COGNITIVE NEUROSCIENCE

Space-Time-Frequency Features and the Convolutional-LSTM Neural Network for Classifying EEG Signals in an Eye-Brain-Computer Interface

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Brain-computer interfaces (BCI) provide means for communication and for controlling computer-based applications using only brain signals. A subtype of such systems, the Eye-Brain-Computer Interfaces (EBCIs), applies the BCI technology to distinguish between spontaneous eye movements and eye movements intentionally used for control. It was recently revealed that in the presence of intention an EEG negativity is developed along a gaze fixation, presumably due to feedback expectation. Thus, classification based on EEG amplitude features, e.g. using the Linear Discriminate Analysis classifier with shrinkage regularization (sLDA), can be applied to create an EBCI [1]. EBCIs might become useful for healthy users and for paralyzed individuals with preserved gaze control because of the high information transfer rate of gaze-based interaction, but only if their brain signal classifier will become able to accurately differentiate intentional and spontaneous gaze behavior based on short (e.g., 300-500 ms) single-trial signal intervals.

Here we report using space-time-frequency features (frequency components as a function of time and electrode coordinates) from experiments with the EBCI paradigm to train a neural network (NN) that combines convolutional and Long Short-Term Memory (LSTM) layers. Such NNs recently were found suitable for solving certain EEG classification tasks not related to EBCIs [2, 3, 4].

The 19-channel EEG data for training NN were collected from 13 healthy participants who played a computer game EyeLines with their eye movements only [1]. A standard generalized accuracy measure, ROC AUC, for the sLDA applied to the amplitude features extracted from these data was 0.67±0.07 (M±SD). The convolutional-LSTM NN applied to the space-time-frequency features from the same data demonstrated higher average ROC AUC, 0.72±0.03. However, this improvement was not significant, according to Wilcoxon matched pairs test ($p=0.1$).

Thus, we have demonstrated that the space-time-frequency features, even taken without the amplitude features, can also be used for classification of intentional vs. spontaneous fixations with convolutional-LSTM classifier. There is still a room for methodology development and we will attempt to improve EBCI classifier quality in future studies.

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OM&P

Role of Oscillations in Controling Working Memory

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Working memory (WM) is a primary cognitive function that corresponds to the ability to update, stably maintain, and manipulate short-term memory (STM) rapidly to perform ongoing cognitive tasks. A prevalent neural substrate of WM coding is persistent neural activity, the property of neu¬rons to remain active after having been activated by a transient sensory stimulus. This persistent activity allows for online maintenance of memory as well as its active manipulation necessary for task performance. WM is tightly capacity limited. Therefore, selective gating of sensory and inter¬nally generated information is crucial for WM function. While the exact neural substrate of selective gating remains unclear, increasing evidence suggests that it might be controlled by modulating ongoing oscillatory brain activity.

Here, we will present experiments and models that link selective gating, persistent activity, and brain oscillations, putting them in the more general mechanistic context of WM. We do so by defining several operations necessary for successful WM function, namely the loading, maintaining, protecting and clearing of items in WM. We then discuss how such operations may be carried out by mechanisms suggested by computa¬tional models. Specifically we show that the different operations can be subserved by different frequency content of the incoming oscillatory signals, with lower frequencies favoring clearance and gating while higher frequencies favoring activation.

We specifically show how oscillatory mechanisms may provide a rapid and flexible active gating mechanism for WM operations and suggest an experimental paradigm to test predicted consequences of the models.

