machine learning model can be made more powerful by tweaking the stimulus paradigm.

MATERIALS AND METHODS

We modified a visual event-related potential (ERP) speller to meet the requirements of LLP by splitting the train of 68 stimuli to spell one letter (with 4 stimuli per second) in repetitions of two interleaved sequences of length 8 and 18 which have different target to non-target ratios. These known ratios are subsequently used to approximate the average target and non-target ERP responses (see Fig. 1). Based on these continuously improving class mean estimations, a regularized linear discriminant analysis classifier [7] was trained.

RESULTS

An online EEG study with 13 subjects performing a copy-spelling task showed that the proposed LLP approach works well with an average of 84.5% characters decoded correctly (standard deviation across subjects=16.9%, chance level=3%) [13]. Furthermore, the LLP method has the following desirable theoretical property. Under the assumption of independent and identically distributed data points, the mean estimations are converging to the true class means, and hence, one can show that the decoder is converging to the ideal supervised solution which one obtains when knowing the user's intention for all (online) trials.

DISCUSSION

The necessity of frequent (re-)calibration is a major shortcoming of current BCI systems. To circumvent this, we proposed the adaptive LLP approach which utilizes a modification of the stimulus presentation to reliably learn the target and non-target class means even without access to class labels. This was not possible using previous unsupervised methods. Therefore, this is a prime example of how the information theoretical background of a classifier can be used to modify the presentation paradigm to, ultimately, lead to a more robust BCI.

CONCLUSION

By modifying a visual ERP speller, we could introduce a new decoder which is guaranteed to converge to the optimal decoder given enough (unlabelled) data.

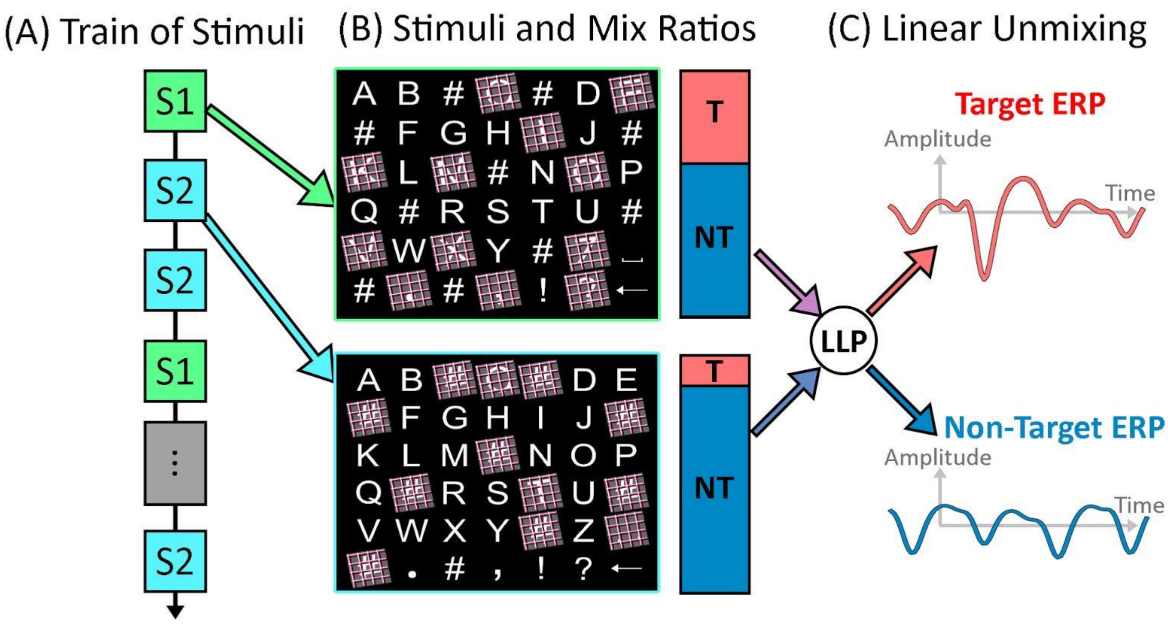

Figure 1: **LLP principle. (A)** A train of stimuli (i.e. spelling one character) consists of several repetitions of two interleaved sequences.
(B) Sequence 1 highlights more normal characters (potential targets) than sequence 2, which highlights more visual blanks ('#' symbols that are not attended by the user and as such are non-targets by definition), resulting in a higher target ratio for sequence 1 than for sequence 2.
(C) Average target and non-target ERP responses can be approximated with LLP based on the known target and non-target ratios of both sequences.

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Learning from label proportions in brain-computer interfaces: online unsupervised learning with guarantees. *PloS one*, *12* (4), e0175856.

Evaluation Methodology

Session All

FROM UNIVARIATE TO MULTIVARIATE ANALYSIS OF fNIRS DATA

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ABSTRACT: The statistical analysis of fNIRS data with a General Linear Model is often made difficult by serial correlations, intersubjective variability of the hemodynamic response and presence of motion artifacts, all of which make some steps in the preprocessing of the data particularly crucial to be able to correctly model it. Here we explore the possibility of extracting information on the pattern of hemodynamic activations without using any a-priori model for the data, by classifying the channels as activated or not activated with Regularized Linear Discriminant Analysis.

INTRODUCTION

Functional Near Infrared Spectroscopy (fNIRS) is a neuroimaging technique based on the measurement of the optical absorption of cerebral blood. Thanks to the different absorption spectra of oxygenated and deoxygenated Hb (HbO and HbR, respectively) in the near-infrared region (650-900 nm), it is possible to estimate their relative concentration changes [1]. To assess if an increase in the local neuronal activity is significant, typically a general linear model (GLM) is used to model the measured data Y as $Y= X\text{ß} + \varepsilon$, where X is the design matrix, embedding the expected hemodynamic responses according to the stimulus design, ß are the regressors, representing the effect of each condition on the responses, and ε defines the measurement error [2]. For the estimation of ß to be valid, the noise must have zero-mean and be spherical ("white noise"); these assumptions are generally greatly violated by fNIRS data, due to physiological noise, temporal and spatial correlation of the samples, and presence of artifact [3]. For this reasons, the method is susceptible to yielding high false discovery rates. A successful approach to overcome the problem is to pre-filter the data with a whitening filter to remove structured noise from the residual term ε, with the autoregressive iteratively reweighted least squares algorithm presented in [4]. As an alternative to this, we propose to use Regularized Linear Discriminant Analysis [5] to classify NIRS signals in two classes: activation and no-activation. The advantage of such a method is that no assumptions on the structure of the noise are necessary and no prior knowledge is needed on the shape of the expected hemodynamic response. Furthermore, GLM analyzes the data with a univariate approach, by investigating time traces from HbO and HbR independently; with LDA, information from simultaneous variations of both hemoglobin components could be combined in a multivariate strategy to search for activations.

MATERIALS AND METHODS

500 synthetic sets of fNIRS data were simulated by producing temporally correlated noise and hemodynamic response functions (HRFs, peak amplitude: 0.04-0.2 µM). The design matrix

comprised a set of 8 trials (10 seconds duration, 30 seconds on average between markers). HRFs were added only to half the channels (true active channels). The data were analyzed with both GLM, with pre-whitening, and LDA with shrinkage [6]. For the latter, amplitude and slope of the signal after stimulus were employed as features [7] and 10-fold cross validation were performed. Features obtained from HbO and HbR of the same channel were combined.

RESULTS

The performances of the GLM and the LDA classifier were evaluated with a ROC analysis (Fig.1A) and in terms of classification accuracy (Fig.1B).

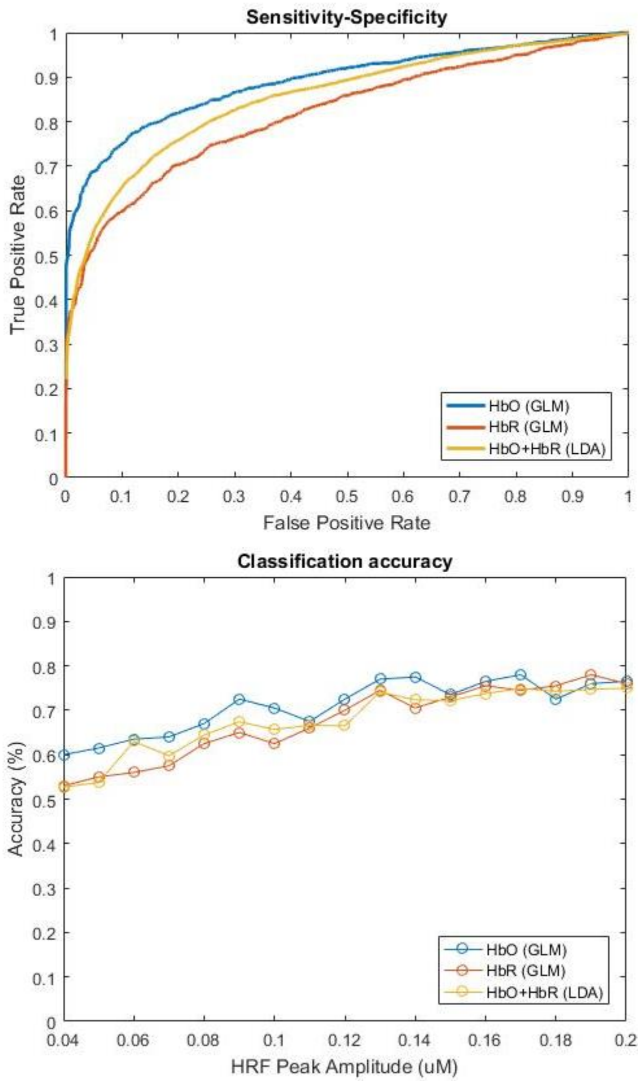

Fig. 1: A) (left) Sensitivity-Specificity of GLM (HbO and HbR channels are analyzed separately) and of LDA on features extracted from simultaneous HbO and HbR. B) (right) Classification accuracies, defined as %(True Positives +True Negatives)

DISCUSSION

The analysis with LDA reaches results comparable to the GLM with pre-whitening, without the need for an a-priori knowledge of the noise model or the expected shape of the HRF. The next step will be to check the robustness of this analysis with real data, with special focus on data contaminated by the presence of motion artifacts, which is a frequent experimental situation when doing an fNIRS experiment on certain populations of subjects, such as children.

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Session Name: AII-2

Room: R2
Session: Evaluation Methodology
Time slot: 11:00 – 12:30
Day: 1

A GENERALIZED DEEP LEARNING FRAMEWORK FOR CROSS-DOMAIN LEARNING IN BRAIN COMPUTER INTERFACES

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ABSTRACT: The utility of brain-computer interfaces (BCIs) is often limited due to their need for within-subject or within-domain calibration. Here, we train a Deep Learning (DL) model to generalize to unseen domains (in our case, experimental paradigms) in which similar neural responses are expected. We build on prior results demonstrating DL's cross-domain capability and investigate how the composition of the training set can improve both performance and generalization of the system.

INTRODUCTION

While much BCI research is devoted to user-user transfer [1], BCI models must also transfer to unseen scenarios. In other words, to be effective these systems must work in scenarios that extend beyond the basic confines from which they were trained. Here, we build upon our previous domain transfer results [2] and evaluate how different training sets affect the model's ability to generalize to unseen test sets. Our long-term goal is to build a more robust generalizable system that can isolate specific responses across data sets in the face of potentially confounding components.

MATERIALS AND METHODS

We train models on: 1) a fixation-related potential (FRP) dataset (3000 trials) where subjects fixated on stimuli and pushed a button in response to targets, 2) a 2 Hz rapid serial visual-evoked potential (RSVP) dataset (3000 trials) in which subjects counted the number of targets present, 3) their down-sampled combination (3000 trials) and 4) their full combination (6000 trials). These 3000 and 6000 trials are subsampled from the full datasets to shed light on data size vs data 'content' effects. We train, and average results over, 10 folds of each model. We test on two hold out experiments: a free-viewing (FV) target discrimination task where subjects looked for, fixated on, and pressed a button in response to targets, and a 1 Hz event-locked visual-oddball (VOB) task with no button presses. All data sets were previously analyzed to contain a P300 response on target trials. We use the EEGNet DL model [3], and use Balanced ccuracy (BA) as our performance metric.

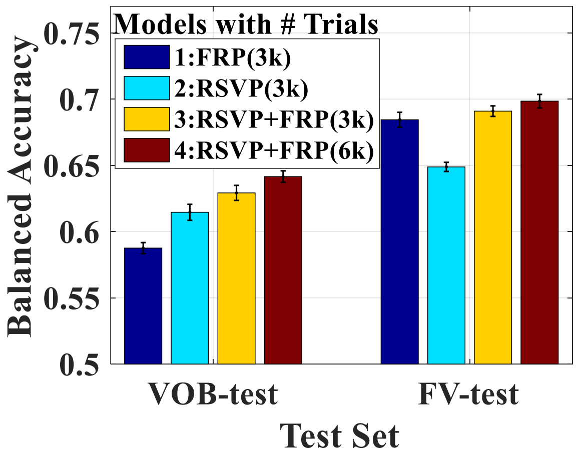

Figure 1: BA with standard error bars

RESULTS

For the VOB test set, model 1 (FRP) performs significantly worse than the other models ($p<0.01$). For the FV test set, model 2 (RSVP) performs significantly worse than the others ($p<0.01$). Model 4 (RSVP+FRP with 6000 trials) outperforms model 3 (RSVP+FRP with 3000 trials), though insignificantly, for both VOB ($p=0.059$) and FV test sets ($p=0.209$).

DISCUSSION

When trained on a single data set, models may fit to all domain specific discriminative features, generalizing poorly to the test set where those features are absent. For example, for model 1 (FRP) the discriminative activity is a combination of the P300 and button presses in target trials, and the FV test set, which has the same features, performs better with model 1 than with model 2 (RSVP).
The VOB test set instead performs better with model 2, with which it shares the same P300-only discriminative activity. Models 3 and 4 capture the best performance of models 1 and 2. From these results, we believe that these models either 1) learned a more generalized representation of the P300, or 2) independently captured features of both training sets. Also, the modest improvements with more training trials indicate a potential benefit of adding more similar domains to the training set.

CONCLUSION

These results further indicate that cross-domain transfer is possible with DL BCI models. While similar experiments transfer well to each other, detection of a P300 signal across different experiments shows improvement as the model is forced to generalize across domains.

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TIME-FREQUENCY SENSITIVITY CHARACTERIZATION OF SINGLE- TRIAL OSCILLATORY EEG COMPONENTS

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ABSTRACT: Spatial filters are useful tools for the analysis of EEG data. Their quality strongly depends on the choice of hyperparameters. We present a hyperparameter sensitivity analysis which reveals the range of validity and quality of single-trial oscillatory components for a given experimental context. The analysis is not restricted to a specific choice of spatial filtering algorithm.

INTRODUCTION

Spatial filtering algorithms are utilized to enhance the low signal-to-noise ratio of EEG data. Supervised spatial filtering approaches allow to extract oscillatory components which explain single-trial label information [1]. They can be applied e.g. to predict single-trial performance of a motor task [2]. However, the performance of spatial filters is strongly influenced by the selection of time-frequency hyperparameters. In this work, the stability of an oscillatory component with respect to these hyperparameters is characterized.

MATERIALS AND METHODS

In [2], we studied a repetitive hand motor task by recording EEG activity. In our analysis, we identified robust pre-trial oscillatory components whose bandpower correlated with single-trial motor performance. The components were computed with a supervised spatial filtering method (SPoC, [2]) using trial-wise continuous labels. The spatial filters were trained using epoched multichannel EEG data on a 750 ms wide time interval relative to time t_{train}. In addition, data were filtered to a passband of 1.5 Hz width around the central frequency f_{train}. For this abstract, we selected a single, representative spatial filter and tested its performance with novel, randomly chosen time-frequency hyperparameter pairs (t_{test}, f_{test}) on the *same* data set. For characterizing the sensitivity of the component with respect to varying hyperparameters, the z-AUC performance based on the derived bandpower features with the known labels is reported (for details see [2]).

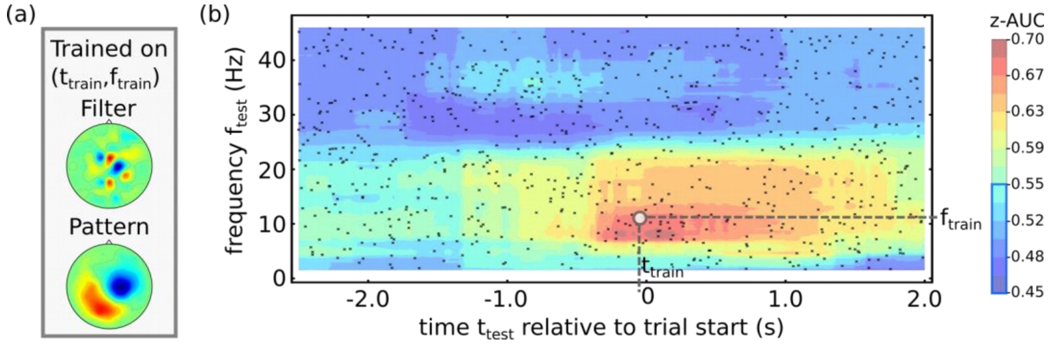

Figure 1: (a) Characterization of an exemplary SPoC component derived by parameters (t_{train}, f_{train}).(b) Performance for varying pairs of hyperparameters (t_{test}, f_{test}) illustrated by single black dots. The chance level is marked by the blue-rimmed z-AUC values.

RESULTS

The chosen value for f_{train} obviously was slightly sub-optimal (see Fig. 1). While stable performance is maintained in the vicinity of the original hyperparameter pair, stronger variations lead to a drop-off in single-trial performance.

DISCUSSION

Our approach realizes an in-depth characterization of an informative oscillatory component for a pair of hyperparameters (here: time-frequency parameters). By that, the component's range of validity in the experimental context is accessible.

CONCLUSION

The methodology serves to optimize and judge the quality of spatial filters. It is not restricted to a specific choice of spatial filtering algorithm.

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Neuroergonomics

Session BI

Room: R1
Session: Neuroergonomics
Time slot: 15:00 – 16:30
Day: 1

EEG, ECG AND EOG RESPONSES TO AUTOMATED, REAL DRIVING

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ABSTRACT: Adaptive neurotechnology is a promising technique in automated driving due to its potential to keep driver and vehicle connected despite the vehicle's partly autonomous behavior. We recorded EEG, ECG and EOG during partly automated driving, and examined responses to different types of (un)expected events associated with automated braking. We conclude that physiological responses can be informative, depending on the relevance of the event and alertness of the driver.

INTRODUCTION

While automated driving may improve comfort and safety, it removes the continuous communication between human and machine through using gas pedal, braking and steering. Automated actions (such as braking by an Adaptive Cruise Control system to reach a slower speed) are performed in the same way, regardless of driver state. To preserve the link between driver and vehicle, automated driving may benefit from another, implicit way of communication with the driver: neuroadaptive technology.

MATERALS AND METHODS

15 participants, driving a circular track, activated an ACC after the desire to either brake 'strongly' or 'softly' was aurally presented. Following ACC activation, the car announced whether it was going to brake strongly or softly, and subsequently performed this type of braking. The car's announcement was in line with the wish in 240 (match) trials, and opposite in 60 (mismatch) trials. 64 channel EEG, EOG, and ECG were recorded. Classification models were trained using EEG.

RESULTS

ERP responses to the 'strong' and 'soft' announcement of the vehicle differed (63% single trial classification accuracy). Heart rate and blink duration increased when strong compared to soft braking was announced, consistent with a higher state of arousal or startle. However, this was only found for the first half of the trials, when the driver was expected to be more alert and engaged - as also evidenced by decreasing heart rate, and increasing EEG alpha and blink duration over the duration of the experiment. ICA cleaning of the EEG data resulted in more stereotypical ERPs for certain electrodes but did not improve classification accuracy. We did not find any difference in any of the (cleaned) signals between match and mismatch trials.

DISCUSSION

While we had expected to observe differences between matches and mismatches in EEG error related activity and ECG or EOG arousal or startle measures, we did not find this. However, we did observe effects of the announced type of braking in all physiological measures (at the start of the experiment). Whether the vehicle is going to brake strongly or softly is arguably more relevant for the drivers, especially when they are still alert and interested, than whether the system's action matched expectation such as operationalized here. Thus, our results suggest that neurophysiologicalmeasures can convey information about to the driver's mental response to actions of an automated driving system, but only when these actions are sufficiently relevant to the driver at that time. Future studies and applications should consider collecting training data in the lab to mitigate the lengthy collection of field data (causing events to loose relevance). Applications may focus on information as collected over time and/or over participants e.g. for evaluation purposes rather than the utilization of data in real-time, on a single-trial basis. Likewise, peripheral signals may be combined with brain signals for better estimation of the driver state.

Session Name: BI-2

Room: R1
Session: Neuroergonomics
Time slot: 15:00 – 16:30
Day: 1

CLASSIFICATION OF CONCENTRATION LEVELS USING DEEP NEURAL NETWORKS

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ABSTRACT**:** Concentration is the ability of mind to maintain focusing on an attended task while ignoring distractions. Related studies thus far evolve into the examination of Electroencephalography (EEG) signal analyses. EEG is electrophysiological monitoring method that detects and tracks the brain’s electrical wave patterns for diagnosing brain disorders. The potential differences between the sensors (electrodes) attached on scalp are measured, recorded, and processed by computer. This study intends a data analysis of concentration measurements yielded by EEG tests to be conducted on a group of volunteer subjects that will be exposed to normal and various adverse physical, mental conditions. However, measurement periods and data magnitudes necessitate big data processing. Therefore classification of big data shall be performed by Deep Neural Network, an advanced type of artificial neural network based methodology.

INTRODUCTION

Classification of EEG signals by ANN is the foremost technique implemented in Human Machine Interaction (HMI) studies. This approach is efficient, becoming widespread in rapid detection of early indications of crisis [1]. This study delineates an ANN based computational model for processing the EEG signals and therewith measures human mind’s concentration levels.

MATERALS AND METHODS

The electrical brain activities throughout varying psychological states are collected as EEG signals are tracked collected and recorded; datasets are formed and processed; classified with *Deep Neural Networks* and then concentration levels are detected. The main objective of the project is to discriminate between different levels of concentration in terms of alertness and focused attention.

For alertness, response time will be evaluated to rate levels. A sample experimental setup will include computer games in which user is asked to click instantly appearing targets on the screen or control an object to avoid obstacles. In another setup, user presses button following a stimulant (sound or image) emerges. Focused attention or response time is measured by scores collected during cognitive games such as finding a missing object (or person) in two consecutive images, rearranging numbers and recognition of cards or order of objects’ movements. The measured criteria (score or response time) will be scaled into an interval [0,100]. However since an average performance depends on age, limits will vary [2]. Therefore statistical information shall be taken into consideration in determining age-based evaluation. At the outset, system's learning is figured as offline.

RESULTS & DISCUSSION

Collection of EEG generated data shall obviously be time indefinite, prompting a big data involvement. ANN is a robust classification technique for coping with the challenges of big data environment such as compilation time and accuracy. To begin with, the subject who is under the physical condition of well-being, contentment or relief from pain or stress, is presented a set of brainy games aimed at cognitive capacity (i.e. attention, memory, flexibility, speed etc.) System is trained on the basis of individual EEG data obtained from that subject during his/her performance. Then, subject is re-examined while he/she is under the exposure of abnormal circumstances (restless, exhaustion, hunger, etc.) and related EEG data is loaded to system. System shall make the classification according to game results and in the view of corresponding EEG data.

CONCLUSION

Trained datasets will enable the system to measure the concentration level of the same subject any time by applying similar games or training tools. Long haul airliner pilots or fighter pilots constitute suiting subjects where standard simulator flights shall replace the games for system's training. As for the rest, system extracts relevant real time data on board during the flight and thus accomplishes concentration level measurements and monitoring.

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Room: R1
Session: Neuroergonomics
Time slot: 15:00 – 16:30
Day: 1

ASSESSING IMPLICIT ATTITUDES DURING HUMAN-TECHNOLOGY INTERACTION BASED ON NEUROELECTRICAL EVIDENCE

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ABSTRACT: Emotion research in Human-Technology Interaction (HTI) mainly employs subjective, explicit methods. Our study investigates implicit attitudes underlying the user's emotional experience during HTI. 12 Participants were put in two interaction scenarios featuring events that either induced positive or neutral emotional states. Approach and avoidance tendencies towards snapshots of these emotional events were assessed by electroencephalographic (EEG) recordings during the Approach Avoidance Task (AAT). Analysis of event-related potentials (ERPs) showed significant higher cortical activity in the frontal cortex around 300ms for approach tendencies towards snapshots from the positive scenario. Higher potentials in the parietal cortex were found for avoidance tendencies towards the neutral scenario. The findings show that positive and neutral attitudes during HTI can be distinguished based on neuroelectrical data.

INTRODUCTION

HTI research has an increased interest in understanding the user's emotions when interacting with technology [1]. Studies in this domain mainly use explicit, subjective methods, e.g. surveys, while more implicit components of the user's emotions that cannot be assessed by introspection [2] re-main largely unexplored. Our study investigates implicit attitudes during HTI based on EEG and behavioural data. After interacting with two different versions of an ideation software (pUX: a version designed to induce a positive emotional user experience, and nUX: without any emotional features; previously validated through HTI expert reviews and user testing), participants' approach and avoidance tendencies towards the two versions were assessed by the AAT [3]. After interacting with pUx and nUX, Representative snapshots from the interaction sequences were used as visual stimuli for the AAT. EEG was recorded to investigate the neuronal activity underlying implicit attitudes. We expected (1) smaller reaction times (RTs) for approach-pUX than avoid-nUX, and higher for avoid-pUX than approach-nUX, (2) a significant difference in the ERP between pUX and nUX, (3) a higher P300 for congruent (approach-UX, avoid-nUX) than for incongruent stimuli (avoid-UX, approach-nUX), as P300 is modulated by stimulus-response compatibility [4]).

MATERIALS AND METHODS

Participants (n=12, M_{age}=24.42) were exposed to both software versions. RT differences were calculated for congruent and incongruent stimuli for pUX and nUX. EEG was used to examine ERPs during the AAT. Signed r^2-values were calculated defining time windows of interest (TOIs). TOIs were entered in a cluster-based, non-parametric randomization approach including correction for multiple comparisons between approach and avoidance trials for pUX and nUX. [5,6].

RESULTS

The RTs of the AAT showed no meaningful differences. The ERP analysis revealed significant dif-ferences in the P300 potential (Fig. 1), i.e. higher potentials for approach-pUX in frontal and motor electrodes and higher potentials in bilateral centro-parietal electrodes for avoid-nUX combinations.

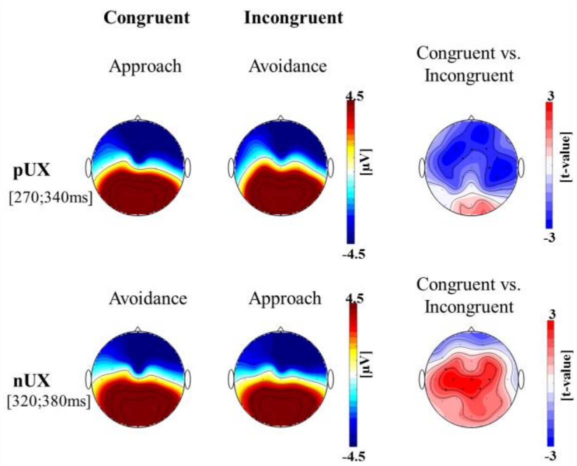

Figure 1: ERP signal comparison – congruent vs. incongruent trials of pUX and nUX stimuli. The topographical plots on the left and in the middle column represent the conditions ‘congruence’ vs. ‘incongruence’ per pUX or nUX stimuli and show the spatial topographies of the grand-average voltage distributions (colour-coded in µV) in the selected time interval of P300. The column on the right shows the t-value topographical differences between ‘congruence’ and ‘incongruence’. Black filled circles indicate significant electrode clusters. The blue colour displays an increase in negativity, while the red colour displays an increase in positivity.

