Master classes of the tenth international brain-computer interface meeting: showcasing the research of BCI trainees

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Abstract

The Tenth International Brain-Computer Interface (BCI) Meeting was held June 6-9, 2023, in the Sonian Forest in Brussels, Belgium. At that meeting, 21 master classes, organized by the BCI Society's Postdoc & Student Committee, supported the Society's goal of fostering learning opportunities and meaningful interactions for trainees in BCI-related fields. Master classes provide an informal environment where senior researchers can give constructive feedback to the trainee on their chosen and specific pursuit. The topics of the master classes span the whole gamut of BCI research and techniques. These include data acquisition, neural decoding and analysis, invasive and noninvasive stimulation, and ethical and transitional considerations. Additionally, master classes spotlight innovations in BCI research. Herein, we discuss what was presented within the master classes by highlighting each trainee and expert researcher, providing relevant background information and results from each presentation, and summarizing discussion and references for further study.

1. Introduction

The Tenth International Brain-Computer Interface (BCI) Meeting provided a venue for trainees to present and receive feedback for their work in BCI. This paper is intended to highlight their work and the innovation occurring in BCI research.

1.1 Purpose and organization of master classes

The master classes were organized by the Postdoc & Student Committee of the BCI Society, whose primary goal is to foster learning and engagement opportunities for trainees. Trainees submitting abstracts to the BCI Meeting could opt if they would like to participate in master classes. Abstract selection is based on evaluations by the Program Committee, considering reviewers' scores, diversity, and inclusion. Trainees could submit their abstract under seven general themes including BCI implant - control, BCI implant - other, BCI non-implanted - control, BCI non-implanted - other, signal acquisition, signal analysis, and user aspects: experience, ethics, target populations. Out of 93 potential candidates for master classes, 42 trainees (45%) were selected. These trainees, along with 14 masters, were organized into 21 master classes. Of the 42 trainees, 34 were graduate students, 7 were postdoctoral fellows, and 1 was a medical student. Classes were held in seven parallel sessions on three separate days of the meeting.

The master classes are meant to promote opportunities for trainees to showcase their work and to encourage relaxed interactions with senior members of their field. The master class format is as follows: two BCI trainees present their work for 10-15 minutes and one senior researcher, or master, provides constructive feedback. Additionally, any participant of the BCI Meeting may attend a master class and take part in the discussion.

The summaries provided by the master class trainees in this paper create a convenient overview of the range of topics included in BCI research, and the challenges current BCI researchers face as they advance the technology and the field. We have divided the summaries into eight specific themes: speech decoding, motor imagery, BCIs for pediatric populations, platforms for closed-loop BCIs, deep learning applications, neurorehabilitation, sampling for sensorimotor BCIs, and novel BCI techniques for improved performance. For each summary, we report the trainee, the title of their presentation, the initial theme, and the master assigned to each class, as shown in Table 1. Each summary introduces the trainee's presentation, their preliminary findings and their conclusions. Note, that 'we' within each summary refers to the trainee and their initial abstract submission co-authors.

Theme	Presenter	Master	Initial Theme	Title
Speech decoding	Julia Berezutskaya	Sergey Stavisky	Signal analysis	Optimizing feature selection for word decoding with high-density electrocorticography
	Richard Csaky	Christian Herff	Signal acquisition	Inner speech decoding from electroencephalography and magnetoencephalography
	Maxime Verwoert	Sergey Stavisky	Signal analysis	Evaluating implant locations for a minimally invasive speech BCI
Motor imagery BCIs	Daniel Polyakov	Christian Herff	Non-implanted – control	Recruiting neural field theory for motor imagery data augmentation
	Sotirios Papadopoulos	Richard Andersen	Signal analysis	What is the exact relationship between beta band activity and hand motor imagery?
	Valeria Spagnolo	Ning Jiang	Non-implanted – control	Towards co-adaptive BCI based on supervised domain adaptation: results in motor imagery simulated data
	Juliana Gonzalez Astudillo	Richard Andersen	Signal analysis	Network features for motor imagery-based brain-computer interfaces
	Satyam Kumar & Hussein Alawieh	Fabien Lotte	Non-implanted – control	Transfer Learning Promotes Acquisition of Individual BCI Skills
BCIs for pediatric populations	Dion Kelly	Camille Jeunet	User aspects	The effect of gamified calibration environments on P300 and MI BCI performance in children
	Joanna R.G. Keough	Camille Jeunet	User aspects	Mechanisms and Impacts of Brain-Computer Interface Fatigue in Children
	Araz Minhas	David E. Thompson	Non-implanted – other	Does my Child Know I'm Here? EEG Signatures of Parental Comfort for Disorders of Consciousness in a Critically Ill Child
Platforms for closed-loop BCI research	Matthias Dold	Aysegul Gunduz & Andreea Ioana Sburlea	Implanted – control	Platform for closed-loop deep brain stimulation research: DAREPLANE
Deep learning in BCIs	Yiyuan Han	Christian Herff	Signal analysis	Offline Prediction of Prolonged Acute Pain by means of Convolutional Neural Network Model applied to Electroencephalographic Oscillatory Connectivity
	Alexander McClanahan	Xing Chen	Signal analysis	Decoding Visual Scenes from Visual Cortex Spikes Using Deep Learning