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Action in Auctions: Neural and Computational Learning Mechanisms of Repeated Bidding

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Bidding is a pivotal socioeconomic process underlying consumer behavior dynamics. Yet how humans learn to bid efficiently in complex markets remains an open question. We used model-based neuroimaging to investigate the neural mechanisms of bidding behavior. Twenty-seven subjects (nine male) played a prototypical bidding game: a double action, with three market types, which differed in levels of supply and demand. We compared different computational learning models of bidding: directional learning models (DL), where the model bid is "nudged" depending on whether it was accepted or rejected, along with standard reinforcement learning models (RL). We found that DL fit the behavior best and resulted in higher payoffs. We found the binary learning signal associated with DL to be represented by neural activity in the striatum distinctly posterior to a weaker reward prediction error signal. We posited that DL is an efficient heuristic for valuation when the action (bid) space is continuous. Indeed, we found that the posterior parietal cortex represents the continuous action-space of the task, and the frontopolar prefrontal cortex distinguishes among conditions of social competition. These findings provide a conceptual model that accounts for a sequence of processes that are required to perform successful and flexible bidding: (a) market competition type recognition, (b) bid choice informed by the game structure, and (c) feedback-driven learning by means of a DL algorithm. Our results suggest that an efficient DL heuristic underlies price adjustments during repeated bidding.

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Neural Decoding: Accounting for Overt Behaviors, Plasticity and Information Transfer Rate

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We have seen a remarkable progress in brain-computer interfaces (BCIs), particularly BCIs that decode multiple behavioral variables simultaneously and bidirectional BCIs that enable artificial sensory feedback. Yet, many issues remain unexplored. One such issue is the involvement of overt behaviors (i.e. voluntary movements of body parts) in BCI operations. For example, BCIs for whole-body navigation are currently being developed. To this end, many studies have demonstrated decoding of position from the activity of hippocampal formation that, according to the prevailing theory, represents cognitive spatial maps. However, overt behaviors also contribute to hippocampal responses. Similar confounds exist for the problem of assessing plasticity during BCI control: neuronal tuning properties enforced by a BCI decoder are often taken as evidence of cortical plasticity; such an argument easily gets circular. Finally, one should be careful when measuring information transfer rate of a BCI. Solving these issues will help us to develop better BCIs in the future.

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Integration of Rewards and Beliefs in Human Decision-Making

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In uncertain and changing environments, optimal decision-making requires integrating reward expectations with probabilistic beliefs about reward contingencies. In this talk, I will address how the prefrontal cortex (PFC) subserving decision-making combines these quantities. Using computational modelling and neuroimaging, we will show that the ventromedial PFC encodes both reward expectations and proper beliefs about reward contingencies, while the dorsomedial PFC combines these quantities and guides choices at variance with the optimal decision theory: instead of integrating reward expectations with beliefs, the dorsomedial PFC built context-dependent reward expectations commensurable to beliefs and used these quantities as two concurrent appetitive components driving choices. This neural mechanism accounts for well-known risk aversion effects in human decision-making. These results reveal that the irrationality of human choices commonly theorized as deriving from optimal computations over false beliefs actually stems from suboptimal neural heuristics over rational beliefs.

OM&P

Classifying Short EEG Epochs with a Compact Convolutional Neural Network

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Non-invasive brain-computer interfaces (BCIs) suffers from low accuracy of their mental state classifiers. Recently, attempts to increase the accuracy with deep learning approaches has become popular, but difficulty to collect sufficient amount data to train such classifiers in real application conditions undermines the power of such approaches. The problem of classification accuracy is especially important for the eye-brain-computer interfaces (EBCIs) which control computer applications using brain signal and eye movements [1]. An EBCI distinguishes intentional gaze fixations on control keys in a graphic user interface from spontaneous gaze fixations, thus it is potentially a strong enhancer for the traditional gaze interaction systems. However, an EBCI classifier should be able to make its decisions using very short (<< 1 s) intervals of single-trial electroencephalogram (EEG), which make the problem especially challenging. In this study, we addressed it with two approaches: (1) adapting a recently proposed powerful compact convolutional neural network (CNN) architecture [3] to the EBCI data, (2) designing a new transfer learning method aimed on the use of data from different users for reducing time required to obtain data for classifier training.

We used 19 channel EEG data previously recorded in our lab from 13 healthy participants during gaze fixations used for control (these fixations triggered a response of a gaze interaction system when their duration reached a 500 ms threshold) and during spontaneous gaze fixations (also 500 ms or longer) (experiment design and feature extraction procedure generally followed [1]). The portion of the "controlling" fixations varied among the participants from 0.49 to 0.84. EEG features were extracted from 200-500 ms interval relative to the gaze fixation onset (the earlier portion of signal was excluded to prevent the influence of eye movement artifacts and irrelevant fixation-related EEG activity).