DISCUSSION

The results suggest that positive implicit attitudes during HTI are represented by increased frontal cortex activity and less positive (neutral) ones by increased parietal activity.

CONCLUSION

We found that positive attitudes can be distinguished from neutral attitudes based on neuroelectrical data. This dissociation was not reflected in the RTs, which suggests that EEG is a promising tool to assess implicit attitudes during HTI that are too weak to be visible from the user’s behaviour.

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EEG Methodology

Session BII

BETWEEN-SUBJECT TRANSFER LEARNING FOR CLASSIFICATION OF ERROR-RELATED SIGNALS IN HIGH-DENSITY EEG

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ABSTRACT: We recorded error-related signals with non-invasive electroencephalography (EEG) in an optimized environment. For the first time, we show the feasibility of between-subject transfer learning for decoding of error-related signals with a suitably large subject group. Our findings could thus help to facilitate the development of adaptive brain-computer interfaces (BCIs).

INTRODUCTION

In order to assist paralyzed patients effectively with the help of BCIs, even state-of-the-art decoders are not satisfactory in real-life use, and reliable error-detection could improve their practicability significantly [1,2]. Moreover, the ability to use a pre-trained decoder on new users without extensive training could enable a more efficient use of adaptive BCIs. To this end, we compared state-of-the-art decoding methods commonly used with EEG data for error decoding across subjects. As our main result, we demonstrated the feasibility of using a pre-trained rLDA classifier for decoding of motor response errors in unknown subjects.

MATERIALS AND METHODS

30 healthy subjects participated in a study using 128-channel high-density EEG and an Eriksen flanker task paradigm, as classically used to study error-related signals [3,4,5], with 1000 trials per subject. EEG was recorded employing waveguard caps (ANT Neuro, Netherlands) and NeurOne amplifiers (Mega Electronics Ltd., Finland) with a sampling rate of 5 kHz in an electromagnetically shielded cabin. We evaluated regularized linear discriminant analysis (rLDA), optionally with filter bank common spatial patterns (FBCSP) feature extraction, and artificial neural networks (ANN) in a 10-fold cross-validation. After a preceding hyperparameter optimisation within subjects, we either used power features from 2 to 8 Hz, or voltage features from -0.5 to 1 s relative to EMG onset as classifier input. Transferability of the best classifier was tested using inter-subject cross-validation.

RESULTS

An rLDA classifier yielded the best accuracy in discriminating correct and erroneous responses (Tab. 1). Between-subject classification was tested both with features of all 128 electrodes and of 7 selected midline electrodes that were expected to exhibit the strongest error-related activations. Using all channels, the optimal sampling rate range was 1.25 - 25 Hz with 70.39 ± 1.02 (mean ± SD) normalized accuracy (Fig. 1A). In the case of the midline electrode selection, the optimal range for error decoding was between 25 - 125 Hz with 76.04 ± 0.31 % decoding accuracy (Fig. 1B). For all methods, the total classification accuracy was above chance level at $p < 0.001$ (sign test [6]).

Table 1: Comparison of classifiers & features for decoding of error-related signals in EEG.
The decoding accuracy ± standard deviation was calculated for different approaches in a within-subject 10-fold cross-validation. Normalized accuracy was defined as average accuracy of correct and erroneous trials; in that way, the unequal number of trials in the two response conditions had no distorting effect. The table shows the mean accuracy of the subject population. As identified via hyperparameter optimisation, features were extracted from 7 midline channels (Fpz – POz).

Classifier	Features	Accuracy correct trials (%)	Accuracy error trials (%)	Normalized accuracy (%)
rLDA	FBCSP (Voltage)	79.8 ± 7.6	70.7 ± 8.9	75.2 ± 7.2
rLDA	Voltage	84.0 ± 8.6	77.8 ± 8.2	80.9 ± 7.8
rLDA	Power	81.9 ± 8.8	67.8 ± 13.9	74.8 ± 8.2
ANN	Voltage	90.3 ± 6.5	61.6 ± 10.2	75.9 ± 6.3
ANN	Power	91.0 ± 6.7	60.9 ± 9.0	75.9 ± 6.5

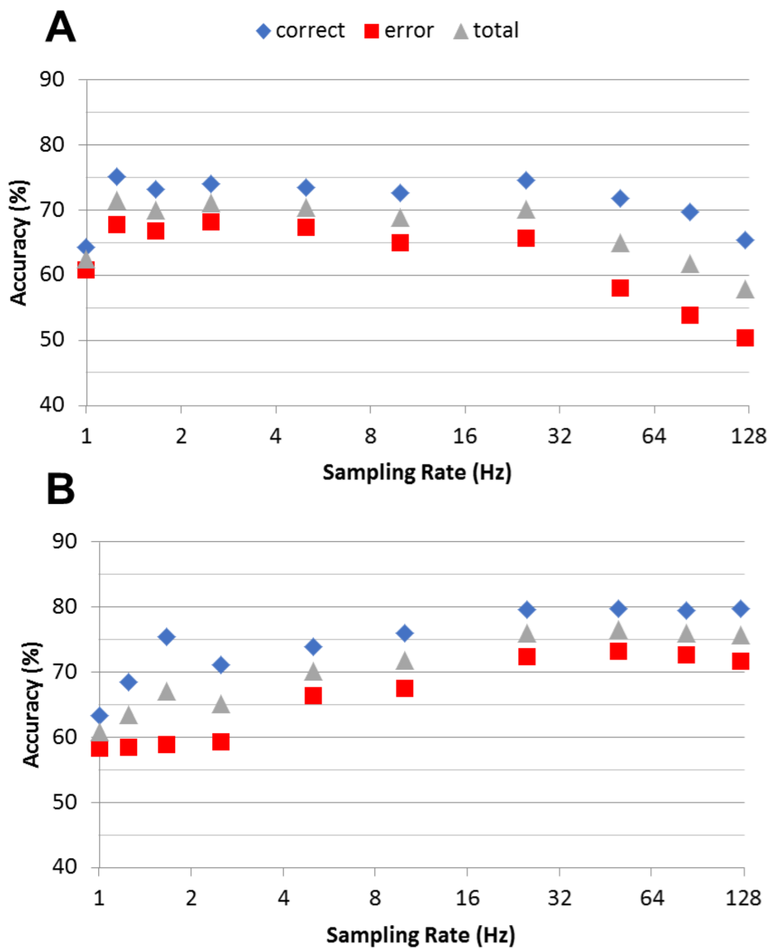

Figure 1: Between-subject transfer learning for error decoding using an rLDA classifier. We evaluated between-subject classification accuracy with a leave-one-subject-out cross-validation. **A)** Signals of all 128 EEG channels as decoding features. Here, resampling to lower sampling rates resulted in better decoding accuracies, with a maximum of 71.48 % at 1.25 Hz. **B)** Voltage Features of selected channels (Cz, CPz, FCz, Fz, Pz, POz, Fpz), cp. Tab. 1. In that case, higher sampling rates yielded the best mean decoding accuracies, peaking at 50 Hz with 76.45 %.

DISCUSSION

In this study, we show that between-subject transfer learning for error decoding in non-invasive EEG is possible. An rLDA classifier offered the best performance with voltage features, as other publications also showed [7,8]. As a leave-one-subject-out cross-validation with different numbers of channels and sampling rates revealed, selection of informative decoding features improved the classification accuracy. Notably, when using a selected group of channels, higher sampling rates up to 150 Hz resulted in an improvement of classification accuracy, suggesting that frequencies in the gamma band range might hold decisive signals for classification of response errors.

CONCLUSION

Pre-training of classifiers to enable transfer learning may generally facilitate BCI development. As next step, we want to test deep convolutional neural networks to potentially improve the accuracy and generalization ability of EEG-based error classification further.

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Room: R2
Session: EEG methodology
Time slot: 15:00 – 16:30
Day: 1

TRACING RHYTHMIC REGULARITY PROCESSING: BEAT-BASED BETA POWER MODULATION IN EEG SOURCE SPACE

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ABSTRACT: This work examines the postulated relationship between the processing of a regular, rhythmic beat and EEG activity in the beta band. We combine an experimental approach of auditory regularity processing with a machine-learning based analysis pipeline targeting beta band power and its modulation by the beat. We show a significant difference in beat-related, beta-band power modulation for the processing of regular compared to irregular sequences at the group level. Future work will test the behavioural relevance of beta band activity, and target their possible use in BCI.

INTRODUCTION

The ability to process and detect a more or less regular "beat" is essential to our perception of both music and speech [3]. In search for neural correlates of "feeling the beat", previous research has described effects in the beta band of the EEG, typically showing one peak, i.e. synchronisation and one trough, i.e. desynchronisation per beat cycle for regularly but not randomly timed sequences [5, 6, 7]. We here tackle those beta power modulations in a customized analysis pipeline using Spatio-Spectral Decomposition (SSD) [1] and Source Power Co-modulation (SPoC) [2]. This approach allows us, in a hypothesis-driven way to extract the maximally relevant EEG source-space component, and test for the presence of beat-based modulations in beta-band power.

METHODS

The experiment was an active listening task, using sequences of 9-11 tones, of different tempi (340, 400, or 460 ms) and degrees of irregularity (jitter: 0% to 30%) [4]. EEG data were high-pass filtered (0.2Hz), segmented into 2 beat-period epochs, onset-aligned with even tones; evoked activity removed by subtracting the ERP. SSD was applied to maximize signal power in the beta band (15-25Hz), followed by SPoC analysis to extract the source component with the largest co-modulation of time-resolved beta power and beat frequency. Time-frequency analysis (TF) using Morlet wavelets was applied to the SPoC component's time course in order to extract beta band power modulations. Finally, frequency content of modulations in beta power was assessed by Fourier analysis of the envelope time courses obtained from TF (FFT-of-TF). Parameters of this analysis pipeline were trained at participant level, on the EEG data from tones 2, 4, 6 from 0% jitter (324 epochs/participant). Results were then tested on epochs of tone 8 for 0% and 30% jitter (216 epochs/participant).

RESULTS

Fig. 1 shows TF spectrograms of the SPoC component, limited to the beta band, averaged across epochs and participants. The figure also shows FFT-of-TF results, with FFT bins corresponding to beat-frequency (and harmonics) highlighted. Statistical comparison of the relative modulation power (calculated as the mean difference in power to its two neighbouring sample points) for 0% vs. 30% jitter yields a borderline significant difference averaged across tempi ($p=0.05$; paired t-test for local peak at the beat frequency).

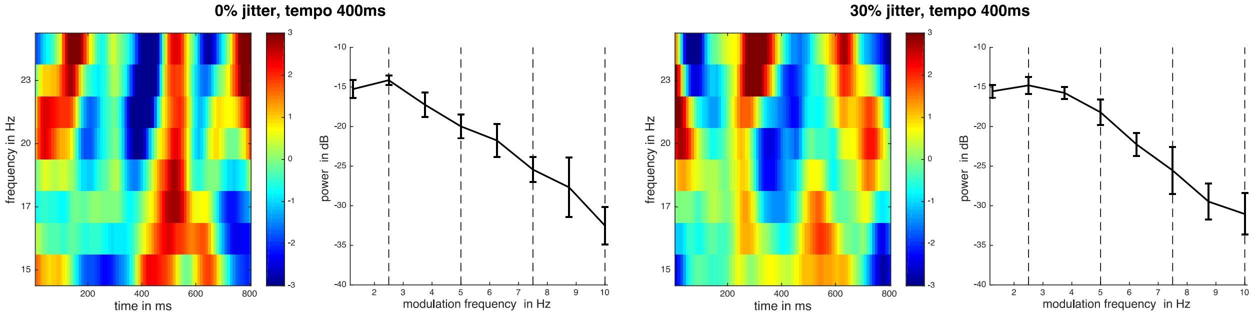

Figure 1. Results of the wavelet and FFT analyses, comparing 0% and 30% jitter, shown for the middle tempo (400 ms)

DISCUSSION

Our present EEG analysis compared hypothesised beat-based modulation of beta band oscillatory activity for the processing of highly regular (0% jitter) vs. highly irregular (30% jitter) sequences. Using a customised machine-learning based analysis pipeline enabled us to obtain maximally relevant source space components at the individual level. Whilst the beta-band peaks and troughs appear less clear than in previous reports, we demonstrate a group-level difference in beat-based modulation of beta band power for regular compared to irregular sequences. Further work is needed to find out whether this modulation is an epiphenomenon or a relevant feature of rhythm processing [8] and decide whether and how to implement their intended future use in auditory BCI.

CONCLUSION

The data provide limited support for the beat-based modulation of beta power during auditory rhythm processing of sequences with a regular beat compared to irregular ones.

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EXPRESS ESTIMATION OF BRAIN RHYTHM POWER FOR LOW-LATENCY NEUROFEEDBACK

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ABSTRACT: The problem of brain rhythm power estimation arises in implementation of real-time EEG paradigms such as neurofeedback (NFB) or brain-computer interface (BCI) [1]. Fundamentally, the need to estimate band power requires time and therefore the estimated rhythm power is delayed which hinders the efficiency of NFB learning and slows down BCI applications. We propose a method to estimate band power using the complex demodulation approach followed by the minimum-phase implementation of Savitzky–Golay filter [2]. Compared with classical methods, the proposed approach reduces the delay and preserves the quality of power estimation.

INTRODUCTION

Brain rhythm power estimation is by far the most frequently used module in the BCI or NFB processing pipeline. Fundamentally band power estimation incurs delay. The accuracy of envelope estimation and the required time both influence NFB and BCI tasks efficiency and thus can be used to benchmark envelope extraction techniques. Classic approaches for real-time band power estimation, such as causal filtering followed by the envelope detection or sliding window based Fourier transform introduce delay (with fixed smoothnesses of output signal) which is comparable to the average brain state duration of 250-300 ms. Here we propose a method that allows to reduce the delay as compared to classic approaches currently employed in the field.

METHOD

To extract the envelope, we first perform complex demodulation (CD) of the input signal by multiplying it with a complex exponential sequence with the argument corresponding to the central frequency of the band of interest. This transposes the spectrum of the signal so that the band of interest central frequency is aligned with $f = 0$. First order Butterworth low-pass concludes the complex demodulation step and yields the envelope estimate which is then smoothed with a minimum-phase proxy of Savitzky-Golay (SG) polynomial filter with frame length of 151.

RESULTS

The developed method was tested on the model and real data and benchmarked against several other techniques. Figure 1 shows the performance of the proposed approach (CD-SG) as compared against two basic methods – windowed short-time Fourier transform (STFT) and 1-st order Butterworth filter followed by the envelope detection (BE). The ground truth signal was obtained by non-causal order 2000 finite impulse response band-pass filtering, which cannot be performed in real time. An example of the band power reconstruction for a real data segment (250 Hz sampling rate) is shown in Figure 1.a. The comparison of efficient delay (Fig. 1.b), reconstruction accuracy (Fig. 1.c) and relative smoothness (Fig. 1.d) for three different envelope estimation methods illustrates that CD-SG approach results in the smallest delay and the highest smoothness and yet yields high envelope reconstruction accuracy which has a potential to improve the efficiency of the real-time EEG paradigms.

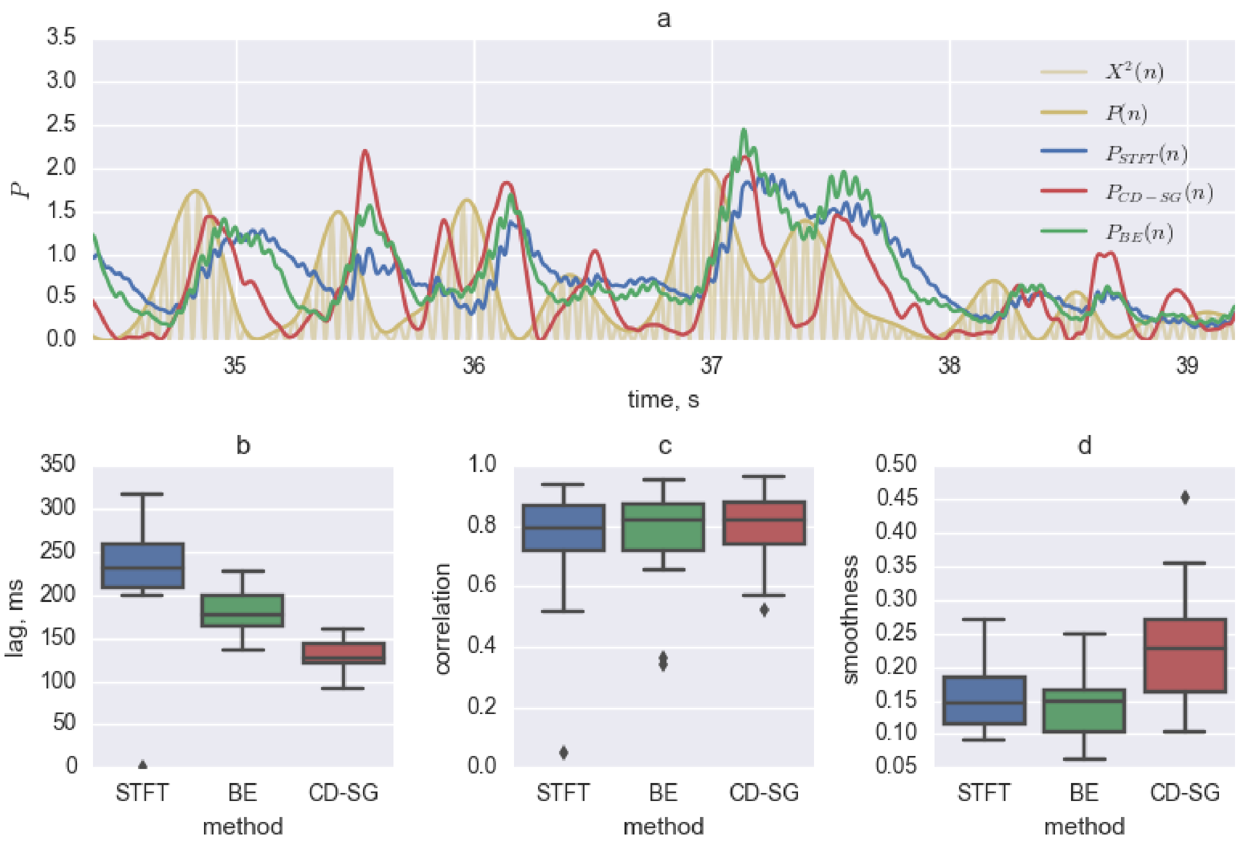

Figure 1. Band power reconstruction for a real data segment: a. example of the bandpower reconstruction: yellow – the ground truth squared signal and corresponded envelope, red – proposed method band power reconstruction, blue – STFT band power reconstruction, green – BE power reconstruction, b. efficient delay for the three envelope estimation methods, c. reconstruction accuracy (correlation between reconstruction and the ground truth), d. relative smoothness of reconstruction (ratio of 2-nd order discrete difference of ground truth signal and 2-nd order discrete difference of reconstructed signal).

CONCLUSION

The proposed method allows for express estimation of brain-rhythm power and is implemented as a part of the in-house developed software for EEG/MEG neurofeedback experiments [3]. The next step is to study the extent to which the obtained feedback latency reduction improves the efficiency of operant conditioning within the NFB paradigm.

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Neuroadaptive Technology: Applications

Session CI

Room: R1
Session: Neuroadaptive Technology: Applications
Time slot: 10:30 – 12:00
Day: 2

INVESTIGATING NEUROADAPTIVE TECHNOLOGY FOR SPEED READING APPLICATIONS

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ABSTRACT: Rapid serial visual presentation can be a useful reading technique for text presented on small screens. Readability is an estimate for the ease with which a reader can understand a written meaningful text. We investigated whether a passive Brain-Computer Interface (pBCI) can be used to distinguish between texts of distinct levels of readability presented at different presentation speeds. A predictive model was trained on EEG data derived from a cognitive load paradigm. The model was applied to data collected while participants read easy and difficult texts at a self-adjusted and an increased speed level. Results suggest that predictions by the model could be used for categorization and adaptation of text passages. Robustness and potential for the use in neuroadaptive reading applications should be further investigated.

INTRODUCTION

Recently developed speed reading applications employ rapid serial visual presentation (RSVP) [1] for text presentation on small screen devices. Words are presented at a fixed screen position and reading speed is manually adjusted by the user. Among other factors the optimal presentation speed depends on the reader's abilities and features of the text. Readability is a measure which estimates the ease with which a reader can understand a written meaningful text. In this study we investigated whether a passive Brain-Computer Interface (pBCI) [2] can be used to distinguish between texts of distinct levels of readability presented at different presentation speeds.

MATERALS AND METHODS

EEG data was collected while participants completed a cognitive load paradigm [3] inducing levels of low or high cognitive load. A predictive model was trained to distinguish between these levels of cognitive load (Table 1). The predictive model was then applied to EEG data collected while participants read easy and difficult texts at a self-adjusted speed and at an increased speed level. Predictions made for all words contained in the different text categories (difficulty x presentation speed) were analyzed for differences. The relationship between average predictive model output and sentence length was also investigated. Moreover, the effect of word position within a sentence on predicted values was examined.

Table 1: Crossvalidation results of the cognitive load paradigm. Obtained error rates (ER) in percent and standard deviations (SD) are reported.

participant	*ER* (*SD*)
1	14.1 (3.2)
2	28.5 (14.7)
3	14.8 (4.9)
4	14.5 (2.5)
5	44.3 (7.8)
6	18.9 (4.1)
8	8.3 (1.5)
average	**20.5 (5.5)**

RESULTS

Permutation tests performed on predictions of full texts were all highly significant (all *ps* < .0001), except for predictions from easy texts presented fast against predictions from difficult texts presented at normal speed ($p = .961$). Effect sizes were small to medium ($M = .266$, $SD = .116$). Linear regression analysis was not significant for differences in sentences length. No significant regression equation was found when data of all participants was collapsed for word positions within a sentence, all *ps* > .053. On single subject level, four regression analyses were significant. Half of the slopes for significant equations were negative while the other was positive, ranging between -.003 and .006.

DISCUSSION

The results suggest that predictions made by the cognitive load classifier could be used as an estimate for categorization and adaptation of longer text passages. It is not suitable though for detection of readability differences on sentence or single word level.

CONCLUSION

The investigated predictive model based on cognitive load potentially could be applied in neuroadaptive [4] reading applications to enable individual readability level and reading speed adjustment. Its robustness and applicability to other text material should be further investigated.

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TOWARD NEUROADAPTIVE PERSONAL LEARNING ENVIRONMENTS

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ABSTRACT: Clickstream data of student actions within a personalized learning environment can include correct steps, errors made, and help-requests. However, processes related to *robust learning* that transfers to novel scenarios, such as reflecting on errors and confronting one's misconceptions, often occur at times where students are thinking and thus, during a pause in the log data. To better understand these pauses, we investigated fNIRS brain data during pauses resulting in correct and incorrect responses and found significant differences. These initial results show promise for combining brain and log data to enable neuroadaptive learning technology.

INTRODUCTION

With the increasing ubiquity of online and computer-based learning environments, researchers and practitioners now have unprecedented access to data on how students solve problems and build knowledge [1]. A large focus in intelligent tutoring systems (ITS) research has been to predict learning outcomes using ITS logs [2,3]. Research has shown that pauses play an important role in the learning process [4], but, by definition, result in no log data. Functional near-infrared spectroscopy (fNIRS) is an emerging non-invasive neuroimaging tool that has been used to measure cognitive state continuously in real-time while participants complete computer-based tasks [5,6].We explore its use in disambiguating what is occurring during pauses in learning log data.

MATERIALS AND METHODS

We conducted a pilot study in which we collected fNIRS data and log data from five participants as they used the ASSISTments platform [7] to solve math problems. fNIRS sensors were placed on the participant's forehead to continually record brain data. Then participants proceeded through several sections of tutored problems, where they could request help and get feedback.

We extracted events from the ASSISTments log data, focusing on the pauses in the data. We categorized pauses based on three factors: *pause length* (very short, short, medium, long and very long), *preceding action* and *subsequent action*. From these pause events, we extracted the corresponding fNIRS data. This consisted of the change in oxy-hemoglobin (HbO) and deoxy- hemoglobin (HbR) at each of six sensor locations on the forehead. The expected hemodynamic response during increased workload is an increase in HbO and a decrease in HbR. We were interested in seeing how the changes in HbO and HbR differ, depending on the subsequent action.

Particularly, we wanted to explore whether there was a difference between the correct and incorrect responses. We focus on the medium-length pause events occurring after a problem is loaded (i.e. where the preceding action was *load-problem*).

RESULTS

Across all participants, there were 69 medium-length pauses after a new problem loaded. These pauses ranged from 7.2 to 22.2 seconds. Out of these, 56 resulted in a correct response, 8 resulted in an incorrect response and 5 resulted in a request for help. For each of the 6 sensor locations, we looked at the maximum value of HbO for each event. Figure 1 shows the mean and standard error of these values across these pauses. Across almost all of the channels there was a statistically significant difference between correct and incorrect responses.

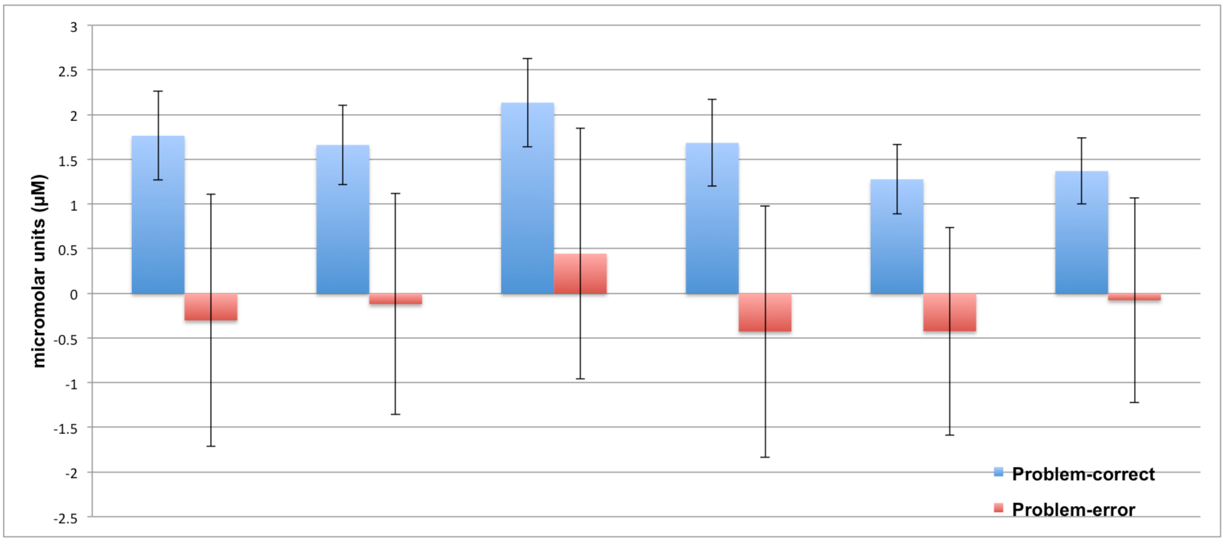

Figure 1. Maximum change in oxygenated hemoglobin (HbO) for medium-length pauses (7.2-22.2 seconds) after a problem is loaded across 5 participants across 56 correct responses and 8 incorrect responses. Each pair shows the response in one of the six sensor locations. For most channels, there was significant difference in HbO, depending on whether the participant had a correct or incorrect response.

DISCUSSION AND CONCLUSION

Our work shows preliminary results in using physiological data from functional near infrared spectroscopy (fNIRS) brain imaging to enhance learner models during pauses in intelligent tutoring system log data. We aim to continue exploring this dataset while we are collecting a larger dataset to enable us to build real-time neuroadaptive personal learning environments.

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GAZE DIRECTION AND THE EEG MARKER FOR INTENTION/EXPECTATION IN HYBRID INTERFACES

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ABSTRACT: Hybrid eye-brain-computer interfaces (EBCIs) can employ a slow negative EEG wave as a marker for gaze dwells used for interaction. This study examined previously reported relation of the marker's lateralization to the direction of gaze. It turned out that the marker itself is not related to the gaze direction and the apparent lateralization is caused by another signal superimposed on it. Thus, the marker can be used in BCIs/EBCIs independently of gaze direction.