	Mousa Mustafa	Marianna Semprini	Implanted – other	Decoding Invasive Brain Signals Using Deep Learning
Exploring BCIs for neurorehabil-itation	Jose Gonzalez-Espana	Ning Jiang	Non-implanted – control	NeuroExo: A Low cost Non Invasive Brain Computer Interface for upper-limb stroke neurorehabilitation at home
	Florencia Garro	Ning Jiang	Non-implanted – control	Effects of Robotic Assistance in ERP Modulation for Upper-limb Exoskeleton Control
	Angela Vujic	David E. Thompson	Non-implanted – other	Joie: An Affective Brain-computer Interface for Learning Mental Strategies for Positive Affect
Advanceme-nts in sampling the sensorimotor cortex	Kriti Kacker	Richard Andersen	Implanted – control	Spectral features of endovascular ECoG signals recorded from a Stentrode in human motor cortex
	Christoph Kapeller	Christian Herff	Signal acquisition	Increased spatial resolution reveals separated EEG activation of individual finger movements
	Simon Geukes	Victoria Peterson	Signal analysis	Ultra-high-density electrocorticography recordings of the human sensorimotor cortex
Novel techniques for advancing BCI performance	Tan Gemicioglu	Ning Jiang	Non-implanted – control	Transitional Gestures for Enhancing ITR and Accuracy in Movement-based BCIs
	Ceci Verbaarschot	Marianna Semprini	Implanted – other	The effect of artificially created sensory feedback on motor cortex activity during task performance
	Michael Wimmer	Marianna Semprini	Non-implanted – other	Toward Hybrid BCI: EEG and Pupillometric Signatures of Error Perception in an Immersive Navigation Task in VR
	Mushfika Sultana	Eli Kinney-Lang	Non-implanted – other	Assessing the impact of transcranial Direct Current Stimulation on the enhancement of race driving skills
	Sara Ahmadi	Xing Chen	Signal analysis	A model-based dynamic stopping method for code-modulated visual evoked potentials BCI

Table 1. Summaries included in this paper and presented during the master classes, arranged by theme and following the same order as the sections.

2. Master class themes and summaries

2.1 Speech decoding

In recent years, there has been an influx of research focused on the potential use of BCIs as augmentative and alternative communication devices for patients with damage or degeneration of speech motor pathways [1,2]. Understanding optimal temporal and spatial neural recording resolution, advantages of different recording modalities (e.g., noninvasive or invasive) or decoding strategies are a few aspects that are critical to the tailoring of speech BCIs for clinical populations. Additionally, there is increased interest in decoding covert speech and discerning the fundamental differences between covert and overt speech production [3].

2.1.a. *Presenter*: Julia Berezutskaya, PhD (University Medical Center, Utrecht, Netherlands)

Title: Optimizing feature selection for word decoding with high-density electrocorticography

Master: Sergey Stavisky, PhD (University of California, Davis, USA)

Theme: Signal analysis

High-accuracy individual word decoding from brain activity is crucial for the development of speech BCIs for people who cannot speak due to paralysis [4]. Here, we investigated a) how accurate word decoding is from brain signals obtained with high-density electrocorticography (ECoG) grids, and b) what neural features are most informative for high decoding performance. Five subjects participated in a word reading experiment during which their brain activity was recorded with high-density ECoG. There were 12 unique words, and each word was spoken aloud 10 times. ECoG signals in alpha (8-12 Hz), beta (13-30 Hz) and high frequency band (HFB, 70-170 Hz) were downsampled to 75 Hz and arranged into word trials using windows from 250 milliseconds prior to word onset to the length of the longest pronounced word (about 1.1 second). We used a support vector machine classifier with leave-one-out cross validation to test five feature selection strategies: 1) all electrodes & alpha, beta, HFB; 2) a subgrid of 32 electrodes & alpha, beta, HFB; 3) all electrodes & HFB; 4) a subgrid of 32 electrodes & HFB; 5) recursive feature elimination & alpha, beta, HFB.