CNN are advanced machine learning algorithms that allows to extract local, low-level features from the raw input and then increasingly more global and high-level features in deeper layers [2]. In this work a compact CNN architecture described in [3] was used. Its hyperparameters was tuned using binary cross-entropy as the loss function. We achieved a statistically significant improvement for the ROC AUC metric of the classification performance compared to the algorithm previously used in [1] (the linear discriminant analysis with shrinkage regularization, sLDA): M±SD was 0.67±0.07 for the sLDA and 0.75±0.06 for the compact CNN, $p = 0.0018$ (Wilcoxon matched pairs test). Thus, this architecture of the neural network classifier appears promising for further use in the EBCI instead of the sLDA.

In the second stage of the study we first found that the compact CNN classifier demonstrates acceptable performance when trained on one participant and applied to several other participants. A special procedure was designed to find such "neighboring" subjects. For 5 participants in our dataset "training neighbors" were identified allowing to obtain acceptable performance without any additional training on these participants (ROC AUC was in the range 0.65 to 0.71). In future, we plan to use larger datasets as a mean to increase the probability to find even better "training neighbors". We will also try to combine this approach with classifier training on the same data from the test participant that were used to search for the "neighbors", which may lead to higher classifier performance.

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Transcranial Oscillatory potentials of the Human Motor System

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Transcranial Alternating Current Stimulation (tACS) is an emerging technique which allows to modulate endogenous oscillatory activity of a target cortical brain region located under the stimulating electrode in a frequency and state-dependent fashion. Although the exact action mechanisms are still under debate, tACS has been shown to induce the so-called "entrainment-like" phenomenon likewise to increase the oscillatory power of a selected brain region and/or network of regions thereby to enhance both physiological and behavioral indexes. Here we will review studies that adopted tACS to investigate physiological and behavioral effects on the sensorimotor system spanning from resting state, motor imagery to the up-to-date effects of tACS on the motor mirror neurons system which is the logical continuation of a research topic which follows a series of two previously published papers (Feurra et al., 2011; Feurra et al., 2013).In a first pioneering study we investigated the effects of Transcranial Alternating Current Stimulation (tACS) on the primary motor cortex (M1) by showing that external oscillatory frequency delivered through the scalp induce frequency-specific enhancement of the corticospinal output (Feurra et al., 2011) which led us to question whether specific external frequency may interact with endogenous oscillatory activity, the so-called "entrainment" phenomenon (Thut and Miniussi, 2009). In a second study, still on the M1 and still by keeping the same setup, we showed that tACS induces not only frequency-specific effects but also state-dependent effects. Specifically, whereas stimulation in beta frequency induced modulation of the corticospinal output at rest, during a motor imagery task theta and alpha stimulation induced enhancement effects while beta stimulation was ineffective (Feurra et al., 2013), thereby a state-dependent effect through tACS. Finally, we investigated tACS state-dependent effects of the M1 during an action observation pinch-grip task which reflect the so-called "mirror neurons effect" (Rizzolatti and Craighero, 2004), thereby testing if action observation might be modulated in a state-dependent effect likewise motor imagery (Feurra et al., 2013). This contributed to disentangle differences between motor imagery and action observation processes inside the sensorimotor system too, an issue which is currently very much debated (Eaves et al., 2016; Fadiga et al., 2005; Munzert et al., 2009). On the one side, we replicated effects of "beta" (20Hz) tACS at rest by showing robust increase of the corticospinal output detected from both the FDI and ADM muscles. On the other side, we showed not only frequency- and state- dependent effects of M1-tACS, but also muscle-specific effects: "alpha" (10Hz) tACS robustly increased the corticospinal output, an effect detected only on the FDI muscle whereas "gamma" (40Hz) tACS induced a similar effect through both the FDI and ADM muscles. We believe that these findings, together with the possibility to interact with brain activity trough different frequency of stimulation accordingly to the brain state (Silvanto et al., 2007; Silvanto and Pascual-Leone, 2008), represent a robust conceptual advance for the actual neuroenhancement topic, thus very relevant for the scientific community. tACS effects are state-dependent and this technique represents an optimal tool to investigate perceptual, motor and cognitive processes with potential outcome in clinical applications.