INTRODUCTION

Commands to computers can be sent using gaze. This technology depends on the differentiation of intentional vs. spontaneous gaze dwells, because the latter interfere with control but cannot be fully suppressed by the user [1]. Differentiation using a passive BCI [2] was proposed in [3]. Recently, an EEG marker, a slow negative wave with a posterior localization, was described and used to classify intentional vs. spontaneous 500 ms gaze dwells collected in a realistic gaming scenario [4].

We currently analyze the dependency of this marker on factors that may influence it under practical application conditions. One of them is gaze direction, as evidence was found that the marker's focus is contralateral to the gaze direction [4]. Here, we studied this relationship in detail.

MATERALS AND METHODS

14 healthy participants played a computer game using 500 ms gaze dwells, as in [4]. Each move required three dwells: on a switch-on "button", on a ball, and on a free cell where the ball had to be moved (Fig. 1, top). Dwells were deemed *intentional* (and evoked a visual feedback) if followed this order, and *spontaneous* otherwise. We recorded gaze coordinates together with the EEG (19 channels) and the horizontal electrooculogram (hEOG) related to the dwells. To characterize the marker, amplitudes over +400..+500 ms relative to dwell start were averaged, using +200..+300 ms as baseline. Difference between mean amplitude over the right and left posterior channels served as an asymmetry index. ANCOVA and Spearman correlation were applied to individual data.

RESULTS AND DISCUSSION

EEG topographies confirmed the dependence of the EEG lateralization on gaze direction, but the intentional/spontaneous dwell difference showed no such dependence (Fig. 1). EEG asymmetry showed small but consistent correlation with gaze direction (median -0.16; negative in all but one participant) and with the hEOG (-0.22), no effect of the intention factor, no interaction between it and the gaze direction factor, no correlation between the hEOG and gaze direction. Time courses did not reveal hEOG artifacts that could influence the EEG, so the correlation between hEOG and the EEG asymmetry could be caused by the EEG leakage into the hEOG. The asymmetry did not correlate with direction of the next saccade, so it was not caused by saccade preparation. POz amplitude depended on intention, with no interaction between intention and gaze direction factors.
The marker can be seen as the stimulus preceding negativity (SPR), an EEG component specific to feedback anticipation [5]. The marker's apparent lateralization [4] contradicted this interpretation, as the SPR is not lateralized, but the new results resolve the contradiction. The use of SPR in a wider range of passive BCIs supporting interaction with machines can be also considered.

CONCLUSION

The EEG marker for the intentional gaze dwells is not affected by horizontal gaze direction.

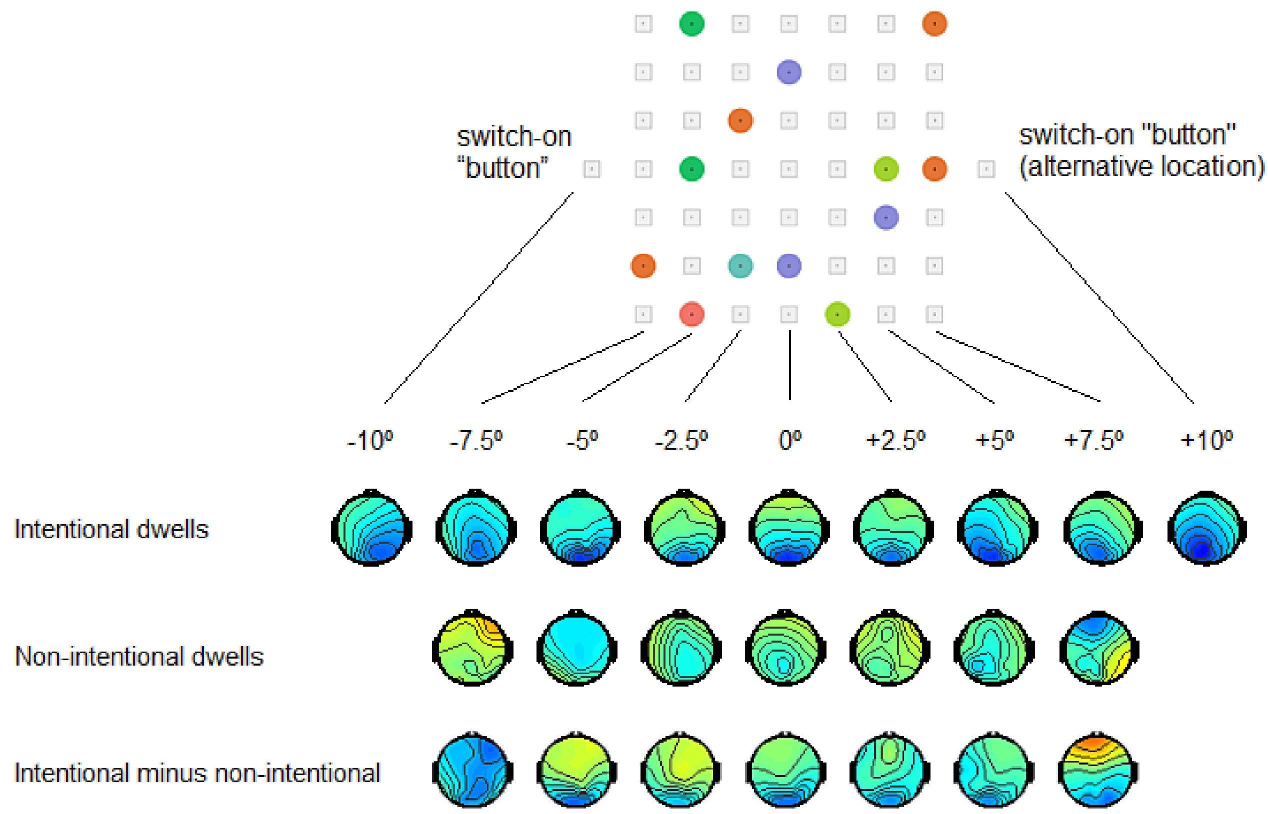

Figure 1: A screenshot of the gaze-controlled game board and the EEG amplitude grand average (n=14) topographic maps. X coordinate is shown with 0° corresponding to the balls in the middle of the screen (gaze straight ahead). +10° and –10° maps are for the dwells on the "button", the other maps represent the dwells on balls. Left and right "button" locations were used in different games (only one "button", left or right, was actually shown along a game; the

game order was randomized across the group). Amplitudes were averaged over the +400..+500 ms interval relative to the dwell start, with baseline +200..+300 ms. Color scale: –5..+5 µV. "Button" maps well reproduced the topographies described for the same extreme locations in [4], however, the difference maps (the lower row) showed no dependence of the "intention" marker on the horizontal gaze direction. (Less data were available for the higher eccentricity locations, especially for non-intentional dwells, therefore –7.5° and +7.5° difference maps were not reliable.)

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Physiological Computing 1

Session CII

Session Name: CII-1

Room: R2
Session: Physiological Computing 1
Time slot: 10:30 – 12:00
Day: 2

WEARABLE SENSORS, DRIVING AND THE VISUALIZATION OF CARDIOVASCULAR STRESS DURING EVERYDAY LIFE

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ABSTRACT: Driving is a common daily activity, where the experience of negative emotions, such as stress/anger, can frequently occur. The repeated experience of cardiovascular activation associated with negative emotions can be detrimental to long-term health. However, these physiological changes can be quantified via wearable technology to enable insight and self-reflection from the perspective of the individual. A study was conducted to explore the impact of data visualization on cardiovascular reactivity and self-regulation in response to driver stress.

INTRODUCTION

High-levels of negative emotions can have adverse implications for health, including inflammation, which can impact long-term cardiovascular health (e.g. developing coronary heart disease and hypertension) [1]–[3]. However, this cumulative damage can be reduced with the use of effective coping strategies, the development of which can be supported using wearable technology [4]–[5]. This work presents our mobile platform, which captures data during daily commuter driving. This includes psychophysiological data collected from wearable devices, including heart rate (HR), heart rate variability (HRV) and pulse transit time (PTT). This was enhanced with contextual data collected via a smartphone, including location, vehicle speed and photographs of the driving view. These data were then used to create an interactive visualization of changes in cardiovascular stress.

MATERIALS AND METHODS

Eight participants took part in the study to collect data during eight commuter journeys to/from work (four during the journey to work and four during the journey back to their residence). The initial two days of data collection were referred to as a pre-test phase. Data from all four journeys during this phase were translated into an interactive visualization of each cardiovascular measure (HR, HRV, and PTT) and mapped on the geospatial route. Participants were invited to explore their data visualization and a structured interview was performed to assess perceptions and insights into the cardiovascular data. After exposure to the interactive visualization, data were collected from participants during four subsequent commuter journeys, known as the post-test phase.

RESULTS

High journey impedance is characterized by slow vehicle speed due to high traffic density and is known to be a source of cardiovascular stress during the driving task [6]. Periods of high journey impedance were identified for both pre-test and post-test phases based on vehicle speed (i.e. <10mph). The impact of the data visualization on cardiovascular reactivity during high journey impedance was explored using a two (before vs. after visualization) x two (AM drive vs. PM drive) repeated measures ANOVA. Results indicate that heart rate significantly declined during high journey impedance during the post-test phase compared to the pre-test phase (see Fig. 1). The analyses also revealed that HRV significantly increased during the post-test phase, which was indicative of reduced inflammation during high traffic impedance (see Fig. 1). The strength of the effects found and the statistical significance is F(1,7) = 22.2, p <.01, effect size = 0.76.

a)

b)

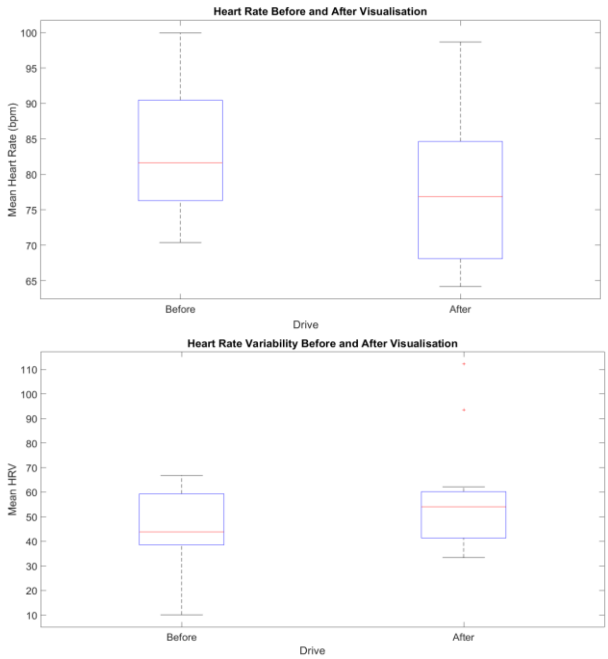

Figure 1: Boxplots that illustrate a) mean heart rate and b) mean heart rate variability before and after exposing participants to the visualizations.

DISCUSSION AND CONCLUSION

The results provide evidence that exposure to the interactive visualization had a positive effect on cardiovascular reactivity to stress during real-world driving. The impact of high journey impedance on the cardiovascular system was significantly ameliorated after participants had been exposed to the data visualization. It is questionable whether the data visualization itself or the introspective exercise was responsible for this effect and further research is required to explore this issue.

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EVALUATING FNIRS-BASED WORKLOAD DISCRIMINATION IN A REALISTIC DRIVING SCENARIO

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ABSTRACT: The detection of mental workload during driving could provide valuable information to car electronics such as the navigation system. Functional Near Infrared Spectroscopy (fNIRS) is a promising candidate for unobtrusive measurement of brain activity and has shown convincing results in the discrimination of different levels of workload in laboratory settings. In this study, we investigate whether fNIRS can be used to robustly discriminate two levels of workload, induced by the *n*-back task, in a realistic driving scenario.

INTRODUCTION

Car navigation and entertainment systems could greatly benefit from information about the driver's current workload to adapt their specific behavior [1]. Monitoring brain activity might yield information about the driver's workload, but the measurement technique would need to be unobtrusive to not disturb the driver. Functional Near Infrared Spectroscopy (fNIRS) is an optical brain activity measurement technique that does not require electrode gel and can be realized using cheap sensors [2] making it a good candidate for consumer products. Previous studies highlight the usability of fNIRS in real-life scenarios [3] or propose fNIRS as a suitable candidate for brain activity measurement during driving [4]. Different levels of workload can be robustly discriminated using fNIRS [5] in laboratory environments, but realistic scenarios place very different demands on the measurement technique. In this study, we investigate whether fNIRS can be used to discriminate between high and low workload during driving.

MATERIALS AND METHODS

Six male participants (mean age of 19.8 years) performed the lane change task (LCT, [6]) in a realistic driving simulator (see Figure 1). To induce different levels of workload, participants also had to perform an auditory *n*-back task (10 trials each of 1-back and 3-back). During the experiment, 8 channels of hemodynamic activity in the prefrontal cortex were recorded using fNIRS (Oxymon Mark III, Artinis). For this purpose, 4 receiver and 4 transmitter optodes were placed on the forehead (see Figure 1). For comparison, driving statistics in the LCT task were used to attempt discrimination of different workload levels.
Participant dependent classification between periods of high (n=3) and low (n=1) workload was evaluated in a 10-fold cross-validation using a LDA classifier.

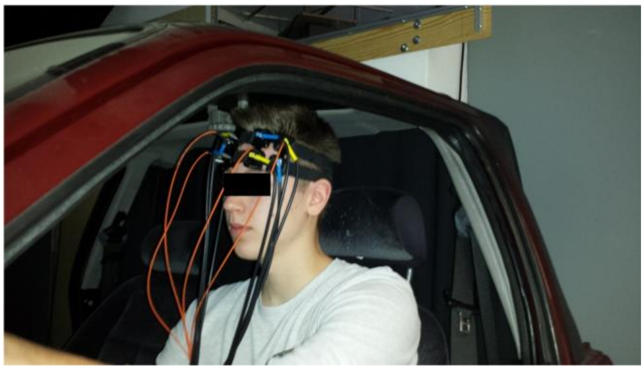

Figure 1: Participant in the driving simulator with fNIRS transmitters and receivers placed on the forehead

RESULTS

Both levels of workload could be discriminated from a relax state, in which the participants were only required to perform the LCT, with good accuracies using the LDA classifier. Classification between high (n=3) and low (n=1) workload performed better than chance level, also.

Driving parameters, such as derivation from reference path, could also be used to identify periods with secondary task and to discriminate the workload level. However, driving parameters were outperformed by fNIRS derived features.

CONCLUSION

Our results show that fNIRS can be used to discriminate workload in a realistic driving scenario. fNIRS is therefor a good candidate for neuroadaptive technology out of the lab.

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Session Name: CII-3

Room: R2
Session: Physiological Computing 1
Time slot: 10:30 – 12:00
Day: 2

FIVE LAYER MODEL FOR PHYSIOLOGICAL COMPUTING

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ABSTRACT: While the theoretical side of physiological computing has received a lot of attention, the practical engineering side is still high unorganized: each new project is usually started from scratch, and there is little re-used of code, resources and best practices. This paper aims to provide a conceptual framework to encompass the whole field of physiological computing in a way that provides designers practical guidelines on how to develop physiological computing systems as well as a repository for researchers to share code, data, and ideas in a consistent manner. The framework consists of five layers that each deal with a particular aspect of physiological computing.

INTRODUCTION

This paper proposes a five layer model for physiological computing to help design future physiological computing applications and experiments. The work builds on the idea of the biocybernetic loop introduced by Pope [1] and further developed by Fairclough[2], as well as on the work of Cowley et. al.[3] who described the physiological signals through indices derived from metrics. It tries to encompass different emotional concepts such as the dimensional model of emotion vs. the categorical view of basic emotions. Furthermore, it aims to cover all the four main categories of physiological computing: classification, prediction, biofeedback, entrainment. Furthermore, it discusses the use of machine learning in the development of physiological computing applications: when should a (part of the) system be devised “by hand” and when a black-box machine learning should be used.

THE MODEL

The five layers are depicted in table 1. At the lowest level, we have the signal layer that is concerned with the low-level details of the physiological signals such as EDA, EEG, and ECG. The layer discusses details such as sampling rates and sensor locations, for example, which EEG sensor locations are suitable for certain purposes.

The next layer is concerned with *metrics* calculated from the raw signals, such as the amplitude of phasic spikes in EDA or the frequency band powers in EEG. The third layer, the *indices* layer uses the metrics to generate indices of the user‘s psychophysiological state, such as arousal and concentration. At this layer the different emotional models and cognitive frameworks are considered.

Next in the model is the *logic* layer that is concerned with topics such as signal fusion (combining input from several physiological signals) as well as context information, user profiling and multimodality in general. The logic of the biocybernetic loop is contained in this layer and suitable feedback and adaptation specified. The final layer, the *application layer* discusses the implementation details of the actual system, whether it is classification (annotation), prediction, biofeedback or entrainment.

DISCUSSION

The final aim is not only to build a conceptual model but also an interactive web repository that contains code, data, articles and best practices in an easily navigable format so a user who is interested, for example, on arousal, can easily check what signals and metrics can be used for arousal detection, as well as what kind of applications have been built on top of arousal and what kind of logic have previous been implemented for arousal adaptation,

Table 1: Five-Layer Model for Physiological Computing

Layer	Example Areas of Interest	Description
Application	Implementation of classification, prediction, biofeedback and entrainment	The layer that deals with actual implementation details
Logic	Multimodality, Context Awareness, feedback	Combining signal sources as well as the logic
Indices	Arousal, Concentration, Cognitive workload	Mapping the metrics into some contextual framework for emotion and cognition
Metrics	SCP, HRV,P300	Calculation of various metrics and features from the underlying signals.
Signals	EDA, ECG, EEG	Details pertaining to the recording of the low level physiological signals.

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Passive BCI

Session DI

Detection Of Feedback-related Mental States With Error-related Spectral Perturbation

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ABSTRACT: Human-computer interaction relies on both the human brain and the computer; hence, inferring mental state is vital for the computer to be able to take relevant actions. In this study, we look into multiple aspects of the error-related brain activity when a BCI makes a mistake.

INTRODUCTION

The use of error-related potentials (ErrP), i.e. time-domain and low-frequency brain signals mostly within 1 to 10 Hz and over midline EEG channels, has been introduced in a few recent studies to improve the performance of brain-computer interfaces [1-8]. We investigated low and high frequencies as well as spatial features of the feedback-related brain activity in a cursor-control motor imagery task. We introduced error-related spectral perturbation (ErrSP) that can go hand-in-hand with ErrPs to detect error-related mental states. This work is published in the BCI Journal titled as "Improving motor imagery BCI with user response to feedback" [9]. Here we review the performance of just the error-related brain activity components.

METHODS

Data were collected from 10 participants with a 64-channel EEG system in a motor imagery task to control a cursor moving one step/second towards a target on the monitor. Participants were instructed to perform right/left hand imagery to move the cursor to the right/left. Even though the participants were led to believe that they were in control of the cursor, the cursor movements were pre-determined and kept the same for all participants. Data were downsampled, filtered and presumed non-brain sources including eye and muscle artifacts were removed using independent component analysis (ICA). Next, data were band-pass filtered in multiple frequency bands to cover low and high theta, mu and beta bands while overlapping to compensate for individual differences. Classification was done in the 150 to 950 ms time interval after each cursor movement to determine if the user perceived a cursor movement good (towards the target) or bad (moving away from the target). Common spatial patterns (CSP) [10] were applied in each frequency band and features were extracted as the log of the power of filtered data with the top 3 CSP filters for each class. The ErrSP classifier was implemented as a linear-discriminant analysis (LDA) in each frequency band and the above chance-level LDA scores were combined with logistic regression. As for ErrP, the average of the signal in 50 ms non-overlapping windows from 150 to 950 ms on centerline channels were selected as features and an LDA classifier was trained. The number of trials in good and bad classes was balanced in all cases and results are reported on 10-fold cross-validation.

RESULTS

In Table 1, the first and second rows show the performance of ErrP and ErrSP classifiers separately. The last row shows the results of a classifier that combines the information from both ErrP and ErrSP with logistic regression. Paired t-tests reveal significant improvements of the combined classifier from the ErrP and ErrSP classifiers. Significance levels of 0.05 and 0.01 corrected for the number of comparisons, are shown with underline and bold fonts respectively.

Table 1: Classification results.

Participant	One	Two	Three	Four	Five	Six	Seven	Eight	Nine	Ten
ErrP	0.73	0.73	0.60	0.78	0.66	0.69	0.72	0.72	0.75	0.70
ErrSP	0.76	0.73	0.54	0.74	0.65	0.71	0.75	0.67	0.76	0.70
ErrP+ErrSP	**0.81**	<u>0.77</u>	0.59	0.81	**0.71**	**0.75**	**0.79**	<u>0.75</u>	**0.81**	**0.76**

DISCUSSION

We investigated new features to identify feedback-related mental states when a BCI makes a mistake. We introduced ErrSPs and showed that in the majority of participants, a combined ErrSP and ErrP classifier performs significantly better in detecting the error-related brain activity than each classifier does separately, implying the presence of somewhat independent information.

ACKNOWLEDGEMENTS: This work was supported by the NSF grants IIS 1219200, SMA 1041755, IIS 1528214 and UCSD FISP G2171.

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A COLLABORATIVE BCI TRAINED TO AID GROUP DECISIONS INA VISUAL SEARCH TASK WORKS WELL WITH SIMILAR TASKS

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ABSTRACT: This study tests the possibility of using collaborative brain-computer interfaces (cBCIs) trained with EEG data collected during a decision task to enhance group performance in similar tasks.

INTRODUCTION

Collaborative brain-computer interfaces (cBCIs) have recently been used to enhance human performance in decision making [1-3]. For instance, [2,3] estimated the confidence of each user in each decision from a combination of neural common spatial patterns (CSP) features and response times (RTs), and used this estimate to weigh individual responses and obtain superior group decisions. In this abstract, we explore the possibility of using a cBCI trained with data gathered in a decision task to estimate the decision confidence of participants doing a different visual search task.

METHODS

Ten participants took part in two visual search experiments in counterbalanced order. In Exp. 1, participants had to say if a vertical red bar was present in a display with 40 bars shown for 250 ms (Fig. 1(left)) [2], while Exp. 2 involved more realistic scenes shown for 250 ms with many penguins and observers had to say if a polar bear was present (Fig. 1(right)) [3]. Decision confidence was estimated by least angle regression (LAR) using four EEG CSPs (extracted from stimulus- and response-locked epochs lasting 1.5 s and recorded from 64 channels) and RTs. Data from Exp. 1 were used to compute the CSP matrices and to train LAR of each participant, while data from Exp. 2 were used to evaluate the performance of groups of increasing sizes formed off-line [2], and *vice versa*.

RESULTS

Fig. 1 shows the mean error rates of groups of increasing sizes making decisions using (a) the majority rule, (b) a cBCI trained and tested on data from the same experiment (using 10-fold cross-validation), and (c) a cBCI trained on data from one experiment and tested on data of the other. Results show that the latter cBCI, albeit worse than the former cBCI, is still significantly better than majority (Wilcoxon signed-rank test $p < 0.05$) for all even group sizes in Exp. 1 and all group sizes 2–8 in Exp. 2.

a)

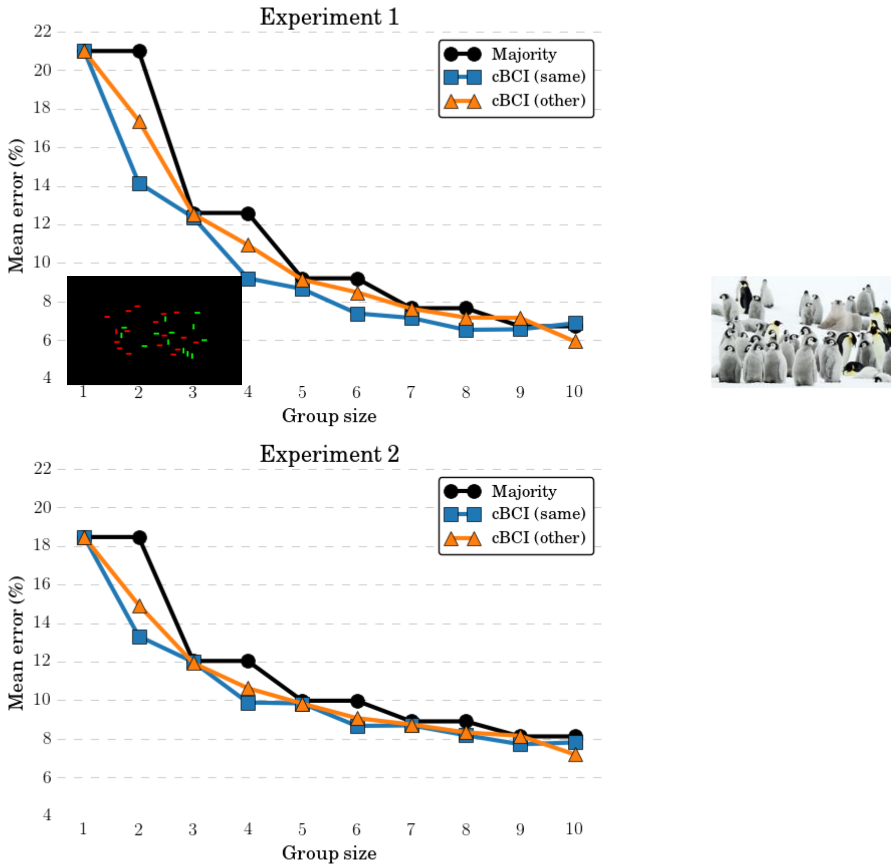

Figure 1. Percentage of erroneous decisions made by groups of increasing sizes using standard majority (black line), and the proposed cBCIs trained on data from the other (orange line) or the same (blue line, used for reference) experiment. Examples of stimuli used are also shown.

CONCLUSIONS

We showed that our cBCI improves group performance in a visual search task over majority even when trained on data gathered in a different search task. This suggests that a form of transfer learning is possible, which may, in the future, lead to marked gains in practicality (e.g., training times).

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ACKNOWLEDGMENTS

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PASSIVE BCI TOOLS FOR MENTAL STATE ESTIMATION IN AEROSPACE APPLICATIONS

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ABSTRACT: Recent progress in neurotechnology and machine learning has enabled the development of biocybernetical systems or passive brain-computer interfaces (pBCIs). There is a growing interest for implementing such pBCIs to monitor human performance under complex real life situations such as operating and teleoperating aircrafts or UAVs. This abstract presents two studies currently under way to illustrate the benefits of passive brain-computer interfaces for aerospace applications in order to move on towards more efficient and safer systems.

RESEARCH

Recent progress in neurotechnology and machine learning has enabled the development of biocybernetical systems or passive brain-computer interfaces (pBCIs). These systems derive the user's mental state from neurophysiological measurements in order to dynamically adapt human system interactions [1-2]. There is a growing interest for implementing pBCIs to monitor human performance under complex real life situations such as operating and teleoperating aircrafts or UAVs. In these particular situations, human operators' executive functioning is highly solicited when facing a highly dynamic and uncertain environment, especially under time pressure. It seems particularly relevant to try and estimate the mental state of such operators to integrate this knowledge into the whole system so as to increase both operation safety and performance as advocated in [3]. Using portable devices such as electroencephalography (EEG) or functional near-infrared spectroscopy (fNIRS) one can explore operators' mental state in ecological settings (e.g. in a motion flight simulator or real light aircrafts). For instance, two of our current projects are focused on i. the detection/classification of pilots' inability to perceive auditory alarms (inattentional deafness phenomenon) and ii. the monitoring of brain dynamics during manual vs. automated landing scenarios. A brief overview of the obtained results is given below:

i. Classification of EEG features that reflect the inattentional deafness phenomenon: The EEG data from 8 participants who performed two piloting tasks (a level flight with visibility and good weather, and a landing task with no visibility, alarms and smoke in the cockpit), along with an oddball task, were classified with success for several comparisons. Indeed, using a signal processing chain that includes a spatial filtering step targets/distractors' and detected/missed targets' event-related potentials were classified respectively with an accuracy of 82% and 70%.
ii. Characterization of mental resources engagement in manual vs. automatic flight modes: The fNIRS data from 12 participants who performed two types of landings (i.e. manual vs. automatic mode) revealed an impact of the flying mode on cerebral oxygenation. What's more, connectivity metrics enabled reaching an intra-subject classification accuracy of 80%, a significant improvement on the 60% obtained using classical oxygenation features.

This work is intended to pave the way towards more efficient and safer aerospace systems which would integrate the operator's mental state into the decisional policy of the global system.

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Physiological Computing 2

Session DII

CORTICO-CORTICAL SPECTRAL RESPONSES ELICITED BY CLOSED LOOP STIMULATION IN THE SHEEP SOMATOSENSORY CORTEX

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ABSTRACT: A chronically implanted micro-electrocorticography-based implant was used successfully to elicit spectral changes by closed-loop direct cortical stimulation in the somatosensory cortex of the sheep. Responses had distinct spatio-temporal distribution, dependent on the used stimulation frequency. These distinctive response patterns could be exploited in an effective way for future clinical and research applications.

INTRODUCTION

Interaction with the neocortex via electrical stimulation promises new therapeutic options for neuropsychiatric disorders. Thus, there is great interest to develop chronically implantable medical devices with closed-loop functionality that can be used to identify appropriate stimulation paradigms. Previous works investigated evoked responses elicited by single-pulse electrical stimulation (SPES), so called cortico-cortical evoked potentials (CCEPs, [1–3]) and their associated spectral changes [4]. Here, the goal was to evoke closed-loop stimulation-dependent spectral changes in brain activity by the delivery of stimulation bursts instead of single-pulse stimulation, via a wireless device in a chronic ovine animal model.

MATERIALS AND METHODS

One sheep was chronically implanted with a wireless micro-electrocorticography(µECoG)-based device. The electrode array (Fig.1a) was placed over the somatosensory cortex. A recording and stimulation contact pair was chosen based on CCEPs elicited by SPES and used for the closed-loop system. Continuous online analysis of cortical activity recorded at the chosen contact was performed in data chunks of 1s. Spectral power in the 60-90 Hz band not exceeding a pre-set threshold triggered either beta frequency or gamma frequency stimulation bursts in the subsequent data chunk, while only one stimulation frequency was used within one experiment. The recorded data underwent stimulation artefact removal and offline analysis. Statistics were used to detect significant spectral power changes across experiments (n=10 for each stimulation frequency).

RESULTS

SPES elicited CCEPs and analysis of the stimulation burst data revealed what we termed cortico-cortical spectral responses (CCSRs, Fig.1b), which showed distinct spatio-temporal patterns depending on analysed frequency band and stimulation frequency. Spatial extents of CCSRs for the different combinations of frequency band/stimulation frequency were, in descending order: beta/beta, beta/gamma, gamma/beta and gamma/gamma. Independent of stimulation frequency, more focalized CCSRs were observed in the higher frequency bands.

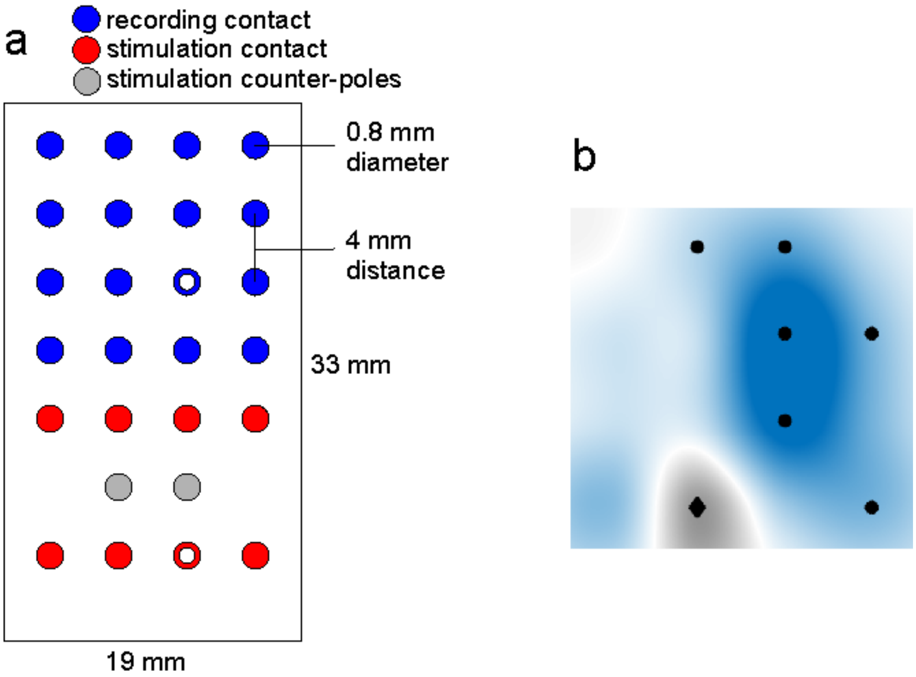

Figure 1: a) Schematic of µECoG electrode array layout. White dots within the contacts depict the recording (contact at which the data for online analysis was obtained) and stimulation contact (contact where stimulation bursts where triggered) that served as closed-loop anchor points.
b) Mapping of CCSRs. The square corresponds to the 16 recording contact shown in a). Illustrated is an example of CCSRs in the beta band elicited by stimulation with gamma frequency bursts. Blue colors: increase in spectral power following gamma burst stimulation. Grey colors: decreases. Black dots depict significant CCSRs (sign test across experiments, $p<0.05$)

DISCUSSION

This work describes the use of a wireless implant with closed-loop stimulation ability to elicit CCSRs via µECoG direct cortical stimulation. The distinct spatio-temporal distributions of CCSRs might be taken into account, depending on which spatial-temporal accuracy is desired for the application. More studies with more fine-grained increments of stimulation-frequency remain to be conducted to achieve a better understanding of closed-loop stimulation-induced response patterns.

CONCLUSION

CCSRs might provide a novel measure to unravel functional connectivity and to guide closed-loop modulation in the cortex. This approach might be helpful for the exploration of the μECoG stimulation parameter space and thus in addressing fundamental physiologic and technical questions that are crucial for the successful clinical application of closed-loop implants in assistive brain-machine interfacing, epilepsy therapies or the treatment of neuropsychiatric disorders.

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Session Name: DII-2

Room: R2
Session: Physiological Computing 2
Time slot: 14:30 – 16:00
Day: 2

CLASSIFICATION OF EMOTIONS USING CONVOLUTIONAL NEURAL NETWORKS – AN EEG STUDY

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ABSTRACT: Classification of various emotions has been very interesting in neuroscience as well as engineering aspects. However, it is not easy to resolve this multi-class classification in a quite accurate manner. Among emerging machine-learning techniques, we introduced the convolutional neural network (CNN) technique to improving the multi-class classification performance of emotions. We instructed subjects to watch emotion-evoking video clips and collected to EEG on the frontal area using BIOS-mini devices. We trained CNN and used it as a classifier of four kinds of emotions. As a preliminary result, we achieved a classification rate of 67% in this four-class emotion classification problem. With more tuning parameters, our approach may increase emotion-classifier performance.

INTRODUCTION

Understanding or detecting one's emotions is one of the key activities in social interaction [1]. Binary emotion classification based on EEG has been studied in many groups [2, 3, 5]. Multi-class classification is necessary because people felt various emotions in real situations. Due to this reasoning, we conducted EEG experiments while watching different genres of video clips and tried to classify multi-class emotional states with convolutional neural networks (CNN).

MATERIALS AND METHODS

The experiment was performed that eight people in a group watch four kinds of emotional video clips (evoking happiness, horror, sadness, and boredom); each clip's duration is 20 minutes. We collected EEG data from 10 groups (total 80) using BioBrain EEG system, which consists of eight channels with 1 kHz sampling rate. We use five EEG (AF7, FP1, FPz, FP2, and AF8), one for each EOG, EMG, and ECG channels. Every frame in a signal recorded from same video clips was labeled with same emotions. Signal was cut in every second without overlap. Then, eight bins of band powers (1-50Hz) in every frame were calculated and used as input of CNN without noisy channels. CNN consists of three 2d-convolution layers as shown in Fig. 1. We used more filters in the deeper layers. Rectified linear unit (ReLU) function was used as a kernel. Classification accuracy was calculated by averaging data from 10-fold cross validation.

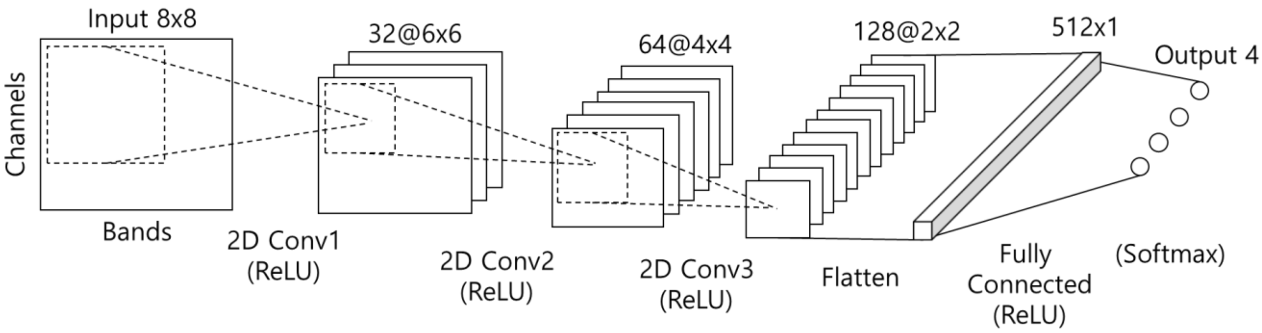

Figure 1: CNN structure proposed for 4-class emotion classifications.

RESULTS

Tab. 1 showed four-class classification results using CNN. Averaged classification accuracy was 67%. We noted that happiness and horror were relatively higher in accuracy than the others; more often boredom and sadness emotions were misclassified as horror.

Table 1: Classification rate (%)

Input \ Classified	Happiness (Comedy)	Boredom	Horror	Sadness
Happiness(Comedy)	71	6	17	5
Boredom	6	59	29	6
Horror	8	10	76	7
Sadness	7	12	20	61

DISCUSSION

In this preliminary study, the average of classification accuracy for the four genres was 67% (25% is random chance level in 4-class classification), which is insufficient result compared with another study [4]. However, our study yielded similar accuracy with fewer channels and showed the possibility of classifying the emotional status using the neural network technique. With more tuning parameters of the neural network and considering better features, our approach may be promising.

CONCLUSION

In our preliminary study, we achieved that 67% of averaged classification accuracy for four kinds of emotional states using CNN with EEG data.

ACKNOWLEGEMENT

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CLASSIFICATION OF CORTICAL RESPONSES TO VISUAL TARGETS DURING A PHYSICAL-COGNITIVE INTERACTION TASK

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ABSTRACT: To build robust neurophysiological monitoring systems and brain computer interfaces (BCIs) it is critical to understand how neural responses change under realistic task demands and how signal quality is affected by real-world artefacts. We applied machine learning techniques to EEG data collected while subjects walked on a treadmill for an hour carrying 40% of their body weight while performing a visual oddball task. Previous work has shown differences in cognitive neural activity associated with variations in physical demands at the electrode level [1] and using cortical source localization techniques [2]. Here our goal is to determine if machine learning can classify single-trial neural responses. This work is an important step towards fielding brain-computer interface (BCI) technologies in real world environments.

INTRODUCTION

In recent years, machine learning techniques have been successfully applied to electroencephalography (EEG) data to classify neural responses associated with visual target detection [e.g., 3,4]. Although significant progress has been made to improve these algorithms for use on noisy data by enhancing the signal-to-noise ratio with novel transforms [5] and accounting for temporal variability through sliding windows [6], the application of these algorithms to data obtained during more complex, military-relevant scenarios remains unclear.

MATERALS AND METHODS

Subjects (n=18) performed a two-stimulus visual oddball task under walking and seated conditions. Subjects performed both conditions while wearing an unloaded rucksack, then again while wearing a rucksack loaded with 40% body weight. While walking with the loaded rucksack for an hour, subjects identified oddball images using a button-press. We used hierarchical discriminant component analysis (HDCA) [7], common spatial patterns (CSP) [8], and xDAWN [9] to classify the neural response to each image as either a response to an oddball or standard image. We performed 5-fold cross validation within each condition. Using balanced accuracy, we compared the performance of each BCI classification method across conditions to determine if walking, load, time-on-task, or any interaction of these conditions had an effect on classification accuracy.

RESULTS

We found that classifier accuracy was lower for walking data than for seated data for all classification methods ($p<0.01$). Classification accuracy when using loaded data was lower than when using unloaded data for HDCA and xDAWN ($p<0.01$), but not CSP. Within the interaction of loading and walking, we found that for all classification methods, the loaded walking condition had lower classification accuracy than the unloaded walking condition ($p<0.01$), but there was no significant difference in performance between loaded and unloaded seated conditions (Figure 1).

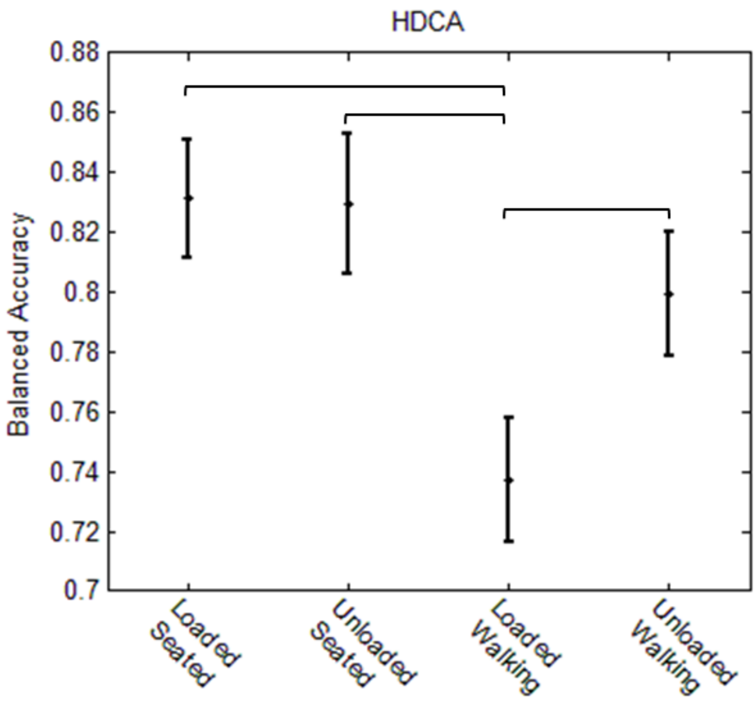

Figure 1: Group mean balanced accuracy values for HDCA with standard error bars. Brackets indicate significant differences ($p<0.01$). Other classification methods (CSP and xDAWN) showed a similar trend in performance.

DISCUSSION AND CONCLUSION

We were able to show that single-trial detection of the P300 response is feasible for data collected while the subject performs a realistic, demanding physical task. The diminished performance in walking relative to seated conditions may be due in part to the observed decreased amplitude of the P300 response. In addition to this, the increased severity in motion artefact in the loaded and unloaded walking conditions may also lead to a decrease in classification accuracy due to a reduced ability to resolve the neural response in the presence of noise. In order to create fieldable BCI systems, overcoming signal changes due to increased noise and changing neural responses is necessary. Ongoing work will investigate the extent to which each of these factors affects BCI accuracy and methods to overcome these factors.

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Neuroadaptive Technology: Methods

Session EI

Session Name: EI-1

Room: R1
Session: Neuroadaptive Technology: Methods
Time slot: 10:30 – 12:00
Day: 3

INVESTIGATING RESPONSES TO LETTER PRESENTATIONS IN A SEGMENT SPELLER

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ABSTRACT: The importance of spatial independence in Brain-Computer Interface (BCI) spellers is significantly underestimated. To this end, we have designed a spatially independent speller using subsets of letters as stimuli, allowing us to cue multiple letters in parallel with the use of common segments, without requiring constant foveation [1]. A final letter cue to confirm the selection could yield a significant increase in information transfer rate (ITR); we investigate if responses to whole letters are affected by being interspersed with segments.

INTRODUCTION

An underestimated cost associated with the diverse family of grid spellers is the matter of spatial independence [2]. Individuals suffering from neurodegenerative illnesses like ALS have reduced capacity to direct overt attention, and many BCIs are dependent on eye gaze [3]. Our system uses letter segments to cue letters in parallel, iteratively identifying the desired letter [1]. We have recently experimented with using presentation of whole letters as additional probes.

MATERIAL AND METHODS

For our stimuli, we projected the 26 letters of the English alphabet onto an altered version of the ‘scoreboard’ font (Fig. 1). To investigate the context-specificity of letter responses, we investigated the responses of five subjects to a) solo-letter blocks, b) solo-segment blocks and c) mixed-letter (both) blocks. For letter-blocks, nontargets were drawn uniformly from the other 25 letters with a randomly selected probability of 50% or 80%. For mixed-letter blocks, each given stimulation in mixed-blocks had a 20% (S1) or 30% chance of being a whole letter, of which 50% were the target, and the rest were a random letter. All blocks consist of 45 stimulations, with a duration of 380ms, and an inter-stimulus interval of 150ms, following the assignment of a target letter. I, V, Y and X were disallowed as targets. Pseudo-online training implemented LDA on [target] and [nontarget] letter class means, specified using 5, 100ms windows ranging from 300ms to 800ms.

	***S**Train_**S**Test*	***M**Train_**M**Test*	***A**Train_**A**Test*	***S**train_**M**Test*	***M**Train_**S**Test*
S1	28.84%	35.71%	27.90%	**31.75%**	42.32%
S2	45.43%	34.43%	37.05%	40.13%	**34.94%**
S3	18.71%	24.78%	19.53%	26.56%	30.65%
S4	21.90%	18.71%	20.68%	35.20%	36.98%
S5	24.35%	26.86%	28.00%	40.86%	38.21%
AVG	27.85%	28.09%	26.63%	34.90%	36.62%

*Table 1: Misclassification rates, per subject, for pseudo-online train/test set divisions. (**S**) Solo: independent letter blocks. (**M**) Mix: blocks with letters and segments as stimuli. (**A**) All: All stimulations included. Classes were balanced via random removal of trials from larger class. 10-fold cross-validation was used when training and test sets matched.*

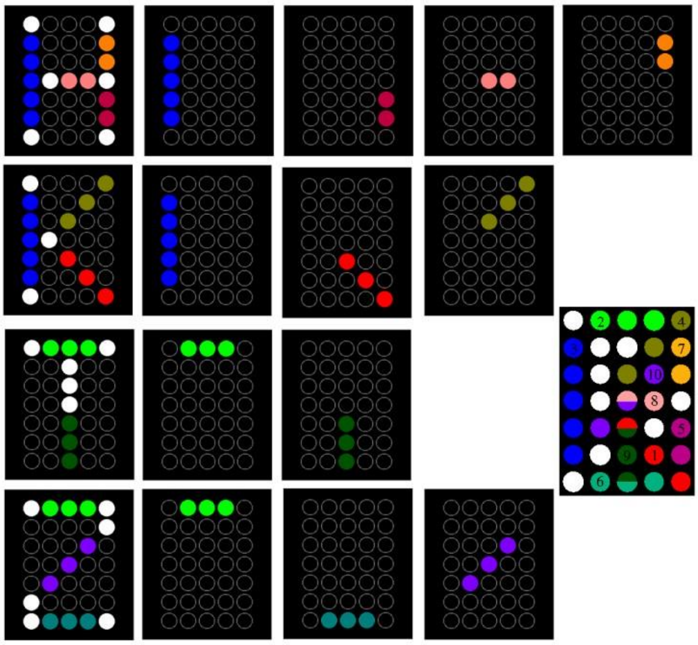

Figure 1: Sample letters, along with all 10 segments (2 repeats) present in the segment library. Additionally, a grid showing the overlap of the respective segments, and their numbers.

RESULTS

Subject 1 shows improved performance on mixed-letter presentations versus solo-letter presentations. Conversely, S2 shows a slight decrease in misclassification percentage when the classifier is trained on mixed-letter data and tested on solo-letter data. These two subjects exhibit the worst performance. All other subjects pay a considerable cost when trying to train and test across block-conditions.

DISCUSSION

Pseudo-online classification of the collected data suggests that it would be advisable to train letter- specific classifiers using interleaved segment/letter blocks with letter frequencies similar to online.

ACKNOWLEDGEMENTS

This study would not have been possible without the support of our funding agencies. This work was supported by the NSF grants SMA 1041775 and IIS 1528214.

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Session Name: EI-2

Room: R1
Session: Neuroadaptive Technology: Methods
Time slot: 10:30 – 12:00
Day: 3

USING BCIS FOR BENCHMARKING ADAPTIVE AND LOW-RESOLUTION DAQ EEG APPROACHES

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ABSTRACT: Traditionally neuroscience has focused on improving our understanding of the functional underpinnings of neural activity, leading scientists to seek ideal data resolution because the outcomes and future direction of their work is often uncertain. However, in the pursuit of moving into real-world, non-ideal scnarios where power and space are limited, we must develop ways to pragmatically evaluate the efficacy of our data acquisition (DAQ) methods and understand the functional minimum performance for the target application. Here we espouse the notion of using BCI classification accuracy as a metric for DAQ performance evaluation, and demostrate by applying it to a novel self-adapting system designed for performance at ultra-low power.

INTRODUCTION

In recent years, the cost and fidelity of EEG has improved dramatically **[1]** while becoming more fieldable **[2]**. A continual problem is power, limiting long-term monitoring to about a half day, especially in high-density systems, creating a challenge for daily monitoring **[3], [4]**. This is due in large part to the inherently low SNR which requires high-fidelity ADC components. While some lower-power, and subsequently lower-fidelity approaches have been proposed **[5], [6]**, an ongoing challenge is in how to quantify the usefulness of these approaches and validate DAQ performance. In this work, we propose use of an online adaptive analog front-end to minimize power consumption and demonstrate its efficacy using a battery of BCI paradigms, using classification accuracy as a figure of merit.

MATERALS AND METHODS

Sample system: An adaptive analog front-end is proposed wherein data from a low bit-depth ADC is evaluated on a sample-by-sample basis by an onboard high-efficiency DSP. The DSP then manipulates a voltage offset controller (VOC) and variable gain controller (VGA) to adjust the offset and gain of analog signals coming into the ADC. This reduces the dynamic range of the signal arriving at the ADC, which reduces the bit-depth requirement of the ADC while maintaining signal resolution.

RESULTS

Pre-recorded raw, unreferenced data, acquired using a 24-bit high-fi commercial system from multiple BCI paradigms were fed through a realistic simulation of the above system, yielding re-digitized data with varied degrees of fidelity loss, depending on DAQ factors such as ADC bit depth, VOC resolution and update rate. Data from each paradigm and DAQ factor were then classified using conventional approaches (e.g. HDCA, [7] and compared against a randomized baseline to ascertain performance. Results to date (based on RSVP) for this system suggest that accuracy is not statistically impacted until ADC resolution drops below 24µV, and that VOC rate had a relatively small impact. Ongoing work focuses on performance using other paradigms, such as SSVEP and motor movement tasks.

CONCLUSIONS

Quantifying the performance of novel EEG DAQ approaches is difficult, particularly due to the lack of a ground-truth for baseline comparison. We propose that use of application-specific metrics, such as classification performance, can serve as one surrogate approach. In the case of low-power DAQ design, we have demonstrated that acceptable performance can be achieved even with low-fidelity components and resulting data suggests that BCI implementations may not require high-resolution data as is often preferred.

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INTELLIGENT THRESHOLD SELECTION FOR BIOCYBERNETIC LOOP IN AN ADAPTIVE VIDEO GAME CONTEXT

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ABSTRACT: A common challenge with the development of adaptive systems is the choosing and optimizing of the thresholds in the values of the neurophysiological signal at which the system triggers an adaptation. This paper presents a new approach for continuous calibration through dynamic threshold selection. Participants' game experience is compared between a no adaptation control condition, a condition with an EEG cognitive load adaptive system and a condition with the EEG with a dynamic thresholding system. The thresholding is adjusted with a second neurophysiological signal, emotional valence.

INTRODUCTION

Biocybernetic adaptive systems or passive brain-computer interfaces (BCI) are closed loop systems that can respond to the user's neurophysiological state to modify the system's parameters to reach a user's desirable state. While multiple research groups have been building functional biocybernetic adaptive systems[1–5], many technical challenges remain to be addressed [6–8]. One such challenge is the choice of the thresholds that the system uses to decide when to trigger an adaptation. Previous works have used validation studies to define a given population's optimal threshold [2]. Developers who desire a more precise adaptation will often use personalization tasks to individually tailor thresholds just before the use of the system [9]. Both these approaches require time and resources. To overcome these challenges, we look to hybrid BCIs (hBCI) which combine two neurophysiological signals and triangulate them to improve system accuracy [10]. We also look to other BCI models that employ continuous calibration [11, 12]. In this paper, we propose a new approach for dynamic threshold selection that calibrates the system based on a secondary neurophysiological signal.

MATERALS AND METHODS

The biocybernetic loop adapts to one physiologically inferred metric, in this case, cognitive load, using electroencephalography (EEG), while the thresholds are continuously adjusted using a reinforcement learning model [13] based on a second metric, in this case, emotional valence, inferred using facial expression analysis (FaceReader, Noldus, Wageningen, Netherlands). The experimental design is based upon Ewing et al. [2]. Each participant plays 10 minutes of Tetris under three experimental conditions, a no adaptation control condition, a cognitive load only condition and our proposed biocybernetic loop using dynamic threshold selection condition. Player experience is measured with the Game Experience Questionnaire (GEQ) [14], the score at the end of the game and the number of times the player lost (ie the screen filled with pieces and the game started over).

In this first use case, the auto adaptive system manages the game difficulty as in the Dynamic Difficulty Adjustment framework [15]. More precisely, the actions that the reinforcement learning model chooses are the system's adaptations (speed +1, speed -1, and speed + 0). The problem space in which the model evolves and tries to find an optimal path is composed of the two dimensions of cognitive load and current speed of the game. Each action undertaken by the model is rewarded by the local changes in the subject's valence following the adaptation. Doing so, the system should converge towards an optimal state of difficulty vs cognitive load that is specific to each subject and that may change over time. In this approach, the adaption thresholds are replaced by the transitioning policy optimised over time that the system uses to decide which action to take.

DISCUSSION AND CONCLUSION

Experimental testing is currently underway to validate the improvements provided by this system to the current model of biocybernetic adaptation. It was built with the intention that it should be generic and easily reusable and signals with other variables such as arousal measured from electrodermal activity and any other frequency band from EEG data. As it is, it will be tested next with a serious game to measure its effect on learning outcomes.

This hBCI introduces a new way to combine multiple neurophysiological signals. Until now, most hBCI combined neurophysiological signals by using both streams as conditions to be met to trigger an adaptation. This system however, uses the second signal to modify the parameters of the system that uses the first signal. We hope this will inspire others to triangulate multiple neurophysiological signals in this manner to continuously calibrate their BCI.

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MoBI

Session EII

MOBILE BRAIN / BODY IMAGING (MoBI) OF PHYSICAL INTERACTION WITH DYNAMICALLY MOVING OBJECTS

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ABSTRACT: The non-invasive recording and analysis of human brain activity during active movements in natural working conditions is a central challenge in Neuroergonomics research and a step towards applying neuroadaptive technology in the context of human-environment interaction.
To investigate the brain dynamics accompanying rapid volatile movements we used a visual oddball paradigm requiring variably interactive responses due to a color change of an object moving on a projection screen. Using a mobile brain/body imaging (MoBI) approach including independent component analysis (ICA) with subsequent backprojection of cluster activity allowed for systematically describing and quantifying the contribution of brain processes and non-brain sources as muscle activity and eye movements to the sensor signal. Using this approach allowed to analyze visual event-related potentials even for rapid volatile arm movements.