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Electrophysiological Activity of the Cerebral Cortex in Children with Arthrogryposis

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Arthrogryposis is one of the most serious congenital malformations of the musculoskeletal system, characterized by the presence of two or more major joint contractures, muscle damage, and motoneuronal dysfunctional in anterior horns of the spinal cord. One of the main problems that determine the limitation or impossibility of self-care of patients is the lack of active movements in the joints of the upper limbs, which is restored by autotransplantation of the muscles of various donor areas.

Rehabilitation processes after such operations are connected, including with neuronal rearrangements in the central nervous system (CNS), both in the spinal and in the brain, in particular in its cortical areas. In this work, the electrophysiological indices of the activity of the cerebral cortex in children diagnosed with arthrogryposis and in healthy children of similar age were studied. The parameters of the electroencephalogram (EEG), such as power and long-time correlations (a method for estimating the dynamics of neuronal activity) in the ranges 4-8, 8-12, and 12-16 Hz were evaluated. The analysis of the data showed that in children with arthrogryposis, in comparison with children without pathologies, there is a significant decrease in EEG power in all the studied ranges. In addition, a significant correlation between EEG power and the degree of recovery of motor functions of the upper limbs after the operations of autotransplantation of various muscle groups to the position of the biceps arm muscle was demonstrated. The results reflect the relationship of the electrophysiological parameters of the cerebral cortex and the processes associated with the pathology of arthrogryposis. Neurodynamic parameters in children with arthrogryposis do not differ from those in healthy children.

Neuroscience and Social Science: the Growing Link

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Recently, social neuroscience, which investigates interactions among people, has been developed into a multidisciplinary field by combining brain-imaging methods with social research methodologies. Currently social neuroscience is the growing interdisciplinary field devoted to the study of neural, hormonal, and genetic mechanisms of social interactions. Here I will discuss neuroimaging studies of social conformity. Defined as a tendency to align one's attitudes, beliefs and behaviors to match group norms, social conformity is a well-documented phenomenon in psychology. Yet, neuroscience research has only recently focused on the neurobiological mechanisms underlying conformity to group norms. A number of functional magnetic resonance imaging (fMRI) studies demonstrated that being exposed to a group opinion conflicting with one's own opinion triggered activity in the medial prefrontal cortex (MPFC) and ventral striatum. Interestingly, the MPFC has been also implicated in the generation of a so-called "reward prediction error" signal when the outcome of an action differs from the expected one. This signal presumably guides future action selection by updating predictions of action values. These findings suggest that social behavior may be based on general action-monitoring and reinforcement-learning mechanisms.

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Consciousness and Volition as Obstacles and as Goals in Human-Machine Interaction

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Brain-computer interfacing is often believed to be a mean for the augmentation of brain function. A well-known technology entrepreneur Elon Musk even proposed recently to save humans from enslaving by machines by closely connecting human brains and computers using advanced brain-computer interfaces (BCIs) (CNBC, 2017). However, due to the elusive nature of intentions (Uithol et al., 2014) and non-deterministic nature of BCIs it is often unclear who is responsible for an action, a human or an artificial intellectual system supposed to implement human's intentions (Haselager, 2013). This problem appears even under slow interaction rates (Haselager, 2013). With an increase of interaction speed required for pronounced augmentation, most of the system's actions would be responses to pre-conscious phenomena, such as early physiological phenomena of intention formation: but how can we be sure that a BCI has indeed recognized such an early, hidden intention and not just made a recognition error?

Moreover, conscious control of artificial system's interpretation of human's intentions is limited by the inherent limitations of consciousness, such as working memory capacity. Finally, multiple and even conflicting wishes or urges can correspond to a single possible action, and it is not possible to determine the will of a person until an intention is formed, as only intentions can be mapped one-to-one to planned actions (Razeev, 2017).