INTRODUCTION

The embodied cognition paradigm claims that the body's interactions with the world are an essential root of cognitive processes [1]. Thus we should use naturalistic conditions to study human brain dynamics accompanying natural cognition [2]. Here we investigated the feasibility of MoBI [3] and ICA during physical interaction with a dynamic system. It was examined whether it is possible to record and analyze an event-related P3 component during rapid pointing movements that include strong eye movement and neck muscle activities.

MATERALS AND METHODS

We recorded high density EEG synchronized with motion tracking of participants physically interacting with a dynamically changing system. Changes in the system were simulated using a three- stimulus visual oddball paradigm [4] with participants reacting either by simple button presses, by pointing to a fixed location or by pointing at the moving stimulus. ICA guided separation of brain processes from activity generated by muscles and eye movement allowed for a quantification of how much specific ICs contributed to the event-related surface signal depending on the response type.

RESULTS

MoBI proved feasible for analyzing event-related EEG dynamics of participants performing rapid pointing movements in a realistic 3-D environment. Parietal clusters and brain processes located in or near the ACC contributed the most to the P3 in line with previous findings [5,6,7].

DISCUSSION

An increase of artifact contaminated trials and channels as well as higher residual variances compared to EEG studies with stationary participants indicate potential constraints of the MoBI approach for investigating natural movements. Moreover brain processes repeatedly correlated with non-brain related activity might not always be successfully separated with ICA.

CONCLUSION

When studying natural cognition, analyzing ICs contributing to the surface signal should be preferred over standard sensor based analyses approaches. For highly artefact afflicted data other source separation algorithms than ICA which consider time and location information should be examined.

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Session Name: EII-2

Room: R2
Session: MoBI
Time slot: 10:30 – 12:00
Dav: 3

EEG AND EMG SYNCHRONIZATION AND JITTER ESTIMATION FOR MOBI EXPERIMENTS

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ABSTRACT: Electroencephalography (EEG) and Electromyography (EMG) synchronization are of paramount importance in Mobile Brain Imaging (Mobi) experiments. Here we tested a method to estimate the synchronization jitter when online data streams are not available, e.g. in most clinical environments. We demonstrated that it is possible to obtain satisfactory synchronization results (Jitter<5ms) even without the availability of a TTL trigger port.

INTRODUCTION

EEG and EMG are the techniques of choice in the rapidly emerging Mobi research field, especially in walking-related tasks, mainly due to their high time resolution, noninvasiveness, portability and overall ease of use [1, 2]. Other techniques such as NIRS or fMRI do not have the necessary high time resolution and portability required to detect intra-stride changes in brain activity during ambulation [3, 4]. However there are challenges posed by the presence of artifacts (e.g, movement artifacts, cable movements, non-stationary line noise, etc.) and the difficulty of synchronization of different data streams. Here we tested a method to synchronize EEG and EMG and to estimate the jitter in light of a Mobi experiment reproducing the constraints usually imposed by the clinical environment (e.g. unavailability of data streams or Application Programming Interfaces - APIs).

MATERALS AND METHODS

The experiment was carried out at the Villa Beretta - Ospedale Valduce, LC, Italy with a EEG Neuroscan SynAmps2 and the BTS Free EMG 1000. Neither APIs nor TTL input synchronization port were available for the EMG. We used an ARDUINO, connected via a serial port to a PC to deliver a 0.5Hz spike train (10 minutes) simultaneously to both platforms, respectively via a TTL port (EEG) or directly to the electrodes (EMG) as shown in Fig. 1. Data were cut, shifted and linearly interpolated so that the first and last spike coincided. The Jitter was estimated as the 95th percentile of the distribution of the displacements between middle spikes (Fig. 2).

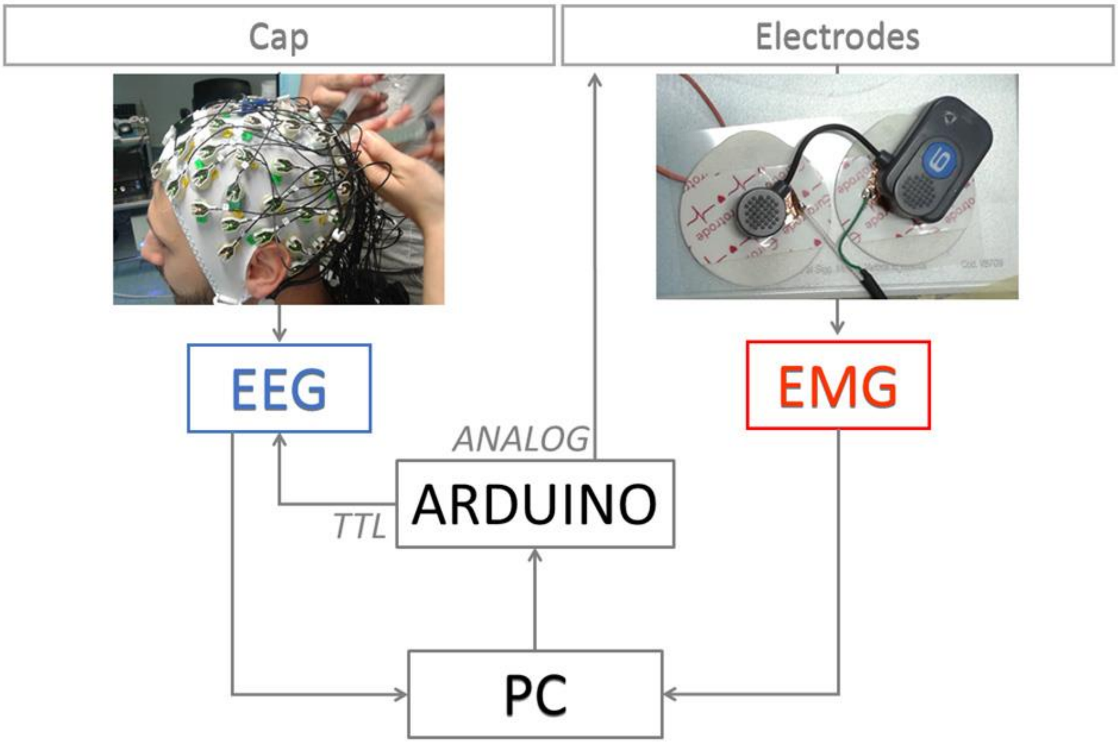

Figure 1: EEG EMG synchronization set-up

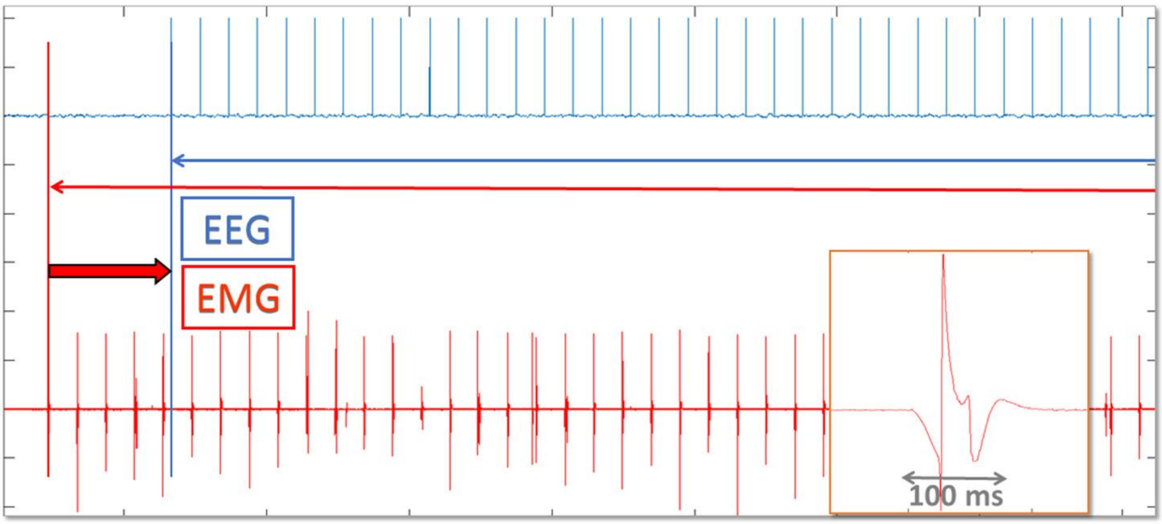

Figure 2: EEG (top) and EMG (bottom) synchronization spikes. EMG data are translated and interpolated so that the first and last spike coincide. On the lower right a one analog EMG spike is magnified.

RESULTS

Results demonstrated a 5ms Jitter within a 10 minute-recording. Spike displacement was distributed in a Gaussian fashion. Particular care however had to be taken in determining the actual timing of the analog spike, as hardware filters may delay or spread the peak up to 100ms (Fig. 2).

DISCUSSION

Artifacts and synchronization issues restrict acess to the Mobi framework to laboratories with state of- the art equipment and high level of data analysis expertise. Consequently its usability e.g. in clinical settings is reduced [5]. The Lab Streaming Layer platform [6] enables state of the art on-the fly multiple streams synchronization. Often however this is not an option due to unavailability of APIs, reliable networks or technical expertise. This is often the case with hospitals due to device certification requirements. Spike delivery to electrodes should be considered as a fallback solution when a TTL synchronization port is not available. In fact hardware filters might interfere with spike recording (See Fig.2, lower right). Jitter was the result of hardware filters, threshold selection, sampling rate variability etc. In conclusion we showed here that it is possible to perform offline EEG and EMG synchronization even without the availability of API, data streams and a TTL port. The 5ms Jitter demonstrates the Mobi framework can be safely exported to clinical settings.

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NEURAL CORRELATES OF HUMAN SINGLE- AND DUAL-TASK NATURAL WALKING IN THE URBAN ENVIRONMENT

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ABSTRACT: Nowadays mobile technologies can translate research methodologies to daily-life activities away from the lab environment. We created a fully-mobile setup for multi-level analyses of walking in the real world and observed behavioural and neurophysiological aspects of single- and dual-task locomotion in healthy adults (N=14). Gait kinematics were recorded simultaneously along with 64 channel-EEG whilst walking 200m around campus and sensor-level spectral activity confirmed previous findings using lab-based treadmills and circumscribed indoor pathways. In both single- and dual-task conditions, gait variability (measured via vertical acceleration intensity) positively correlated with gait speed and spectral activity of the left posterior parietal cortex. Results validate the reliability of our setup for real-world applications and prepare the ground for future investigations of modelling interactions of brain activity and cognitive-motor behaviours in health and neurological conditions in hitherto untested environments.

INTRODUCTION

Several studies have focused on both healthy and impaired features of gait, such as acceleration profiles [9] but, due to hardware limitations, very little work has been done on the underpinning neural control of gait [8] [11] [12] [15] [16]. Employing recent developments in mobile technologies, studies have demonstrated that (Pre)Frontal Cortex (PFC) and bilateral Posterior Parietal Cortex (PPC) are actively involved in monitoring of gait and of dual-task performance in the lab [1] [6] [14]. In the present study, we combined mobile neuroimaging and gait monitoring during “real-life” experimental-conditions outside the lab with the aim to assess mobile EEG reliability and investigate preliminary relationships between activity in specific brain regions and ambulatory behaviour.

MATERALS AND METHODS

Healthy subjects (N=14; 26 (± 3) years old; 5 male/ 9 female) walked at their preferred, natural speed along a predefined path (200 m in the University of East London garden) naturally (ST) or while simultaneously conversing (DT) continuously without external cues. Contact switches detected times of heel strikes, while 64 channel EEG was recorded by an EEGoPro amplifier (ANT Neuro, Enschede, NL) carried in a backpack by the subject. A Samsung Galaxy S4 mini smartphone was fixed on the subject's lower back and recorded linear accelerometer data from which gait measures, such as velocity (m/s) and acceleration Root Mean Square Ratio (RMSR) [13] were extracted (iGAIT [17]). EEG data were synchronized to heel strikes, pre-processed, segmented into epochs (capturing a full stride) and analysed at sensor-level in the time-frequency domain (EEGLab [7]). Single-epoch spectrogram changes with respect to the baseline (i.e. standing still eyes-open resting state prior to walking) were computed via Morlet wavelet decomposition and time warped to the heel strikes median (across subjects) using linear interpolation. Secondly, the mean Power Spectral Density (PSD) in the Frequency bands of Interest (FOI), θ (4-7 Hz), α (8-12 Hz) and β (15-30 Hz) was calculated for each epoch (i.e. only frequency domain) and then averaged across epochs (ST = 179 (± 28) epochs, DT = 148 (± 20) epochs). PSD in three Regions of Interest (ROI) (PFC, right/left PPC) was calculated in each FOI and in each condition for each subject. Three multiple linear regression models were stepwise fitted for each condition with acceleration RMSR in each direction (x3; vertical, antero-posterior, medio-lateral) as Dependent Variables (x3; DVs), and velocity and PSD in each FOI (x3) and ROI (x3) as Independent Variables (IVs) for each model.

RESULTS

Table 1 reports group average PSD in each ROI and in each FOI for ST and DT conditions: paired-samples t-Tests showed significant increase of activity in DT in comparison to ST in θ in PFC and right PPC, as well as in α and β in right PPC only. Figure 1A shows an example of single subject time-frequency spectral decomposition from the P3 electrode (as a comparison with previous findings [12]). Sustained α and β desynchronization (ERD) through the whole stride duration and modulated γ oscillations are visible at specific points in the stride. Figure 1B shows the outputs of two regression models successfully fitted (from a total of 6 possible models). For the single-task condition, a model was generated (R^2 = 0.725, p = 0.001) with vertical-RMSR as DV and velocity (B = 0.355, p = 0.001) and left-parietal θ PSD (B = 0.009, p = 0.026) as IVs. For the dual-task condition, a model was generated (R^2 = 0.727, p = 0.001) with vertical-RMSR as DV and velocity (B = 0.029, p = 0.003) and left-parietal α PSD (B = 0.021, p = 0.020) as IVs.

Table 1 – Power Spectral Density (PSD). Average PSD (mean (±std)) across subjects (N = 14) is here reported for each region of interest (PFC = (Pre-) Frontal Cortex, PPC = Posterior Parietal Cortex), for each frequency band of interest (θ (4-7 Hz), α (8-12 Hz) and β (15-30 Hz)) in each experimental condition (St = Single-Task walking; DT = Dual-Task walking). Reported values are in dB. Paired-samples t-Test (St vs. DT) statistical values and significance p-values are reported in the last two columns.

ROIs	FOIs	ST	DT	t-value	p-value
PFC	θ	-3.0 (± 2.4)	-2.6 (±2.2)	-3.314	**0.006**
	α	-5.3 (± 3.1)	-5.0 (±2.9)	-0.795	0.441, N.S.
	β	-11.1 (± 3.1)	-10.6 (±2.8)	-2.090	0.057, N.S.
right PPC	θ	-1.2 (± 2.1)	-0.7 (±2.0)	-5.120	**0.001**
	α	-2.9 (± 2.5)	-2.2 (±2.7)	-2.795	**0.015**
	β	-9.0 (± 3.2)	-8.3 (±2.9)	-3.577	**0.003**
left PPC	θ	-1.9 (± 2.4)	-1.6 (±2.3)	-1.902	0.080, N.S.
	α	-3.4 (± 3.0)	-3.4 (±2.8)	0.066	0.948, N.S.
	β	-9.1 (± 3.7)	-8.7 (±3.4)	-1.346	0.2014, N.S.

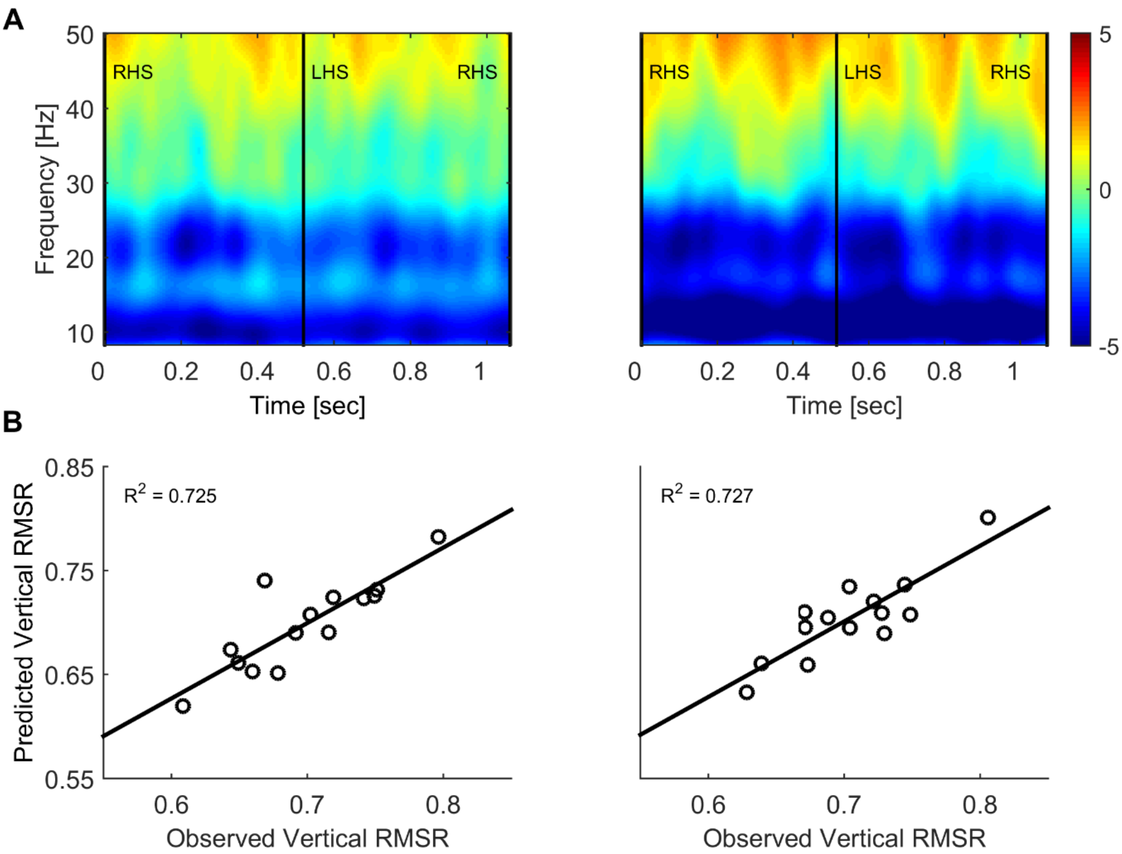

Figure 1 – Time-frequency spectral power (A) and Multiple Regression models output (B) for each condition (ST = single-task, DT = dual-task). (A) Single-subject time-frequency spectral decomposition averaged across epochs in P3 electrode. Colorbar (dB) represent increase (red) and decrease (blue) of power with respect to the baseline (resting state prior to walking). Vertical black lines represent heel strikes (right and left) median across subjects (N = 14). **(B)** Group-level (N = 14) multiple linear regression models output (Observed vs. Predicted values). Condition-specific measures of Goodness-of-Fit of the models (R^2) are reported in the graphs.

DISCUSSION

Neural correlates of walking during daily-life situations in the real-world are presented [10]: first, typical sustained α and β ERD and phasically modulated γ oscillations through all the stride duration are recorded over the left parietal area in line with previous literature [12]; second, a positive relationship exists between vertical RMSR, velocity and left PPC PSD in θ (single-task) and α (dual-task) frequency bands. PPC is thought to act as a sensorimotor integrator and online updater of movement planning [2] [3]. We confirm the relationship between vertical RMSR and velocity [13], and show that a neural correlate exists. We suggest that, the higher the left PPC activity, the stronger is the sensorimotor integration [4] [5] regardless of any secondary task undertaken and thus the more stable is gait behavior.

CONCLUSION

Our study reliably and successfully investigated human walking while giving the participant freedom of movement as in real daily-life. Vertical RMSR is here proposed as a marker of the quality of walking as it correlates with other biomechanical features (i.e. velocity) and neural activations (i.e. left PPC sensor-level PSD). Our motivation is to design a fully-mobile setup transferable to different applications, for example monitoring of stroke patients in their local environment during recovery time. Our findings pave the path for more complex experimental design and analyses of the relationship between brain and behaviour in the real-world.

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Neuroethics

Session FI

Room: R1
Session: Neuroethics
Time slot: 14:30 – 16:00
Dav: 3

NEUROETHICS FOR NEUROADAPTIVE TECHNOLOGY: THE CASE OF PASSIVE BRAIN-COMPUTER INTERFACES

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ABSTRACT: In neuroscientific research and development, brain signals are increasingly utilized to analyse unconscious processes and translate them into real-world actions. In particular, passive brain- computer interfaces rely on covert brain signals without the subject's conscious effort. Neuroethical issues concern the areas of privacy, informed consent, personal identity, accountability, data protection, and the potential for misuse because of possible threats to the principles of respect for autonomy and non-maleficience in biomedical ethics. Consequently, neuroethical considerations should continuously be integrated into neuroscience research.

INTRODUCTION

Neuroscience has resulted in advanced methods to assess human brain functions. For example, passive brain-computer interfaces (pBCIs) react to covert and unconscious signals from users [1]. This situation evokes questions regarding the responsible conduct of research and innovation in the discipline of neuroethics.

MATERIALS AND METHODS

Materials included publications from the areas of ethics, applied biomedical ethics, and neuroscience, and methods included search for publications in databases with appropriate keywords.

RESULTS

Neuroethical concerns are related to privacy, informed consent, personal identity, accountability, data protection, and the potential for misuse. Thereby, novel neuroscientific methods like pBCIs may infringe ethical principles like the respect for autonomy and non-maleficience in biomedical ethics [2].

DISCUSSION

Given the research and development features of neuroadaptive technology, both the experimental subject and the neuroscientist may be partially ignorant concerning the nature of the data that emerges out of the experiments. For the subject, the decision to participate is influenced by insecurities and the need to overcome scepticism about the measurement of unconscious, but meaningful brain signals. The research subject is confronted with a divergence between the usual active and the uncommon passive effects on situations because the pBCI mediates passive reactions in real settings. An informed consent [3] regarding data collection of automatic responses needs to be held to high standards because the data could allow unexpected and unwelcome insights that limit everyday privacy. For the neuroscientist, the questions ensue how to present which information to the participant and to which extent to train her to operate the device [4]. The subject, as a layperson, cannot comprehend all technical details; yet, she needs to understand the basic mechanisms and potential pitfalls. The accountability for actions, which are mediated by a computer, remains unclear because the subject's brain signals are unconscious and the computer acts according to preset decision rules. This may unsettle her feeling of identity [5]. The neuroscientist has to comply with policies for data protection regarding delicate data.

CONCLUSION

Neuroscientific research endeavors, particularly in highly innovative and uncompleted areas, would benefit from continuous attention to and consideration of social, legal, and ethical aspects.

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Room: R1
Session: Neuroethics
Time slot: 14:30 – 16:00
Day: 3

HACKING MINDS, HACKING BRAINS, HACKING AUGMENTED BODIES: ETHICAL ASPECTS OF NEUROHACKING

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ABSTRACT: Emerging trends in pervasive neurotechnology and robotics are rapidly enabling novel opportunities for human-machine interaction and reshaping the human cognitive ecosystem. Clinical applications of neurotechnology such as brain-computer interfaces (BCIs), neuroprosthetics and wearable robotics enable to restore cognitive or motor function in patients with neurological disorders as well as to enhance their interaction with the world. While these trends can provide immense benefit for neurology and neurorehabilitation, they also open breaches for privacy and security of neural information [1-3]. The more the human body becomes intertwined with digital technology, the more it becomes vulnerable to cyber-risk.
This emerging domain of brain-machine interaction can be labeled *neurohacking* since it encompasses hacking activities which (either directly or indirectly) target neural information [4].

MATERALS AND METHODS

Literature review of experimental and real-world case studies in relation to neurohacking.

RESULTS

Review results show that assistive neurodevices can be potentially co-opted for malicious activities such as extracting concealed private information from users without their consent [5-7], cracking encrypted repositories of neural recordings [8] or even interfering with the device's functionality [9]. These findings open the prospects of extending the range of computer-hacking to neural computation. In parallel, ethical neurohacking strategies could enhance security and open development in neurotechnology.

DISCUSSION

In light of these results we identify three different types of neurohacking based on their level of penetration into neural computation. In addition, we distinguish malicious forms of neurohacking
–characterized by the unauthorized misuse of neurodevices by malevolent actors- from what we call *ethical neurohacking* –characterized by the open and collaborative development of new neurotechnologies for the benefit of users.
Finally, we delineate the normative and conceptual implications of neurohacking. At the normative ethical level, we address the issues of neuroprivacy, neurosecurity, self-monitoring and de-anonymization raised by emerging trends in neurohacking.

CONCLUSION

Neuohacking poses novel ethical and regulatory issues at the interface between neurodaptive technology and society which require proactive assessment.

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Session Name: FI-3

Room: R1
Session: Neuroethics
Time slot: 14:30 – 16:00
Day: 3

EVALUATING BRAIN READING'S PRACTICAL APPLICABILITY

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ABSTRACT: brain reading technology is becoming increasingly able to read mental states in human subjects. We propose some criteria to evaluate the extent to which this capacity could be utilized, currently or in the near future, for practical, societally impacting applications.

INTRODUCTION

Contemporary brain reading methods and technology promise to provide significant insights on human mental states and processes. Together with important scientific advances, such technology could bring up numerous societally relevant implications. In particular, the private character of mind might be affected to a certain extent, generating ethical and legal concerns [1], [2]. Orwellian scenarios, where brain reading technology could be misused by ill-intentioned agents to invade our privacy against our will, have been in numerous occasion devised by mass media and popular press [3]. This possibility, however, depends in large part on the extent to which brain reading technology can be translated from (neuro)scientific research into practical application. A clear and widely usable conceptual framework to estimate the actual current and near future applicability of brain reading methods to different scenarios is currently missing. We propose an evaluative framework that is based on three criteria: performance, concealability and enforceability of a technology.

MATERIALS AND METHODS

Our work, in the fields of neuroethics, takes advantage of scientific literature and popular media to create an informed and reciprocally constructive dialogue between science and society. We use the method of philosophical inquiry, aiming at clarifying concepts and facilitating practical ethical discussion.

RESULTS

The three factors we outline -performance, concealability and enforceability-, though not necessarily the only ones, constitute useful criteria through which to produce an estimate of whether, when and in what practical scenarios a certain brain reading method could be adopted and utilized.

DISCUSSION

In order to be considered for adoption in most, if not in all, practical applications, brain reading methods must achieve certain *performance* standards. This is not only in terms of outcomes' accuracy and reliability, but also in terms of the relevance the obtainable data has for the question that is investigated. Many potential, potentially concerning scenarios, in particular those where mental privacy and civil rights are at stake, will also need the brain reading process to be *concealable* from a subject's awareness. Furthermore, the most concerning ones among those scenarios involve the possibility to *enforce* the technology, and reliably read somebody's brain against his or her will.

CONCLUSION

The three criteria we outlined facilitate a realistic understanding of the potential brain reading applications, allowing for a preliminary evaluation of the eventual implications. In turn, this might result in better general awareness and more timely reaction to potential ensuing ethical, legal and societal issues.

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Wearable Sensors

Session FII

Room: R2
Session: Wearable Sensors
Time slot: 14:30 – 16:00
Day: 3

INTERACTING WITH WEARABLE COMPUTERS BY MEANS OF FUNCTIONAL ELECTRICAL MUSCLE STIMULATION

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ABSTRACT: We present and discuss recent advances in the field of Human-Computer Interaction that utilize Functional Electrical Stimulation (FES/EMS) to enable users to interact with computers via their muscles. We analyse these interactive systems by: (1) discussing the novel opportunities and application scenarios; (2) draw analogies & idiosyncrasies between FES actuation and mechanical actuation; (3) identify challenges addressable by means of neuroadaptive technologies.

INTRODUCTION: INTERFACES BASED ON ELECTRICAL MUSCLE STIMULATION?

For the past six years, the Human-Computer Interaction (HCI) research community has been exploring functional electrical stimulation of human muscles (FES, also sometimes denoted as EMS) as a means for creating novel interactive systems. FES matured in the field of rehabilitation medicine [1]. Mostly, it assists patients in regaining motor functions, such as grasping [2], walking [3], swallowing [4] and standing upright [5]. On the other side, applications in HCI are simpler but interestingly different from their medical counterparts; these revolve around the actuating the users' body as a means to represent computer feedback. We discuss interactive devices based on EMS by presenting four of our own works and two additional projects form the HCI community.

NOVEL INTERACTION OPPORTUNITIES: ADAPTIVE WEARABLE INTERFACES

As depicted in Figure 1, interactive applications of the FES technology tend to fall into three main areas: **(1) Training.** (a) In *PossessedHand* [6], EMS was employed as an output system to learn haptic tasks such as playing a string musical instrument. Similarly, (b) *Affordance++* [7] relies on this principle to allowing everyday objects to communicate their usage (e.g., a spray can that shakes by itself). **(2) Information Access.** By adding input to EMS-based systems researchers closed the I/O loop. Hence, providing a platform for information I/O [8]. This concept allowed for notification systems that communicate, for example, (c) walking directions [9]. Also, (d) by persisting the EMS output (e.g., as a physical trace of pen on a paper), we see a new generation of systems that aims at supporting sensemaking activities [10]. (**3) Immersion.** The first interactive applications of EMS show that it provides stronger sensations than the traditional vibrotactile feedback, for virtual experiences [11]. In fact, researchers showed how EMS effectively miniaturizes typical force feedback hardware (which is comprised of motorized actuators [12]), making it available, for instance, on mobile devices [13]. With this wearable approach, researchers investigated, how EMS counter-forces can simulate (e) collisions with objects or (f) walls in virtual reality [14].

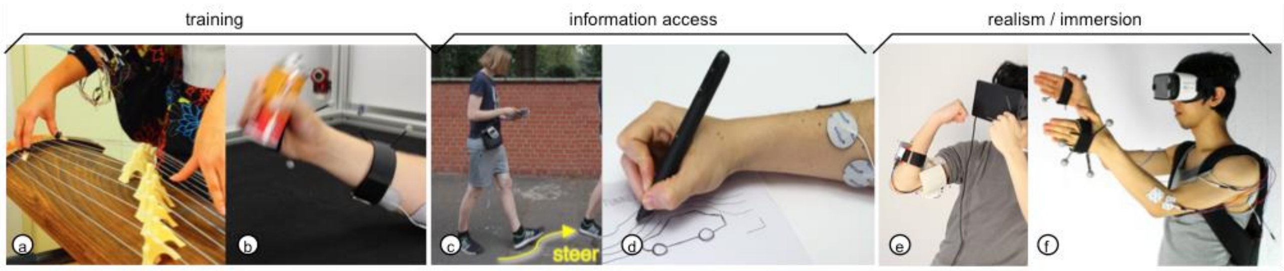

Figure 1: Examples of interfaces, which actuate the users by means of electrical muscle stimulation.

CONCLUSIONS: TOWARDS NEURO-MUSCULAR ADAPTIVE CONTROL LOOPS

By using EMS/FES researchers created even smaller wearable devices. Since these interfaces share a strong analogy with mechanical actuators (e.g., exoskeletons [15]) it is worth discussing their idiosyncrasies at both the perceptual and hardware level. The next step for FES-based interfaces is to provide adaptability with the user's voluntary intentions, for example, adaptive control loops using physiological data such as muscle tension (EMG [16]) or motor cortex activity (pBCI [17]).

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Session Name: FII-2

Room: R2
Session: Wearable Sensors
Time slot: 14:30 – 16:00
Day: 3

MEASURING ACADEMIC STRESS 'IN THE WILD' WITH WEARABLE SENSORS: REMOVAL OF NOISE FROM WEARABLE SENSOR DATA USING FIR FILTERS

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ABSTRACT: Psychological concepts, such as anxiety, can be measured 'in the wild' using a range of wearable sensors. The measurement of psychophysiological signals in the field naturally includes a number of confounds such as noise, artefacts and baseline wander. Before getting a general idea of what may be possible from working with the data, it is necessary to use data conditioning methods to remove these unwanted influences.

INTRODUCTION

Several studies have attempted to use machine-learning approaches to classify stress using a combination of datatypes, including; physiological [1], activity [2] and locational. However, before classification algorithms can be applied, data must be prepared to enhance the prominence of the psychological influence. The occurrence of noise originating from activity that distorts the original data is unavoidable when collecting data 'in the wild'. Moreover, the wrist sensor that we utilise is susceptible to varying impedance between the electrodes and skin due to poor contact. Thus, making it necessary for pre-processing methods to be used that can remove this unwanted noise.

MATERIALS AND METHODS

Our study involves the collection of psychophysiological data, such as heart rate and galvanic skin response, from ten subjects over the space of ten days, using the Microsoft Band 2 in combination with an Android smartphone. Of these days, five are under what we deem as a 'stressful' condition (i.e. close to academic deadline), the other five days are under a 'non-stressful' condition. This methodology of collecting data from participants 'in the wild', ensures that our dataset is ecologically valid and representative of physiological changes that occur as a result from the natural environment [3].

RESULTS

Part of the ongoing work involves cleaning and removing artefacts from both; the physiological and contextual datasets. Figure 1 illustrates the effect that noise has on the movement signal, and how through appropriate filtering false positives of excessive movement can be removed. If we wrongly label the movement data (high or low movement), the challenge of accurately identifying moments of anxiety becomes considerably more difficult. By applying Savitzky-

Golay and Moving Median smoothing techniques we are able to discern between genuine and artificial peaks within the movement data.

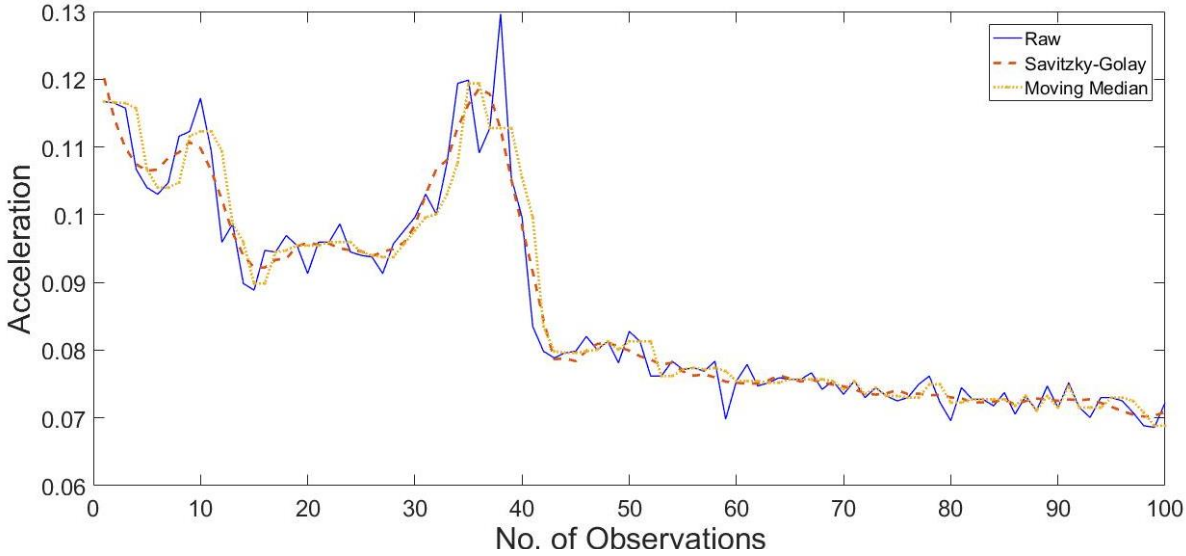

Figure 1. A comparative analysis of three different filtering methods applied on acceleration data for cleaning.

DISCUSSION & CONCLUSION

When participants collect data in the natural environment, this process is unsupervised and the researcher cannot intervene. Moreover, certain activities occur in the real world that multiply the amount of data filtering that is required. This issue exacerbates the challenge of preparing a clean dataset that facilitates machine-learning experimentation. The work presented here is just a single component of a framework that carries the primary focus of identifying anxiety through the utilisation of data collected using wearable sensor technology. It is important to reduce the impact of noise in the data as this can result in the misidentification of anxiety from a classifier. Moreover, we expect to provide clarification as to whether contextual data can enhance the accuracy of a model that can classify anxiety.

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Room: R2
Session: Wearable Sensors
Time slot: 14:30 – 16:00
Day: 3

MOBILE BRAIN/BODY IMAGING (MOBI) OF SPATIAL KNOWLEDGE ACQUISITION DURING UNCONSTRAINED EXPLORATION IN VR

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ABSTRACT: The neuroscientific study of human navigation has been constrained by the prerequisite of traditional brain imaging studies that require participants to remain stationary. Such imaging approaches neglect a central component that characterizes navigation – the multisensory experience of self-movement. Navigation by actual walking or active driving combines external multisensory perception with internally generated self-motion cues. Here we apply Mobile Brain/Body Imaging (MoBI) [1][2] to investigate EEG effective source dynamics during ambulatory spatial exploration in an interactive sparse virtual reality (VR) setup. The analyses focus on spatial knowledge acquisition during unconstrained exploration and navigation. The present findings demonstrate (a) sufficient data quality to allow data analysis and mining procedures of EEG data acquired during real movement through space and (b) substantial findings regarding human spatial cognition.

INTRODUCTION

Navigation relies on idiothetic cues, i.e. information originating from navigators' movements as well as allothetic cues, i.e., information about objects and space unaffected by changes in body position and orientation. A well-established theory of spatial learning in children assumes an ontogenetic sequence from egocentric (body-centered) to allocentric (external world-centered) representations of space implying a sequential development from coarse to complex spatial representations [3].

MATERIALS AND METHODS

We recorded synchronized high density EEG and full body motion capture while participants explored an interactive sparse virtual reality (VR) maze environment by walking and probing for virtual wall feedbacks with reaching movements. An Oculus Rift DK2 was used for visual presentation with changes in position and orientation registered by a PhaseSpace Impulse X2 motion capture system. We analyzed participants' movements to mark and quantify events of navigation behavior that support spatial knowledge acquisition. This was used to weight ongoing behavior with regards to information uptake and resulting representations of spatial information. A single model AMICA was used to separate multivariate EEG input signals into a set of statistically independent components [4]. Subsequent time frequency analyses of clusters of similar independent components was followed by analyses of directed information measures within relevant brain networks [5].

RESULTS

We report work in progress no final significant findings. We present pilot data as an example how data will be processed and what information can be derived from multimodal MoBI data.

DISCUSSION

Data from pilot sessions demonstrate the feasibility of the experimental and analytical approach.

CONCLUSION

Meaningful navigation has been a driving force in human evolution and remains relevant today in the age of globalization and demographically changing societies. Therefore, a deeper understanding of the cognitive processes underlying navigation may lead to useful insights for the development and improvement of novel, mobile navigation assistive systems.

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Poster Session

Session PI

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Dav: 1

SIGNAL ANALYSIS OF MOTOR IMAGERY TASKS FOR SELF-PACED BCI APPLICATIONS

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ABSTRACT: Self-Paced BCI applications usually choose the current motor imagery task based on the last n seconds of the streaming signal. Using a fixed size window disregards the fact that EEG-signal has dynamic behavior. In our work, we propose a different way of selecting the window size dynamically. The decision is based on the behavior of the filtered signal. We used Wavelet transform as filtering method instead of the commonly used butterworth filter, since Wavelet method tries to capture and retain signals with dynamic frequency response, while the butterworth filter modifies the signals and is usually used when the signal has a static frequency response.

INTRODUCTION

Brain Computer Interface (BCI) is a term for technology which enables direct communication between a human and a computer without the involvement of any peripheral nerve or muscle activity [1]. BCI research is commonly based on the Electroencephalography (EEG) technology. Motor imagery tasks are usually used for BCI systems, because they can "modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with a real executed movement" [2].
Important milestones in BCI research are the BCI Competitions. The results of competition III [3] and the experiments conducted by Lotte, Fabien and Guan, Cuntai [4], show that synchronous BCI applications can give reasonable results outside the laboratory. However, this is not the same for self-paced BCI. We believe the reason is the use of fixed size windows. By choosing the last n seconds [5] [6], we ignore the dynamic nature of the signal. We feel that by focusing on the start and end times of the motor task pattern, and also by cleaning it of irrelevant information, the accuracy of classification will be significantly higher.

MATERIALS AND METHODS

We used Datasets 1 and 2a from BCI Competition IV [7] [8] for signal analysis and pattern recognition. We also conducted our research only on EEG-channels that are said to be relevant for motor tasks [9] [10]. One of the essential decisions in BCI applications is the filtering method. Butterworth filter is commonly used, both in synchronous BCI [4] and in self-paced BCI [5] [6]. Stephen Butterworth stated in his work on the filter that "an ideal electrical filter should not only completely reject the unwanted frequencies but should also have uniform sensitivity for the wanted frequencies" [11]. The use of Butterworth filter on EEG signals ignores their dynamic frequency response which is rapidly changing over time. Instead, we suggest the use of Wavelet transform as a filtering method since it has the time-localization property [12] (in contrast to Fourier Transform). Analytic wavelets are used for the purpose of time-frequency analysis [13]. We used the Bump Wavelet, since it exhibits better frequency localization results than the Morlet Wavelet (in other words it is better in describing the global behavior of the signal). We decided to filter the signal to the band of the

Sensorimotor rhythm (SMR 12.5 - 15.5 Hz), since SMR has a very strong role in the context of motor tasks [6] [14] [15]. The signal is transformed using Bump Wavelet and then inverted, keeping only frequencies in range 12.5 - 15.5 Hz. Fig.1 is an example for a signal after reconstruction and filtering (5 seconds of a right hand motor imagery, down-sampled from 2048 Hz to 512 Hz). An interesting behavior appears in the filtered signal: the amplitude is monotonously increasing until reaching local maximum, and then monotonously decreasing until reaching a local minimum. This behavior is consistent for all signals from datasets 1 and 2a. We call the section between every two adjacent local minima a "burst". We explored the properties of the bursts, as described in the next section. The bursts were extracted by the following simple heuristic steps: subtract the mean from the signal, calculate mean frequency (denote as mfreq), find max value in every two non-overlapped intervals of size mfreq, find local minima of the max values.

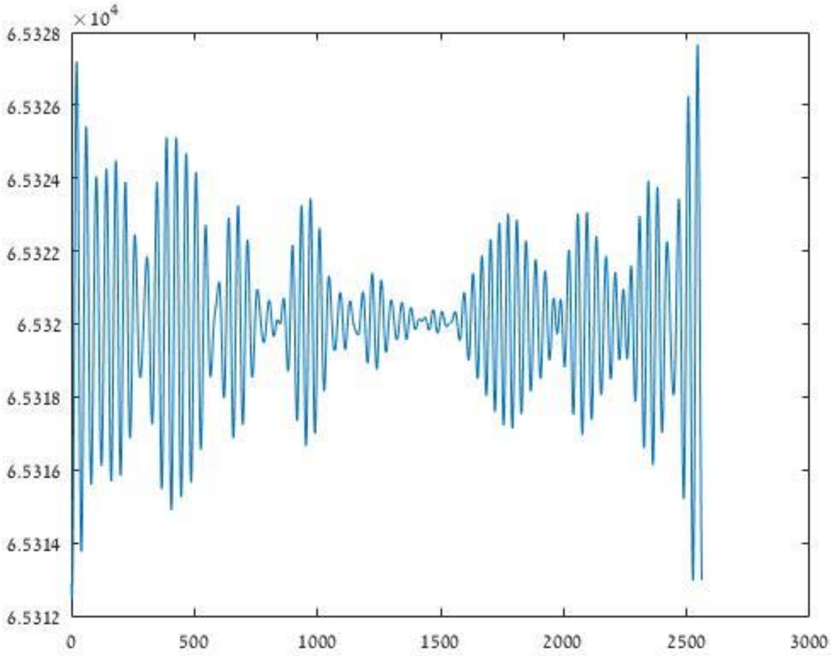

Figure 2 reconstructed signal

RESULTS

The results regards to bursts by channel and motor task type, for each subject. Each tuple of subject:channel:motor-tasktype is denoted here as a group. All groups have a similar number of bursts (about 700 in dataset IV:1, and 500 in IV:2a). We also found that all groups (even those from different datasets) share the same seven dominant burst lengths, regardless the subject, channel or motor task type (which hold an average of 65% of the total burst count for a group). There are approximately 40-45 burst lengths for each group, and for all of them the dominant lengths holds more than 60% of the total burst count.

DISCUSSION

Besides the experimental results, the signal seems to have a "visual" behavior. Our conjecture is that each burst should be treated separately, and instead of using a fixed window size we should adopt a "burst-window".

CONCLUSION

In our work we discovered a new pattern of the EEG-signals. The pattern is strong in the sense of being repeated among subjects, channels, and motor tasks. We suggest a further exploration of them. This might be the key for a real-world self-Paced BCI application.

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Session Name: PI-2

Room: R1
Session: Neuroergonomics
Time slot: 15:00 – 16:30
Dav: 1

FUNCTIONAL CORTICAL NETWORKS FOR AUDITORY DISTRACTOR SUPRESSION DURING A REALISTIC VISUAL SEARCH TASK

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ABSTRACT: In visual inspection it is crucial to detect and react to visual targets timeously and appropriately while ignoring distractions. We designed an experimental set-up that resembles a realistic visual inspection task that people perform in industrial manufacturing on the shop floor. With electroencephalography (EEG) we examined the functional connectivity (FC) in response to different auditory distraction levels while engaged in the task. Our results revealed significantly increased activation in the θ-band for a bilateral frontal-parietal network, in the β-band between left motor cortex and bilateral parietal regions and in the γ-band for an extended bilateral network of occipital, parietal, motor and frontal regions. We found that visual inspection engages extended cortical networks in different frequency bands that are modulated in relation to cognitive demands.

INTRODUCTION

Industrial manufacturing requires inspection processes to guarantee the quality of products [1]. Visual inspection is a highly repetitive and exhausting task prone to human error [2]. The networks of visual search have been extensively investigated [3-5]. While most studies focused on visual distractions [6], other distraction modalities like auditory signals are often neglected. However, in a manufacturing environment sounds are a crucial factor that can increase the cognitive demands during inspection [7]. We expect that a realistic visual search task coupled with auditory distraction is highly cognitively demanding and will lead to additional network changes of cortical FC. Using EEG we examine to what extent search demands are processed in the human brain during different levels of auditory distractor suppression and which cortical regions are involved in visual search.

MATERIALS AND METHODS

We designed a goal-directed visual search task: Participants (n=7) had to press a button whenever they found an error in the scene while being exposed to high (IADS, neutral sounds) [8] and low auditory (pink noise sound) distraction levels. For the FC analysis [9] we focussed on the 4sec window before the button press. We evaluated the FC networks between different regions (defining seed electrodes in bilateral FR, OCC and left M1) and all other EEG channels for frequencies of interest (FOI). FOIs were entered in a cluster-based, non-parametric randomization test including correction for multiple comparisons between high and low distraction levels [10].

RESULTS

Preliminary results of FC revealed significantly increased activation between bilateral frontal and parietal regions in the θ-band, left motor and bilateral parietal regions in the β-band and between bilateral network of occipital, parietal, motor and frontal regions in the γ-band, more so during high than during low distraction. No meaningful differences were found on a behavioural level.

DISCUSSION

Cortical network activity responds to auditory distraction during a realistic visual search task with increased FC in respective FOIs. The results probably indicate a compensation of the distraction level during the search time, since no behavioural differences were observed. However, we cannot exclude that other cognitive processes might contribute to the differences in network activity.

CONCLUSION

We found that visual search engages cortical networks in different FOI that are modulated in relation to cognitive demands, a proposal that warrants further investigation in a larger cohort of participants. While preliminary results are promising, data acquisition is still ongoing.

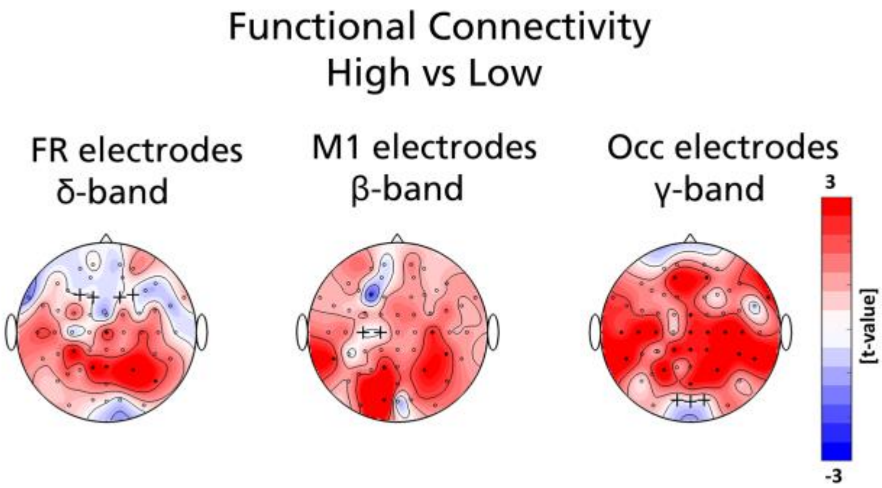

Figure 1: Functional connectivity networks.
The plots show the t-value topographies of functional connectivity (absolute value of the corrected imaginary coherence function) as a contrast between the high and low auditory distraction level for the θ-, β-, and γ-band. The black crosses indicate the seed electrode positions in the frontal cortex (FR: F4, F2, F1, and F3), left primary motor cortex (M1: C3, and C1), and in the occipital cortex (OCC: O1, Oz, and O2). Electrode clusters, showing significant differences in the non-parametric randomization test, are indicated by filled black circles. Colours indicate that the functional connectivity increases (red) and decreases (blue) within the 4sec before the button press during a high distraction level in relation to the 4sec before the button press during a low distraction level.

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Session Name: PI-3

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Dav: 1

RE-THINKING BCI MODELS AS NOISY SENSORS FOR NEURAL ANALYSIS

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ABSTRACT: Brain-computer interfaces (BCI) were originally designed to restore function to clinical populations whose neuromuscular pathways had been disrupted. More recently, BCIs have expanded to state and event monitoring for non-clinical populations [1,2]. In both cases the BCI approach is the same: 1) acquire user and domain specific data, 2) train the model, 3) apply the model to the user/domain for which it was trained, and 4) re-train as necessary. With the emergence of deep learning approaches researchers can now develop BCI models across users and domains. We propose that these Generalized Deep Learning-based Models (GDLMs) can provide a new dimension for neural analysis: one that is not predicated on the assumption that ground truth is clearly established by experimental conditions.

INTRODUCTION

GDLMs isolate spatio-temporal patterns of neural responses and have been shown to work across users and domains [3]. GDLMs offer a probabilistic view of the moment-by-moment fluctuations in the neural data that, we propose, can be incorporated into the analysis of subject behavior or state. The keys to this approach are 1) that the GDLMs are not trained on the data set to which they are applied and, thus, the required assumptions of ground truth for the analyzed data set are not made, and 2) GDLMs respond to generalized patterns of neural response and can ignore neural (e.g. movement related cortical responses) and non-neural (e.g. eye movements) artifacts [4].

MATERIALS AND METHODS

We demonstrate our concept using an experiment involving target detection. In this experiment, 16 subjects performed a free-viewing (FV) task and were instructed to watch for two types of targets. Upon detecting a target, subjects were instructed to discriminate as quickly and as accurately as possible whether the target was a threat (i.e. a human with a weapon or a table oriented such that it could hide an improvised explosive device) or a non-threat (i.e. a human without a weapon or a table that one could see under) and to push one of two buttons accordingly. We trained our GDLM to detect and isolate P300-like events using a combination of experiments: 1) fixation-related potentials, 2) rapid serial visual-evoked responses to targets, and 3) movement-related cortical potentials [4]. In post-processing we labeled all fixations in the FV data set as being 1) target-related fixations (i.e. occurred after target onset and before button response), 2) search fixations (i.e. occurred when no target was on the screen) and 3) everything else.

RESULTS

We applied the GDLM to only the search fixations and found a significant negative correlation ($p < 0.01$, avg. corr. = -0.15) across subjects between the probability of a P300 event given a search fixation and subject reaction time (RT). This correlation was most pronounced during periods of lowest probability for a P300 event (see, for example, Figure 1). This result remained significant using window sizes ranging from 25s – 60s to compute P300 probability and avg. RT.

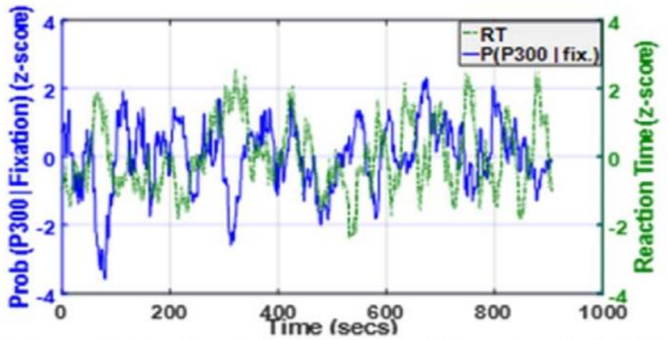

Figure 1: Sample result from one subject. Y-axis (left): the probability of a P300 event given a fixation. Y-axis (right): reaction time. Corr. for this subject was -0.29

DISCUSSION AND CONCLUSION

While the neural mechanisms driving these results are still under investigation, we believe this demonstrates the use of GDLMs for applications beyond just closed-loop BCI. GDLMs enable trial-by-trial analysis of neural data by using models that have never been exposed to that data. These tools are mostly free of assumptions about the data in that they do not require ground truth labeling of the data. This enables more flexible analysis than traditional ensemble approaches.

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Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Day: 1

A BIOFEEDBACK APPROACH TO INVESTIGATE NEUROCOGNITIVE MECHANISMS OF FEEDBACK-BASED LEARNING

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ABSTRACT: Understanding the neurocognitive mechanisms involved in feedback-based learning is a central question for bio/neurofeedback paradigms. We propose incorporating electrophysiological measurements of brain activity into a standard biofeedback approach of control of vocal performance, in order to investigate mechanisms of feedback-based learning. The idea is to use vocal biofeedback as a control task for feedback-based learning while recording electroencephalographic (EEG) activity. We expect this task to unravel neural correlates of learning within the context of a biofeedback interface. The conditions of our experiments will be evaluated using several questionnaires, aiming at helping us analyzing our results depending on the subjects' psychologic profile. The combination of biofeedback training results related to psychology and neural correlates of feedback-based learning provide useful guidelines for designing a neurofeedback protocol.

INTRODUCTION

We propose a method to investigate the neurocognitive mechanisms of feedback-based learning. In our experiments, both beginners and trained singers are asked to perform singing warm-up exercises. A feedback, either continuous or discrete, provides them with information about their singing performance. We expect to find specific brain signatures to learning conditions (successful *vs.* unsuccessful trials) [1, 2], and therefore we investigate brain activity when the feedback is provided.

MATERIALS AND METHODS

Biofeedback training is divided into 5 training sessions, 20 healthy subjects will be collected. There are two kinds of feedbacks, (i) singing power ratio (SPR, [3]) and (ii) feedback about muscle activation using electromyographic (EMG) sensors placed on the upper and lower left masseter, and upper right sternohyoid (see Fig. 1). During the first two sessions, feedback is only continuous. From the third session onward, both feedbacks are continuous and post-trial, helping the subjects gaining autonomy [1, 4, 5]. During the two last sessions, feedback is only post-trial. Brain activity is monitored by a 20 channel EEG Neuroelectrics Enobio device. Data acquisition, data processing, and feedback display are performed under Matlab R2016a. We investigate EEG event related potentials in response to discrete feedbacks (feedback event related negativity, P3a, P3b, Intentional Inhibition Potential), and EEG oscillations (Fourier power, phase synchrony) in response to continuous feedbacks. We control the psychological traits and states of the subjects which may interfere with the feedback learning task (see Table 2).

DISCUSSION

Our data collection is still ongoing. We conducted a preliminary study about muscle activation feedback with a professional opera singer. We could predict singing quality from three EMG sensors placed above and below the masseter, and near the larynx; it confirms previous observations [6]. We also validated the Singing Power Ratio feedback relevance with both beginners, trained singers and a singing teacher from a national music school.