Thus, limitations of consciousness and volition pose serious obstacles for BCI-based brain augmentation. On the other hand, it might be interesting to consider both consciousness and volition as a goal for brain augmentation based on optimization of human-machine interaction. One possible approach to unveiling their potential could be reducing the load of routine tasks which may claim some of their resources. A promising variant of this approach is the development of highly responsive (Jacob, 1991) or even "noncommand" (Nielsen, 1993; Jacob, 1993) interfaces. Such interfaces can be built based on gaze interaction technologies, under condition of solving the "Midas touch problem", the inability of such technology to differentiate intended and spontaneous eye movements, which leads to frequent false activations of an interface by the spontaneous gaze behavior; this problem is the more severe the more responsive is an interface (Jacob, 1991). This problem might be defeated with passive brain-computer interfaces (Zander, Kothe, 2011), e.g. by on-fly classification of gaze dwells into command-related and spontaneous ones (Protzak et al., 2013; Shishkin et al., 2016). However, due to involvement of a passive interface, the problem of conscious control remains crucial even in this case.

Although practically useful solutions are yet to be found, human-machine systems that includes BCI and gaze based noncommand interaction already provides promising instrumentation for experimental studies of conscious and unconscious processes in emerging human-machine systems. This can be illustrated with our experience from online experiments with expectation-based hybrid eye-brain-computer interfaces (EBCIs; Nuzhdin et al., 2017), single-trial P300 BCI (Ganin et al., 2013), eye-gaze based interaction (Velichkovsky, 1995; Isachenko et al., 2018) and ultrafast passive-active movements made with the assistance of special experimental exoskeletons (Dubynin, Shishkin, 2017; Dubynin et al., in prep.), and also the results of other groups' online studies of unconscious brain signal conditioning (Kaplan et al., 2005; Ramot et al., 2016) and vetoing of action (Schultze-Kraft et al., 2016). This experience suggests that human-machine systems that includes BCI and gaze based noncommand interaction provides promising instrumentation for experimental studies of conscious and unconscious processes in emerging human-machine systems.

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EEG Potentials Related to Moving Object Selection with Gaze: a Possible Basis for More Flexible Eye-Brain-Computer Interfaces

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Control of computers with eye gaze is increasingly used in assistive systems for paralyzed people and even in some applications for healthy users. However, spontaneous gaze behavior in many cases is not different from the intentional attempts to send a command to a computer, and false system triggering frequently occurs. An electroencephalogram (EEG) marker that may help to discriminate spontaneous and intentional gaze dwells was recently described (Shishkin et al., 2016). In certain applications, especially in video games, the targets to be selected are often moving. In this preliminary study we checked if we can find the same or different marker(s) of intentional action in the case of moving object selection.

Smooth pursuit eye movements can be used when a user needs to select a moving object. In our recent study (Isachenko et al., submitted) participants selected moving objects with gaze faster and judged this interaction mode as more convenient compared to selection using a computer mouse. The EEG related to gaze pursuit used for selection have never been studied, so the current pilot study was designed to obtain preliminary data related to marker(s) of intention in gaze pursuit.

As in (Isachenko et al., submitted), the participant's "selection" task was to select, one by one, balls with numbers 1 to 15. Each ball was 2.8° in diameter and moved on the screen with 12°/s speed. A ball was "selected" (highlighted) when median of distances between its center and gaze position computed in 866 ms window fell below a threshold. The following task was designed to provoke spontaneous pursuit: a participant was presented with the same numbered moving balls but asked to find a slightly faster (by 2.2°/s) ball among them. The same selection algorithm was applied but no highlighting occurred.