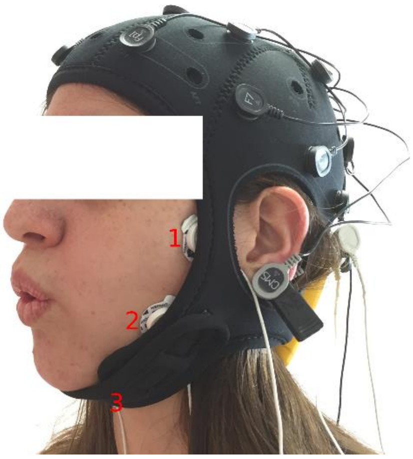

Figure 1 : Recording system including EEG and EMG sensors, placed on 1. Upper masseter, 2. Lower masseter, and 3. Sternohyoid muscle.

Table 2 : Scales used to evaluate psychometric traits and scales.

Scale	Trait (T) or State (S)	Purpose
16 Personality Factors-5	Personality (T)	Confounding factor in feedback learning
STAI-Y anxiety scale	Anxiety (T)	Anxiety bias on error interpretation
Cognitive training expectation	Motivation (S)	Expectations can bias learning tasks
Feedback learning scale : - Brief Mood Introspection Scale - Locus of control scale related to technology (KUT) - Learning Style Inventory - NASA Task Load Index	Feedback learning (T)	Feedback learning scale constructed from significant subitems of BMIS, KUT, LSI, and NASA TLX. Tracking pre- and post-session affective, motivational and cognitive involvement in the task.

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Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Dav: 1

FINDING EEG FREQUENCY BANDS RELATED TO CONCENTRATION

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ABSTRACT: In the present study, we investigated which EEG frequency band is most suitable for developing a concentration-based neurofeedback system. To this end, we measured EEG signals at FPz while twelve subjects played a game (Piano tile 2) for 2 min, and stayed without any particular thoughts (resting state) for 3 min. As a result of comparing spectral powers estimated during resting state and playing game, only delta band showed significant changes while playing game (two-tailed t-test, $p < 0.05$) on group level. From the result, it is expected that spectral powers in delta band might be used for developing a reliable concentration-based neurofeedback system.

INTRODUCTION

Neurofeedback (NF) is a well-known method for treating various cerebropathia [1], [2], [3]. So far, however, there is still no definite indicator to accurately reflect changes in mental states (e.g., concentration) during NF. In this study, we attempted to find out frequency bands most suitable for tracking changes in concentration levels in order to develop a reliable concentration-based NF system.

MATERALS AND METHODS

Twelve healthy subjects participated in this study. In the experiment, each subject played a game (Piano tile 2) for 2 min twice to change their concentration levels, during which EEG signals were measured at FPz with a sampling rate of 512 Hz. EEG signals in resting state with eyes open were also recorded as baseline for 3 min. The subjects took a break without measuring EEG signals for 2 min between resting state and playing game. The raw EEG signals were notch- and bandpass-filtered at 59 - 61 Hz and 0.5 - 45 Hz, respectively. After removing EOG components, time-frequency analysis was performed using a window size of 1,000 ms with 90 % overlap, and frequency powers were normalized by dividing the power of each frequency band by the sum of powers of five frequency bands at each time point (delta: 0 – 4 Hz, theta: 5 – 7 Hz, alpha: 8 – 13 HZ, beta: 14 – 30 Hz, gamma: 31 – 45 Hz). To investigate task-specific frequency bands, mean powers over all subjects were estimated and compared between the two conditions for each frequency band.

RESULTS

All frequency bands show statistically significant changes in spectral powers for most cases on individual session level (delta: 20 of 24 sessions, theta: 17, alpha: 20, beta: 19, and gamma: 21), however only delta powers showed statistically significant changes while playing game on group level (two-tailed t-test, $p < 0.05$), as shown in Table 1.

Table 1: Mean spectral powers of five frequency bands for resting state and game (*: $p < 0.05$)

Frequency band	Resting state	Game
Delta*	0.362 ± 0.126	0.297 ± 0.079
Theta	0.303 ± 0.071	0.341 ± 0.081
Alpha	0.185 ± 0.079	0.215 ± 0.029
Beta	0.194 ± 0.083	0.201 ± 0.062
Gamma	0.085 ± 0.039	0.084 ± 0.045

DISCUSSION

In this study, we confirmed from the results of individual session and group level analysis that delta band is the most related to changes in concentration levels. However, the result may be limited due to using only one channel and task paradigm used in this study, and thus additional experiments should be performed with more electrodes and other paradigms to more precisely find out concentration-specific frequency bands.

CONCLUSION

Delta band is the most associated with changes in concentration levels, and it is expected that it might be potentially used for developing a reliable concentration-based NF system.

ACKNOWLEDGEMENT

This work was supported by Institute for Information & Communications Technology Promotion (IITP) grant funded by the Korea government (No. 2017-0-00451).

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Session Name: PI-6

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Day: 1

DEVELOPMENT OF A NEUROADAPTIVE GAMING TECHNOLOGY TO DISTRACT FROM PAINFUL PROCEDURES

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ABSTRACT: We aim to create a neuroadaptive game based on fNIRS that is designed to maximise the immersion of the player and distract from painful medical procedures. This abstract will describe the first part of this development, to assess simultaneous fNIRS responses to pain and game demand under controlled condition. These data represent the basis of the biocybernetic loop at the heart of the neuroadaptive prototype.

INTRODUCTION

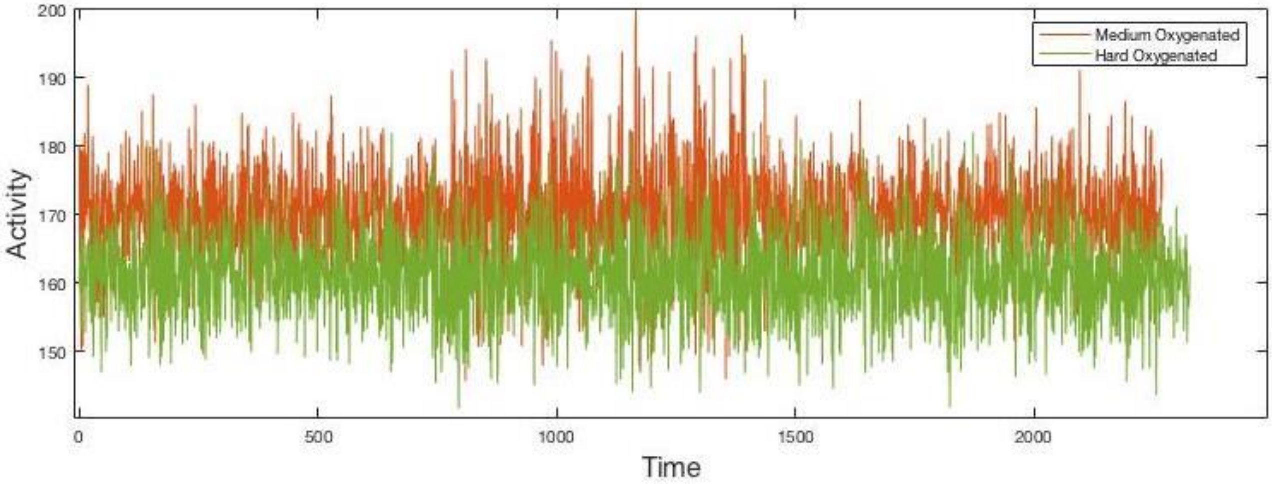
Distraction can increase pain tolerance by diverting attention from the sensation of pain. Adaptive games have proven to be more effective distractions than standard games [1] because the demand of the game is adapted to the skill level of the individual. This neuroadaptive prototype will allow a player to achieve goals in-game regardless of their skill level by adapting to their level of expertise and enabling all players to experience a state of 'flow' or 'high engagement' [2].

MATERIALS AND METHODS

We have opted to create a closed biocybernetic loop, as this loop will receive feedback from neurophysiological activation to ensure that real-time adaptation of the game is an effective process [3]. However, before this loop can be created, we must gather data that describes desirable and undesirable player states. Participants will play four difficulty levels of a racing game (easy, medium, hard and impossible) whilst wearing fNIRS sensors. fNIRS has been chosen because it is comparable to fMRI, but is cheaper and more convenient form of neuroimaging [4]-[5]. The participants will play all four game conditions with and without the cold pressor test. This atypical pain stimulus has been chosen to theoretically enable us to create a game that will effectively distract from different types of pain. The gathering of fNIRS data in three conditions (game alone, pain alone, game and pain in combination) will allow us to determine how the manipulation of game demand and experimental pain impacts on fNIRS activity in two sites of the cortical activity – the frontal cortex, which is sensitive to attentional processes [6], and the somatosensory cortex, which is part of the pain matrix [7]. The different conditions also allow us to determine the participant's baseline pain threshold, so that we can use the potential difference in pain tolerance when the distraction is present as a measure of immersion.

RESULTS

Figure 1 shows lower levels of oxygenated haemoglobin in the frontal cortex during a 'hard' level compared to a 'medium' level. This indicates that the participant has lost interest in the game during the 'hard' level and is not concentrating as much. In this case, the participant was



more immersed in the ‘medium’ game condition, meaning that this level would provide a greater distraction from pain.

Figure 1: A comparative sample of fNIRS data comparing the oxygenated and deoxygenated blood levels during ‘Easy’ and ‘Medium’ level gameplay. This figure shows a higher level of activation in the F1 area of the brain during a medium game than a hard game.

DISCUSSION/CONCLUSION

We expect that results in the final study will show greater neurophysiological activity in the frontal cortex and a higher tolerance to pain when the participant is playing the medium/hard levels of game demand. Conversely, we expect that, when game demand is either easy or impossible, the pain tolerance of the participant will be reduced, and there will be a reduced activation in the frontal cortex. We hypothesise that an adaptive game, which uses fNIRS sensors to monitor the brain and make in-game changes, will allow patients to withstand pain for longer than a standard game.

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Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Dav: 1

CORTICAL SOURCE LOCALIZATION OF EEG BIOMARKERS IN A COGNITIVE BRAIN COMPUTER INTERFACE MONITORING WORKING MEMORY LOAD

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INTRODUCTION

Working Memory (WM) can be seen as the hub of cognition [1], but also as its bottleneck. By definition, it is the system that stores, maintains, and processes information while a subject is performing any cognitive task. It is limited by construction, in time and in capacity [2]. This study aims at localizing the brain sources underlying WM in real time. Electroencephalography (EEG) is an excellent tool for real time studies due to its high temporal resolution; however, its spatial resolution even for high density arrays is poor, and we do not have access to any sub-cortical information.

MATERIALS AND METHODS

The recordings themselves were made during a real time experiment, in which a passive [3] BCI was used to estimate WM load during a mental arithmetic task. The BCI had been trained in a visual working memory task, therefore the mental arithmetic task was a cross-task. The BCI had an accuracy of 78%. Furthermore, subjects performed neurophenomenological validation: presented half of the time with sham feedback, subjects were able to correctly distinguish real from sham feedback on average 82% of the times. Control tests for disentangling potential motor and cognitive confounders were performed.

For addressing the issue of spatial resolution and for reconstructing sub-cortical information, we used the Brainstorm [4] toolbox. In order to solve the forward problem (Poisson’s equation with zero conductivity at the boundary), we used the three shell head model [5]. For the inverse problem (finding the sources more consistent with the observed EEG signal at every time point), we applied the Tikhonov-regularized minimum-normestimation [6].

DISCUSSION

There is not, to our knowledge, any study in the literature combining the characteristics of our WM study: real-time tests in a cross task, confounder disentanglement, and neurophenomenological validation. Based on the latter, we believe that our bio-marker reflects indeed activity of the central executive. As such, the sources associated to this activity might be of interest to researchers studying the neural correlates of WM.

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Session Name: PI-8

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Day: 1

DESIGNING AND UNDERSTANDING CONVOLUTIONAL NETWORKS FOR DECODING EXECUTED MOVEMENTS FROM EEG

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ABSTRACT: We used deep and shallow convolutional neural networks (CNNs) to decode executed movements from the raw time-domain EEG signal. Our CNNs yielded competitive decoding accuracies compared with filter bank common spatial patterns (FBCSP) [1]. Additionally, we developed visualization methods to understand the trained CNNs, including spatial maps that showed how band power features in different frequencies affected the CNN predictions.

INTRODUCTION

CNNs, wildly successful in computer vision through end-to-end learning from raw images [4][5], have so far not taken over the field of EEG decoding. Existing studies on CNNs for EEG decoding have only started to tackle the questions which input representation, network architectures and training methods lead to the best decoding accuracies [3][7][8]. Similarly, methods to understand what EEG features the CNNs learn are still sparse, especially for CNNs that use time-domain input.

MATERIALS AND METHODS

We investigated three CNN architectures of different depths to decode four classes of executed movements from time-domain EEG input, with FBCSP as a baseline (validated against published results) for the decoding accuracies. Our CNNs were designed to extract global spatial patterns and hierarchically nested temporal patterns. We compared different ways of extracting the training data, including a computationally efficient method to use many time windows to increase the number of training examples. Also, effects of numerous design choices, such as the type of nonlinearity, were evaluated. Furthermore, we developed novel visualization methods to understand what band power features the CNNs extract from the time-domain EEG signal. For more details, see [6].

RESULTS

Our CNNs reached or slightly exceeded the decoding accuracies of FBCSP; the use of recent deep learning techniques was necessary to reach these accuracies. Our visualizations provided spatial maps that showed the band power in typical motor-related frequency bands affected the decoding predictions of the CNNs. The spatial topographies of these effects were consistent with existing knowledge about the neural signature of executed movements with regards to the alpha, beta and high-gamma frequency bands.

DISCUSSION

We show that CNNs using the time-domain EEG signal can compete with well-established EEG decoding algorithms for executed movements, which rely on custom feature extraction. Furthermore, important insights can be learned from visualizations of CNN parameters. Validation on other data types, inclusion of newer deep learning methods such as domain adversarial networks [2] to combat non-stationarities and further visualization methods are areas of future work.

CONCLUSION

Our study makes further progress to establish end-to-end trained CNNs using time-domain input as a serious contender for EEG decoding and opens the door for using trained CNNs to gain insights about neural signals.

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Session Name: PI-9

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Day: 1

SIGMABOX: TOWARDS A SIMPLE AND EFFICIENT MATLAB TOOLBOX FOR EEG SIGNAL PROCESSING AND CLASSIFICATION

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ABSTRACT: During the past few years, significant progress was made in devices and software for recording and analyzing bio-physiological signals. This short paper presents a general description of our current project: a new open-source Matlab-based toolbox, designed in order to help with biosignal data processing. SIGMAbox (SIGnal processing and MAchine Learning toolbox) gathers several pre-configured methods and algorithms for signal processing, statistics and classification. This toolbox is based on a graphical user interface (GUI) designed for end-users without expert skills in programming, and should be useable with very limited intervention from the user.

INTRODUCTION

SIGMABOX encapsulates a collection of existing Matlab functions and scripts. Those methods are pre-initialized and configured; however, their hyper parameters may be chosen by the user. The parameters for the implemented functions are initialized according to the best ones found in the literature and validated on our data-base, and can be optimized by the user if necessary. Various visualization options for the data and the results will be included on the GUI.

MATERIALS AND METHODS

The present version of the toolbox allows the design of two-class classifiers for EEG data [1]. It can be used on offline analysis for pre-recorded data-bases. Also it can be adapted for online system such as a brain-computer interface. The data analysis on SIGMABOX is divided into two phases: a training and validation phase, and a test phase. The user selects the database, and chooses the suitable method(s) for preprocessing, artifact detection and rejection, feature extraction and selection, and classification. The implemented features extraction methods include spectral and statistical analysis, complexity and synchrony measures. The classifications algorithms use the built-in Matlab toolboxes [2] for linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and support vector machines (SVM). The users can visualize their data, compare the performance of the different classifiers, and display the sensitivity, specificity, error rate and ROC curves. In the case of EEG signals, options for visualizing the electrical topography of the detected brain activity and for signal source localization are available using the Brainstorm packages [3].

DISCUSSION

Contrary to the other available tools [4][5], advanced skills in programming are not needed to use SIGMAbox, most of the option can be reached from the main GUI. The toolbox offers options that users can select and run to get the desired results, together with illustrations helping in their interpretations. This allows for instance supervisors to verify the proper use of the toolbox by non-experts (*e.g.* master's degree students) involved in a research project. Other options are under investigation, and will be added in future versions of the toolbox for specific types of signals such as electrodermal responses or breathing signals. The first version is expected to be available at the end of this year.

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Session Name: PI-10

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Day: 1

EEG-BASED BIOMETRIC AUTHENTICATION: A PRELIMINARY STUDY

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ABSTRACT: Recently, biometric authentication has received considerable attention because conventional authentication methods (e.g., ID/Password) cannot be fundamentally secure due to personal information extrusion. In this study, we propose a novel biometric authentication method based on EEG, which cannot be replicated by other people. To verify the feasibility of our method, EEG signals were measured while three subjects repetitively closed and opened their eyes. Changes in alpha activity during eyes open and closed were extracted for each channel as features, and inter- and intra-subject cross-correlation was used for identifying each subject. A mean identification accuracy was 90 %, demonstrating the feasibility of the proposed authentication method.

INTRODUCTION

Personal information leaks have been increasing due to advanced hacking skills and internet development, and they sometimes include personal authentication information. Thus, biometric authentication has emerged to overcome the shortcomings of conventional authentication methods (e.g., ID/Password). Representative methods of biometric authentication are fingerprinting and iris scan, but they would not be fundamental solutions because there is the possibility of copying the information of fingerprint and iris. The biometric authentication method based on brain signals would be an alternative because there is no way to imitate others' brain signals with the current technology [1-2]. In the present study, we investigated whether alpha activity changes induced by eyes-closed can be used to develop an EEG-based biometric authentication system.

MATERALS AND METHODS

Three subjects participated in this study. Each subject was asked to close and open the eyes for 15 s, which was performed 20 times. During the experiment, EEG signals were measured using thirty-one electrodes, which were broadly attached on the scalp. We calculated changes in alpha activity (8 – 12 Hz) by subtracting alpha powers estimated from the EEG signals acquired during eyes closed from those acquired during eyes open. This was performed for each channel, and thereby constructing channel-frequency pattern maps of changed alpha activity for each trial. Leave-one-out-cross validation with cross correlation (CC) was performed to calculate classification accuracy, where intra- and inter-subject CC was compared and the trial was assigned to a class (person) based on whichever had the largest mean CC value.

RESULTS

Alpha power significantly increased for most electrodes when the subjects closed their eyes, and importantly changed patterns of alpha activity were different between the subjects (Figure 1). The identification accuracies of the three subjects were 100.0 %, 70.0 %, 100.0 %, respectively.

DISCUSSION

We showed the possibility of using alpha activity induced by eyes-closed for developing an EEG-based biometric authentication system, but an additional experiment with more subjects should be performed to investigate session-to-session reliability and the effect of the number of electrodes on authentication performance for practical use.

CONCLUSION

From the analysis results, we confirmed the feasibility of using alpha activity for developing an EEG-based biometric authentication system.

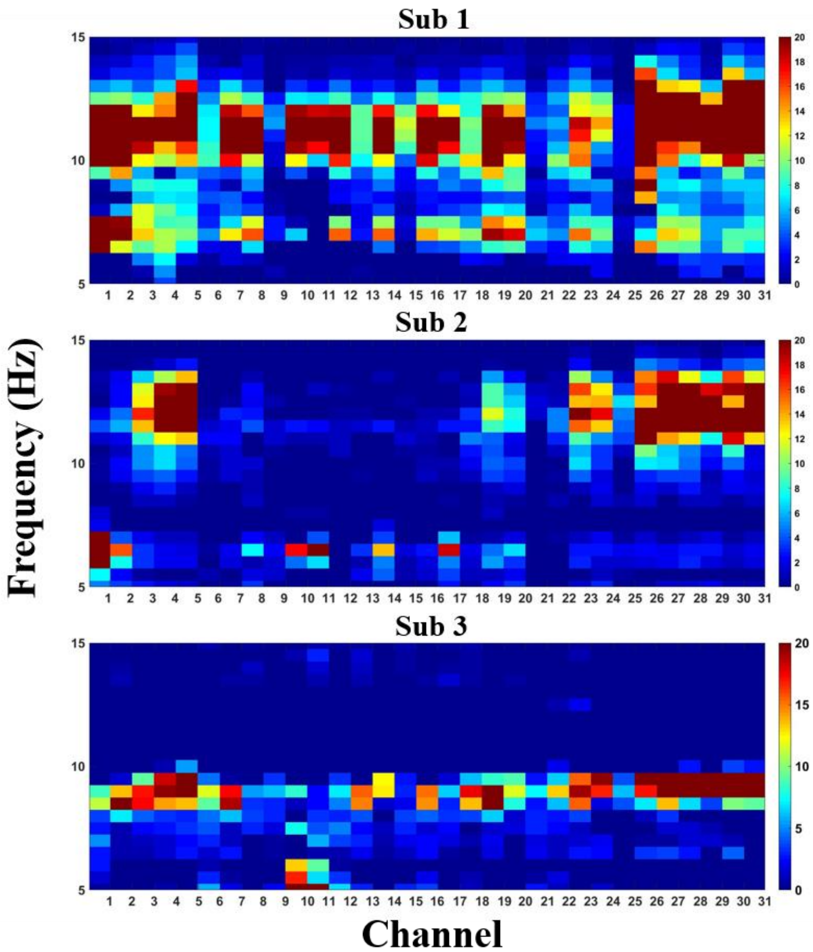

Figure 1: Examples of Alpha Activity Patterns Changed During Eyes Closed for Each Subject

ACKNOWLEDGEMENT

This work was supported by Institute for Information & Communications Technology Promotion (IITP) grant funded by the Korea government (No. 2017-0-00451).

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Session Name: PI-11

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Dav: 1

MEASURING COGNITIVE CONFLICT IN VIRTUAL REALITY

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ABSTRACT: As virtual reality (VR) emerges as a mainstream platform, designers have started to experiment new interaction techniques to enhance the user experience. We propose an EEG-based experiment methodology that evaluates interaction techniques in VR by measuring cognitive conflict through feedback-related negativity (FRN), by applying it to the fundamental task of 3D object selection using direct 3D input, i.e. tracked hand in VR. The cognitive conflict was intentionally elicited by manipulating the selection radius of the target object. We found that the amplitude of FRN highly correlates with the level of realism of the virtual hands.

INTRODUCTION

Recent advances in display and tracking technologies bring affordable and plausible VR experience to the mass market. A range of measurements and visualization tools assists designers in the evaluation of the objective characteristics of interaction. However, for the subjective measurements, such as level of presence, focus, or emotions, still rely on questionnaires and interviews, which cannot reliably address the changing dynamics of the interaction [1, 2].

MATERIALS AND METHODS

Participants. EEG data were recorded from 10 right-handed participants (male). The mean age was 22.7 years (in a range of 20-26 years) with no prior experience of the experiment. This study had the institute's human research ethics committee approval and was conducted in a temperature controlled and soundproofed room.
Equipment. Participants were required to wear a wired EEG cap with 32 Ag/AgCl electrodes, including two reference electrodes (opposite lateral mastoids, modified international 10-20 system) together with HTC Vive [3] as the head- mounted display and Leap Motion [4] for hand tracking. The EEG recordings were collected using a Scan SynAmps2 Express system (impedance <5kΩ, sample rate 1kHz).
Experiment. Each participant performed the 3D object selection task with their hands tracked in VR. At the beginning of the trial, the participant would see two cubes on the table in VR (not physically) and instructed to touch first cube, and then the second cube by stretching their hand horizontally. The cube would turn red when it was touched virtually. Participants need to finish each task within 5s, and there was a 3s resting after each trial. The experiment uses a 3 by 2 with-in subject design. Independent variables are the hand style (realistic hand,

robotic hand, and 3D arrow; see figure 1(c)) and selection distance *D* (*D1*, equals to the size of the cube and *D2* is twice the size of the cube). There are three 20-minute sessions with each session with one type of hand style. We used the oddball paradigm with total 120 trials (30 targets; 90 non-target) that shows three trials with condition *D1* followed by a trial with condition *D2*. All trials were randomized in every session (see figure 1(a))

Method. ERP (event-related potential) analysis has been done on the collected EEG data from the participants performing the object selection task. EEG data were filtered offline with 1-40 Hz and further cleaned for artifacts using ICA (independent component analysis) [5]. An epoch was defined from 200ms prior ande 500ms post-stimulus.

RESULTS

ERP analysis has been performed to find the local minima over the electrode average in the frontal region to find any event related negativity for all condition of trials. It was found that FRN for *D2* is higher than *D1* for S1 and S2 condition whereas there was no difference for the S3 condition (see figure 1(c)). Further analysis of event-related activity has been done for a time range for 120ms-220ms to see if this event related negativity is because of negative feedback due to the conflict in the participant. It is clear from figure 1(b) that participants showed the higher area under the curve (AUC) for FRN around 120-220ms during a change in distance (*D2*) compare to normal distance (*D1*) for the rendering of realistic hand style (S1) while FRN falls off more than half for rendering robotic hand (S2) for change in radius condition. One the other hand rendering of arrow hand style (S3) showed almost negligible AUC for FRN during a change in distance.

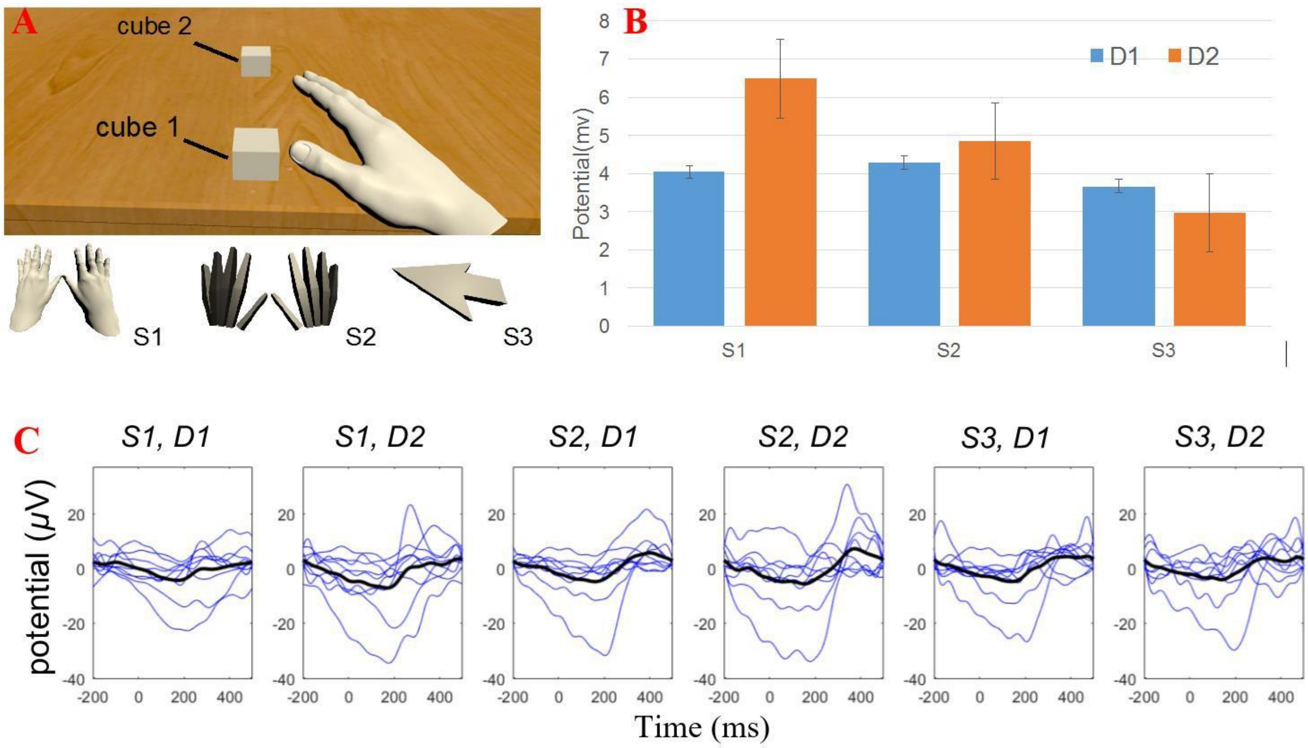

Figure 1. a) Scene of the experiment with hand style; b) Area under curve for S1, S2 and S3 hand style during D1 and D2; c) Average ERP for all participants for all conditions

DISCUSSION

As hypothesized, both FRN and questionnaire suggest a correlation between the amplitude of FRN and the appearance of the virtual hand. This result aligned with the famous Uncanny

Valley theory [6], which states that as a robot approaches, but fails to attain, the likable human-like appearance, there will be a point where users find even the slight imperfection unpleasant. In our case, as the virtual hand becoming more realistic looking, the participants also become more aware of the errors. On the contrary, it is a bit surprising that there is almost no effect in FRN for the condition *S3*. The result implies that the participants are more tolerant or not very responsive to the error when they feel the virtual hand is less like a part of their body. The similar effect can also be found in the rubber hand illusion test [7, 8] where the participants felt less threatened to virtual threat, e.g. knife, saws, etc. when their virtual body counterpart was not rendered realistically.

CONCLUSION

This finding implies that depends on the goals of the interaction and the hardware capability; higher rendering quality might not always be good. For example, if the tracking precision is likely to be compromised or the display quality of an HMD is not ideal, then using a less realistic rendering style might be helpful. On the contrary, if the nature of task and hardware permits, participants favor the more human-like looking of their virtual body.

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NEUROPHYSIOLOGICAL CORRELATES OF EFFICIENT LEARNING IN THE NEUROFEEDBACK PARADIGM

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ABSTRACT: A group of brain structures responsible for the operant conditioning is widely recognized to belong to the rewarding system [2] and the neurofeedback training is considered to be a reinforcement learning paradigm [3]. Depending on the ergonomic parameters of the feedback signal the efficiency of learning and the intensity of plastic changes will vary. Can we identify the correlates of efficient learning in the EEG recording and use them to tune the ergonomic parameters of the feedback?
We exposed our subjects to real and mock feedback and contrasted the EEG during these two conditions to find the neuronal sources explaining the difference between the two states. We found statistically significant differences in the activity of brain structures previously implicated in the operant conditioning process.

INTRODUCTION

Neurofeedback is a reinforcement learning process and its efficiency critically depends on the extent to which the feedback signal is matched to the particular subject. Feedback signal latency, color, shape, pitch, timbre and etc. are the ergonomic parameters that may potentially strongly affect the efficiency of learning and the intensity of plastic changes. Finding the proper ergonomic settings for each particular patient has a potential to boost the efficacy of the neurofeedback therapy and to further prove its usefulness in treating various neurological deceases.

MATERALS AND METHODS

The subjects were trained either with real feedback on their alpha waves instantaneous power extracted from P4 electrode or with mock-feedback. During the training they were instructed to sit as still as possible and were continuously presented visual feedback in the form of a circle with uneven border. The task was to make the circle border as smooth as possible by attempting to up-regulate their P4 alpha power. Mock feedback was derived from the EEG data recorded from the same subject during one of the previous trials and was thus unrelated to the current value of alpha power.

Each session consisted of 8 experimental trials each of duration 45 s and mock vs real feedback condition trials were randomized. Note that in this paradigm we did not aim at training alpha but rather attempted to catch the low-level difference between the consistent and inconsistent feedback as it is perceived by the brain. This explains the use of short trials (45 s duration) to minimize the chances for the subject to consciously disentangle and realize the presence the two types of feedback (real vs. mock).

For each participant we recorded the EEG data for mock and real feedback conditions at 500 Hz sampling rate. The data were then filtered with a band-pass FIR-filter in 40 different frequency bands from 2-40 Hz range with 2 Hz bandwidth. The data from the two conditions (real and mock feedback) were contrasted using the CSP technique.

In order to establish the significance of the observed differences we performed non-parametric randomization test to obtain the *p*-values of null hypothesis of no significant changes between the real and mock feedback conditions.

RESULTS

We found statistically significant components in the beta band, with frontal localization which may correspond to the anterior cingulate cortex (ACC), whose activity contrasts the real feedback and mock feedback conditions. Figure 1 shows the p-values and the topography of the CSP component for the most illustrative subject.

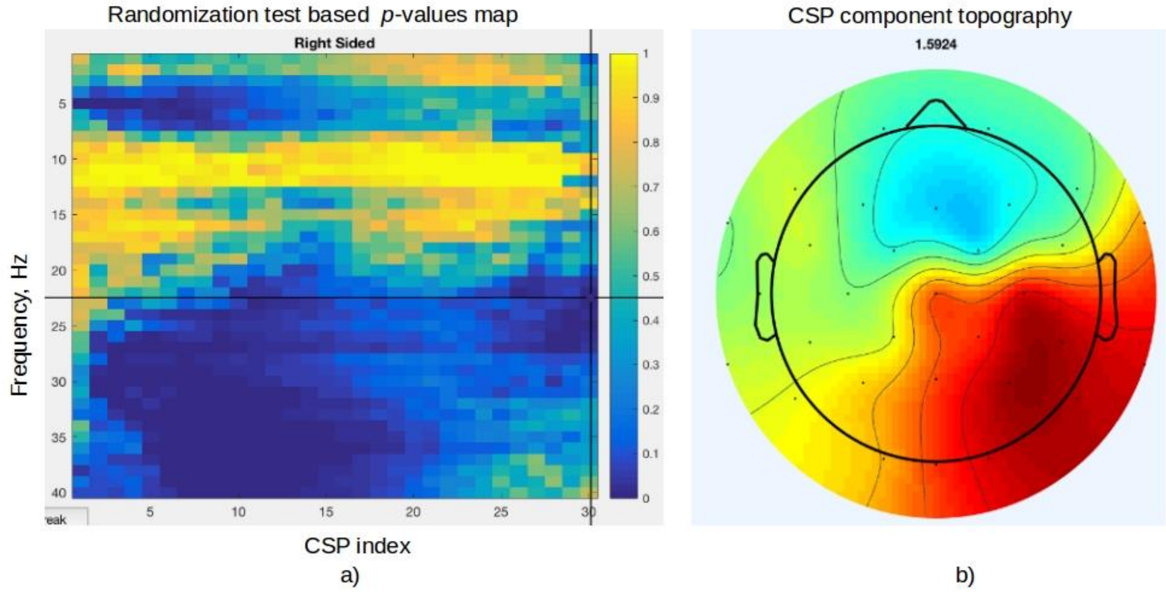

Figure 1: . a) *p*-values and b) the topography of the CSP component for the most illustrative subject. We observe statistically significant differences for components with greatest eigenvalue in beta frequency band (22 Hz) corresponding to the activation in frontal brain areas which may coincide with ACC (Figure 1).

DISCUSSION

Since the ACC is one of the key nodes of the rewarding network our results agree with the previous studies aimed at studying brain activations during the RL process.

CONCLUSION

It remains to be seen whether or not the activity in the rewarding network nodes can be used as a gauge to tune the efficacy of the NFB by adjusting the ergonomic paraemetrs of the feedback signal.

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Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Day: 1

USER IDENTIFICATION FROM FNIRS DATA USING DEEP LEARNING

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ABSTRACT: This paper discusses the potential of functional near-infrared spectroscopy (fNIRS) brain-computer interfaces (BCIs) to identify an individual using only her brain data. fNIRS is a lightweight, portable, non-invasive functional neuroimaging tool that uses light to capture hemodynamic responses in the brain. We show that among 30 subjects, it is possible to determine the subject from whom a segment of the fNIRS data originated with 63% accuracy. Random chance is 3.3% for 30 subjects. Additionally, we explore the effect of the fNIRS brain data window size used during feature construction, on the classification accuracy.

INTRODUCTION

FNIRS has become more prevalent as a brain measurement tool, resilient to noise and artifacts [1,2]. Deep learning has been used to classify data obtained using fNIRS [3,4]. fNIRS has also been used for user identification (picking a specific individual out of a group) [5] and authentication (a binary, “yes” or “no” classification) [6] with SVM and Naive Bayes classifiers. This study uses fNIRS brain data obtained during resting state from a larger group than previously investigated [5] to perform user identification via deep learning.

MATERIALS AND METHODS

The data was obtained from 30 subjects during a study investigating mental workload during long supervisory control tasks [7]. The first 30 minutes (22200 measurements) were used, while the subjects were in a resting state. An ISS, Inc., Imagent device with wavelengths of 690 and 830 nm was used. Each of its two probes, had four linearly spaced light sources, and one detector, with source-detector distances between 2.5 and 3.5 cm. The raw data was processed using Homer 2 [8]. Only data obtained through the two longest channels was used, as it is less noisy. A high-pass filter was applied at 0.5 Hz. Features were constructed over a set time window. The average, maximum, minimum, slope, and standard deviation were calculated for each window, for each channel, for each of the measures oxy-hemoglobin (HbO), deoxy-hemoglobin (HbR), their sum, and their difference---resulting in a total of 40 features. The dataset was classified using a Multilayer Perceptron with 10 hidden layers, each with 200 nodes. The model was trained over the collection of the first 70% of the data for each subject, and tested on the last 29% of the data, removing the middle 1%. Each feature was z-score normalized before classification. This procedure was repeated for varied time windows, to explore the accuracy during each condition. As all the measurements were performed over the same time period, the number of instances per class depends upon the window size for each condition. To minimize the impact of fewer training instances, we modulated the epoch count (training iterations) to keep the total number of training instances constant over all tests (so, conditions with more windows were trained with more iterations of the same samples). Accuracy is calculated as the mean of accuracies of the last 25% training epochs for each condition.

RESULTS

Table 1 shows testing accuracies for each window size. The maximum accuracy achieved under this configuration was 63%, for window size of 1 second, closely followed by 61% accuracy with window size of 3 seconds. As random chance is 3.3%, this is a significant result.

Table 1: Accuracy of classification for each feature calculated over the specified time window, the number of instances per class before splitting into testing and training sets, the number of epochs used, and the standard deviation of the averaged accuracies.

	1 sec	**3 sec**	**9 sec**	**15 sec**	**24 sec**	**30 sec**	**60 sec**	**90 sec**
Unique Instances /Class	1800	600	200	120	75	60	30	20
Epochs	67	200	600	1000	1600	2000	4000	6000
Accuracy	63%	61%	57%	55%	47%	51%	45%	47%
Std. Dev	0.011	0.027	0.013	0.009	0.006	0.003	0.004	0.001

DISCUSSION

These results suggest that there may be a specific brain signature unique to each individual even during a resting state, which could have implications regarding our understanding of the brain, and the systems that can be built using this information. One limitation of the study is that both testing and training data were collected during one sitting for each subject, with sensor placement potentially affecting the classification, despite z-score standardization. Further studies should be done to support and extend these results, examining the aforementioned limitation.

CONCLUSION

We have shown that fNIRS has the potential to identify an individual, suggesting its potential for use in biometrics and active authentication. However, it is important to investigate the privacy threats of mining brain data, and to develop policies to prevent their misuse.

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ENHANCING BCI PERFORMANCE THROUGH COLLABORATION OF EYE GAZE AND SSVEP

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ABSTRACT: A *hybrid* BCI (*h*BCI) based on SSVEP and eye tracking enhanced interaction performance in terms of Accuracy (Acc.), Efficiency (Eff.) and Information Transfer Rate (ITR) in 29 of 30 participants, when compared to SSVEP alone. Decisions were based on collaborative processing. The SSVEP component was used for selection, reinforcing the eye gaze and solving the 'Midas touch' problem associated with eye gaze alone. The overall arithmetic mean Acc., Eff., and ITR for 29 participants completing the four (4-way navigation) tasks was 99.84% (±0.77%), 99.74% (±1.23%) and 24.41 (±6.35) bits/min, respectively. Review of the data shows that adaption of the decision process is possible; this would increase ITR and hence usability of the technology and provide further insight into the decision-making process.

INTRODUCTION

BCI paradigms such as imagined movement, P300 and Steady State Visual Evoked Potential (SSVEP) have been used successfully in *h*BCIs. This work investigated an *h*BCI that combined SSVEP with eye tracking [1, 2, 3]. Eye tracking provides efficient and reliable screen navigation. BCI paradigms lend themselves to the 'selection' component for reinforcement [4, 5].

MATERALS AND METHODS

The hybrid system comprised SSVEP BCI using on-screen low frequency stimuli and the EyeTribe eye tracker. Thirty healthy volunteers (16M, 14F), from 21-73 years, average 37.6 (±14.73) years participated. Participants completed four tasks, controlling an interface to traverse a hierarchal-menu structure and activate functions of a domestic smart-home environment, similar to the approach adopted by Kosmyna *et al.* in [6]. Participants were required to follow verbal instructions to navigate the menu structure and execute 4-way control: left, right, up, and down commands. The first task required participants to interact with smart-home lighting in the dining room of the virtual environment. The second required participants to select a target video for playback on the television and subsequently end playback when requested. In the third task users were required to navigate to the 'talk' menu and communicate using predefined iconography and computer-synthesised speech to indicate 'hunger'. The fourth task required users to freely navigate the interface (without instruction) to complete a goal;in this case to control the extractor fan in the kitchen. SSVEP Signal processing and feature extraction adopted algorithms proposed in [7]

RESULTS

For participants using SSVEP-only Acc. were observed in the range [65%-100%], and Eff. in the range [41%-100%]. The mean Acc., Eff., and ITR over all four tasks was 93.49% (±7.32%), 89.71% (±12.30%), and 23.18 bits/min (±6.83), respectively. Comparatively, *h*BCI, Acc. were observed in the range [94%-100%] and Eff. in the range [89%-100%]. The overall arithmetic mean Acc., Eff., and ITR for all participants completing the four tasks was 99.84% (±0.77%), 99.74% (± 1.23%) and 24.41 (± 6.35) bits/min, respectively.

DISCUSSION

The results show higher levels of Acc. and Eff. for the *h*BCI. However, it was evident that through offline data analyses that decisions could have been made earlier, Fig. 1, if the decision criteria could have been adapted to the performance of the eye tracker and BCI. This would increase the ITR and robustness, thereby reducing the possibility for user fatigue and frustration. In addition, this work has shown that Acc. and Eff. can be improved beyond standard dwell-time based eye tracking alone, which in previous work achieved a mean Acc. of 90.61% (± 4.96%), Eff. of 84.55% (± 8.33%), and ITR of 39.42 (± 5.45) bits/min for 20 participants completing the same tasks.

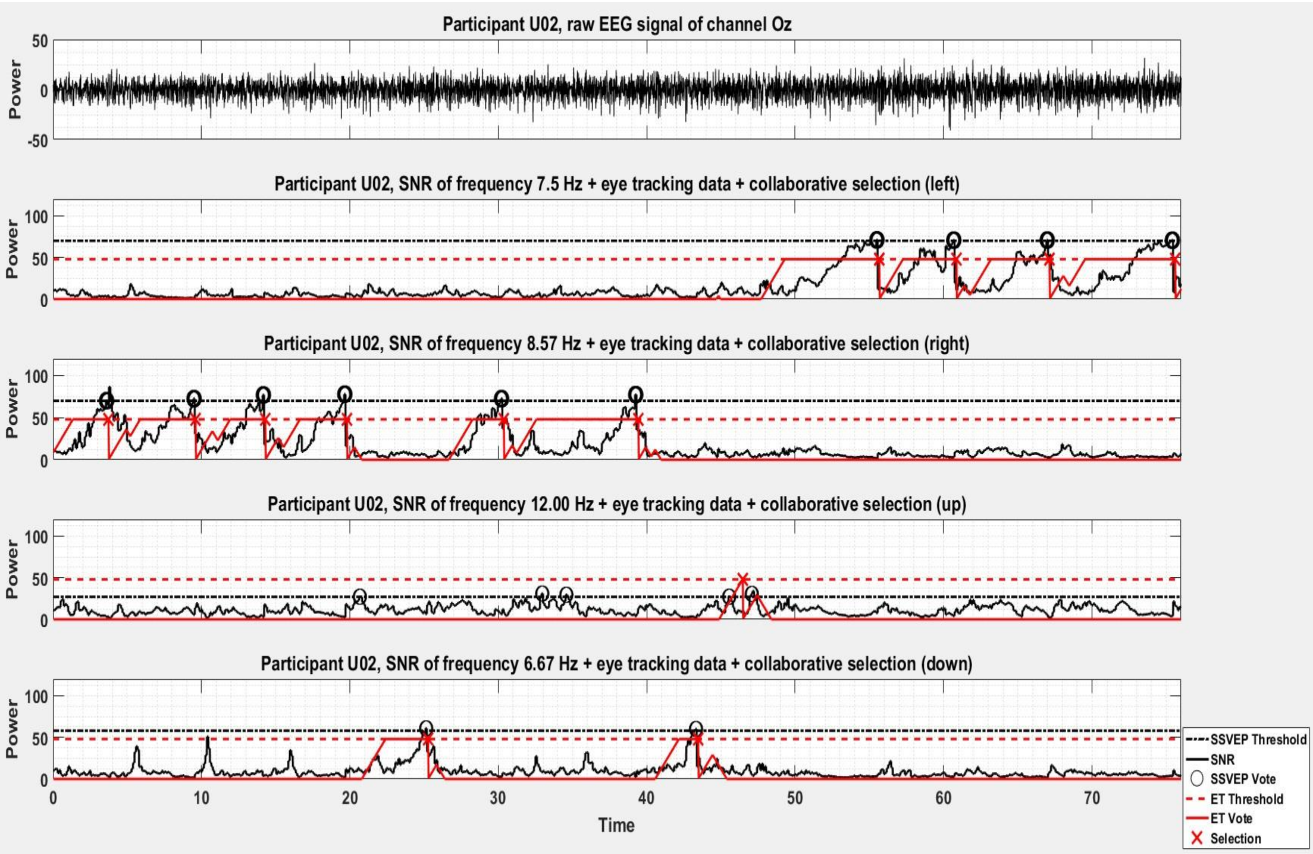

Fig. 1. SSVEP, eye tracking and collaborative decisions for a representative particpant.

CONCLUSION

The *h*BCI performance exceeded the SSVEP-BCI across the performance metrics, returning higher Acc., Eff. and information throughput. It can offer more robust communication, without decreasing the ITR. However, adaptive processing could further enhance performance.REFERENCES

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Session Name: PI-15

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Day: 1

LABELLING OF MOVEMENT ONSETS BASED ON EXOSKELETON JOINT DATA

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ABSTRACT: Real-time analysis of neurophysiological measures for system control or adaptation by means of supervised machine learning methods requires training data that is labelled for specific events. Event labelling is often not automatized and most experiments are bound to a static laboratory setup. However, for example embedded Brain Reading (eBR) for real-world settings requires automated event generation for training and online adaptation of close-loop systems. Here we investigate label generation by means of exoskeleton joint data.

INTRODUCTION

To embed neurophysiological measures such as the human electroencephalogram (EEG) directly into the control of a system, eBR [1] was developed. It requires automated labelling of neurophysiological data. Different data can be used for movement onset detection such as the electromyogram (EMG) [2], motion-tracking systems (MTS), e.g., the Qualisys system [3], or data from external devices (see [4] for a comparison of different sources). What source should be chosen depends on the setup and the goals of the approach. For example, EMG can be used for training and online adaptation of the classification algorithm [5]. However, by means of EMG not all movements might be detected [6]. Thus, to use other or additional sources is reasonable. MTS are often used for movement onset labelling but are stationary and often inapplicable for real-world setups. In this work, we investigate movement onset labelling based on exoskeleton joint data. Results are preliminary since the exoskeleton was designed for teleoperation without a grasping option. Currently an exoskeleton for rehabilitation purposes is built.

MATERALS AND METHODS

We conducted a study with 4 subjects performing movements with both arms wearing an upper body exoskeleton. We recorded the angles of all 18 joints, 32 channels EEG and the 3D-positions of the arms' joints with an MTS, i.e., Qualisys systems with 6 cameras. Passive infrared markers were attached to the subject's wrist to detect movement onsets based on a MTS. For the exoskeleton the forward kinematic was used to derive the hand position in space. For both data sources the movement speed of both hands was calculated as the Euclidean distance between to consecutive samples. For pre-processing we used a mean filter and a variance based filter, for enhancing fast changes in the signals, both filters had a window size of 1s. After normalizing the speeds to values between 0 and 1 a threshold of 0.15 was used to detect rough onsets. From the found onsets the speed was analysed backwards, the first point at which a positive slope was detected was defined as the real onset. Further a minimum resting of 1s was used, i.e., the signals must stay below 0.15 for 1s before a new onset can be detected. For comparison between the two systems, we performed a one-way ANOVA with system as within-subjects factors.

RESULTS

Analysis of exoskeleton data resulted in later onset detection compared to the MTS across subjects [$F_{1, 336}=54.58$, $p < 0.001$, difference between two systems across all subjects: 0.21s].

DISCUSSION

In applications for motor rehabilitation that make use of an exoskeleton, movement onsets can be detected based on the systems' joint data. The delay can be explained by the loose connection of the subject's lower arm to the exoskeleton. We could not use the hand interface, since it does not allow grasping tasks. Therefore, the hand could be moved to some extent without moving the exoskeleton (see Figure1) resulting in an earlier detection with the MTS.

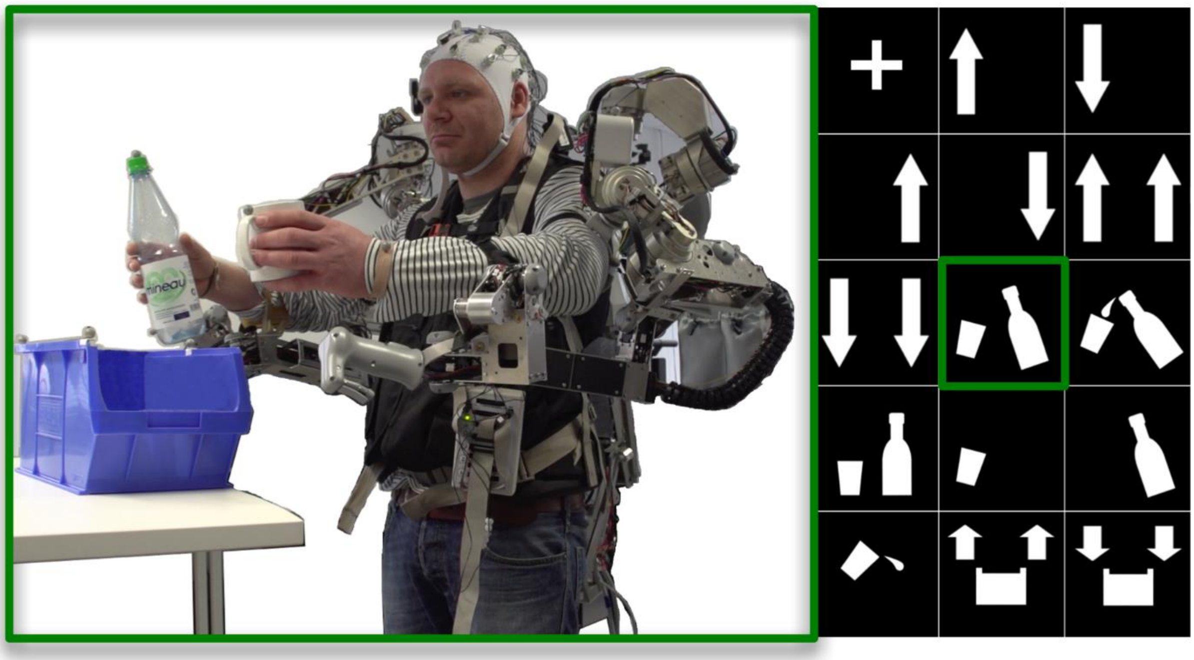

Figure 1: Experimental Scenario. Subjects wearing an exoskeleton performed various movements with both arms. In total 15 symbols (right) instructed subjects which movement to perform next. Symbols were displayed on a monitor approximately one meter in front of the subject. From top left to bottom right symbols meant: relax, lift left arm, lower left arm, lift right arm, lower right arm, lift both arms, lower both arms, grab cup and bottle, pour into cup, put down cup and bottle, grab cup, grab bottle, drink, grab box, put down box. The subject (left) is shown while performing the green-framed movement (grab cup and bottle). Trials without object manipulation lasted 7 seconds and all others 10 seconds, movements were performed by the subjects' own speed.

CONCLUSION

Our method for exoskeleton-based movement onset detection is online capable since the forward kinematic can be calculated from the exoskeleton joint data in real time. It can be used in embedded approaches such as eBR. Similar to EMG data labels can be used to adapt a classifier online or used in a multimodal labelling approaches to achieve more reliable results.

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Session Name: PI-16

Room: R1
Session: Poster Session
Time slot: 17:30 – 20:00
Day: 1

INVESTIGATING METRICS FOR MEASURING AND REMINDING MINDFULNESS OF SCHOOL STUDENTS

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ABSTRACT: Mindfulness has been introduced in schools, e.g., in the USA (http://www.mindfulschools.org/), in UK (https://www.mindfulnessfoundation.org.uk/, http://www.dharmaschool.co.uk/mindfulness-in-education/) in recent years. School students have been trained to be mindful. The effect of mindfulness has been confirmed that it helps among others the concentration of school students and their calmness. What kind of data can be used to model mindfulness states? How can wearable technologies be deployed to give students feedback about their (un-)mindful state? In this paper, we review a range of possible metrics for mindfulness.

INTRODUCTION

Mindfulness has been introduced in schools (e.g., in the USA, in UK[1]) in recent years. School students have been trained to be mindful. The effect of mindfulness has been demonstrated that it helps among other effects the concentration of school students and their calmness. It is therefore useful to remind a student when he/she is in an unmindful state, which may correlate with negative learning outcome. One possible solution for such a situation is that a technological device might control the mindful state of the student and give him/her feedback as a means of reminding. How can mindfulness be determined? Most instruments are based on self-report of mindfulness practitioners, e.g.: The Five Facet Mindfulness Questionnaire (FFMQ) (Baer [1], Van Dam [8]), Mindful Attention and Awareness Scale (Hansen [3], Van Dam [9]), Toronto Mindfulness Scale (TMS) (Davis [2]), The 30- item Freiburg Mindfulness Inventory ([5]). Instead of measuring mindfulness of practitioners by self- reporting, this project focuses on deploying wearable technology to measure mindfulness and to give students feedback. In this paper, we review possible metrics for this purpose.

RESULTS

Electroencephalography (EEG) has been used to measure mindful states in many studies. Lomas and colleagues have reviewed databases of EEG studies from 1996 to 2015 [7]. The authors reported that with a database of 1715 subjects “mindfulness was most commonly associated with enhanced alpha and theta power as compared to an eyes closed resting state” and “no consistent patterns were observed with respect to beta, delta and gamma bandwidths”. This review has not differentiated the population of test persons. Thus, no conclusion about the specific population of school students could be made. Beside EEG, another type of data, e.g., Electrocardiography (ECG) (including Pulse Arrival Time, Heart Rate, Heart Rate Variability (a psychophysiological marker of mental and physical health)) could be relevant for measuring mindfulness. Krygier and colleagues [6] reported that

mindfulness practice increased normalized high-frequency Heart Rate Variability. These types of data can be collected using wearable devices, e.g., a simband (https://www.simband.io/). Howells et al.
[4] used higher heart rate variability high frequency (HRV-HF) as an indicator to measure mindfulness: 12 bipolar patients showed a reduction of heart rate variability high frequency (in addition to other indicators) after attending 8 weeks of a mindfulness retreat.

CONCLUSION

In order to measure mindfulness of school students, in addition to collecting EEG data using a head cap, ECG data can be deployed. These types of data can be collected using wearable technologies such as smartwatch (e.g., simband). The principle investigator plans to conduct this project as following: 1) collecting data (EEG and/or ECG) of expert mindfulness practitioners and developing a computational model, 2) developing a real-time computational model of mindfulness for students,
3) developing a strategy for reminding students in case their mindfulness state is below threshold.

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