A pilot experiment with alternating selection and spontaneous pursuit tasks was conducted in 5 participants. Averaging of pursuit-related EEG was triggered using a sensor activated when a selected ball was highlighted. A number of components were visible in the averaged waveforms (Fig. 1): a positive peak in the posterior EEG about -450 ms relative to selection, in both conditions and in all participants (likely an analogue of lambda wave, a well-known component of fixation-related potentials; note that due to the use of median-based index, selection was ~ 430 ms + system delay of ~ 140 ms = about -570 ms relative to selection corresponded to the pursuit start); a later and slower positive peak seen in the selection condition in all but one participants (possibly a P300 wave); a negative deflection in all participants' parietal EEG developed closely to selection, always most pronounced in the selection condition but also present in the spontaneous pursuit in some participants (likely an analogue of the marker of gaze fixations used for selection); a complex of ERP waves developed soon after selection. The presence of a sharp lambda peak indicates that the selection was well time-locked to the pursuit start, a condition beneficious for expectation; the presence of the P300 might show that the task could not be considered as free from visual search (unlike the task in Shishkin et al., 2016).

ROC AUC index for an LDA classifier with shrinkage regularization applied to amplitudes from a 100 ms interval just before the selection, with baseline -200..-100 ms (i.e., where the P300 could not contribute and only intention-related marker was employed), using 6 EEG channels where the marker was most pronounced, was 0.72 for one participant (with a rather specific pattern in spontaneous pursuit) and between 0.52 and 0.58. Thus, these first classification results were much below any practically useful level. However, the presence of a substantial EEG negativity similar to one described previously for fixations used for control implies that ways can be found to significantly enhance classification performance, e.g., cleaning from EOG artifacts and/or designing a more intention-free reference condition.

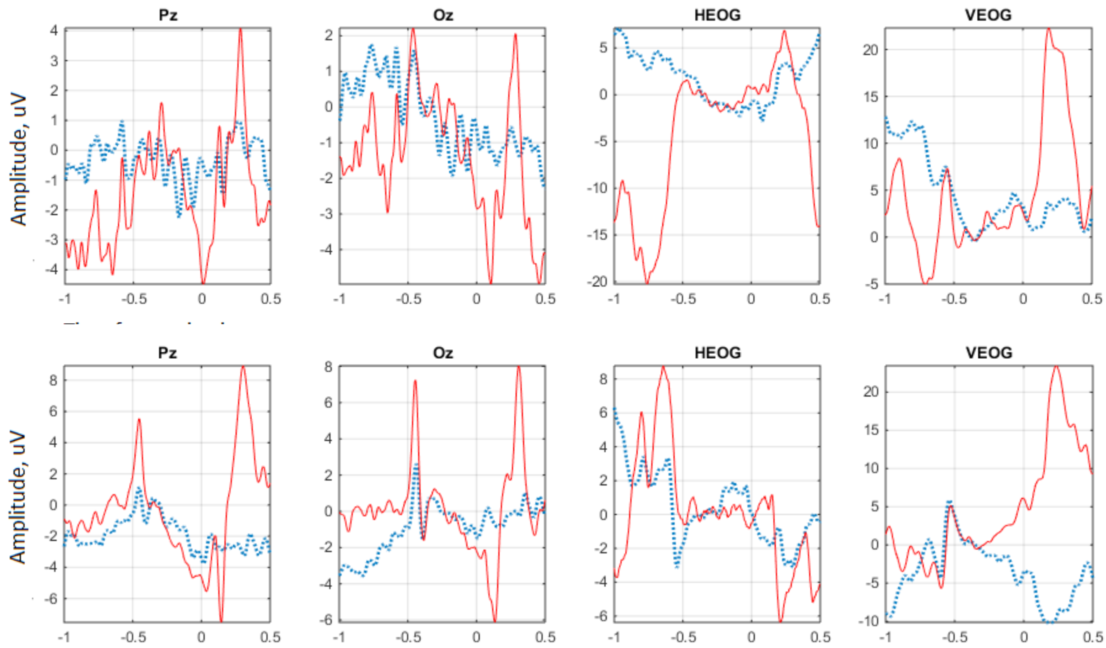

Fig. 1. *Examples of the EEG (Pz, Oz) and EOG waveforms in the intentional (red, solid) and spontaneous (blue, dotted) conditions. Participants 4 (upper plots) and 5 (lower plots).*

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