The best performing algorithm (5) led to the accuracy of 98%, 87%, 67%, 98% and 59% for S1, S2, S3, S4 and S5, respectively (chance is 8%, Figure 1a). On average, this accuracy was at least 20% higher compared to the default strategy of no feature selection (1). HFB features were most informative for decoding. Electrodes that contributed to high accuracy decoding the most were distributed along the ventral sensorimotor cortex (Figure 1b).

This work has several limitations. First, the dataset size was relatively small. Second, the data were collected from able-bodied participants. Both are consequences of doing research on temporary ECoG recordings in human subjects. Despite these limitations, our results offer a methodology for obtaining high-accuracy word decoding from brain activity while optimizing selection of frequency and electrode features. Maximizing individual word decoding performance this way has the potential to further advance the development of speech BCIs. Future work will focus on optimal feature selection in the time dimension with the aim to identify a time window in neural data that leads to best decoding. We will also extend this methodology to tasks other than word reading and release the toolbox for optimal neural feature selection for BCI decoding to the neuroscience community.

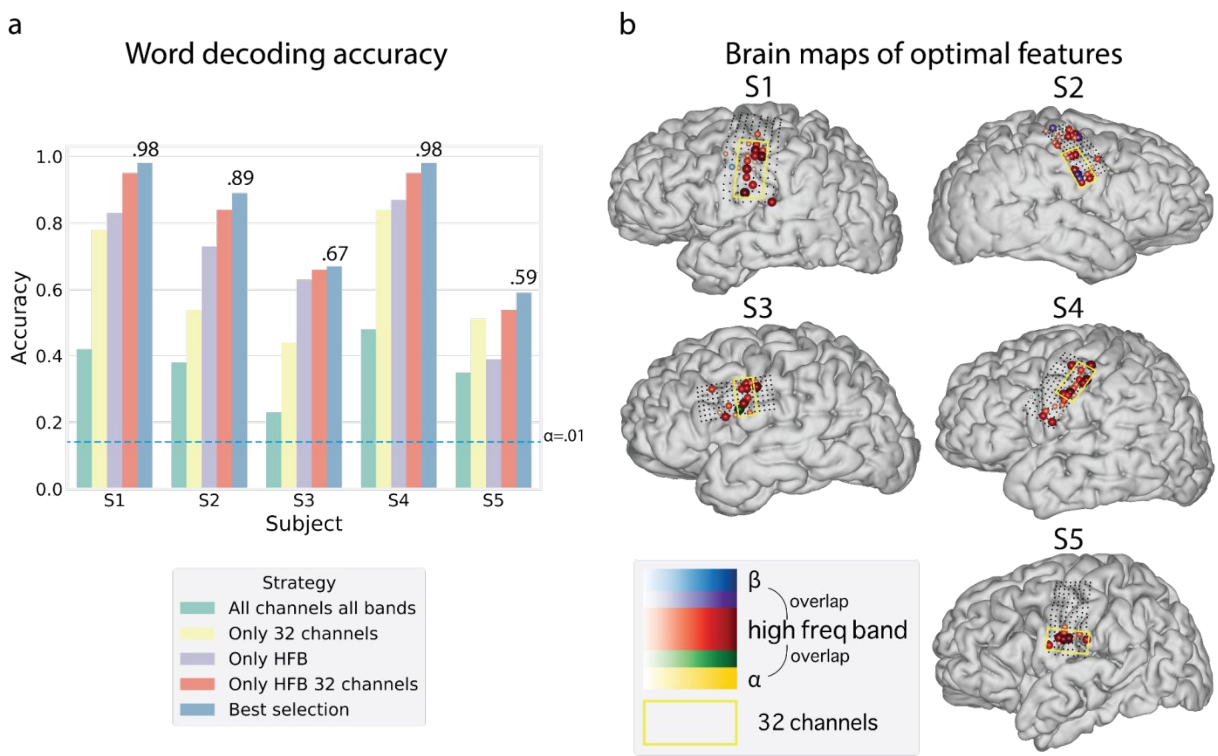


Figure 1. Optimal feature selection results. (a) Word decoding accuracy for five feature selection strategies. Chance level accuracy is shown with a dashed blue line. Since leave-one-

out cross-validation was used, no error bars are shown. (b) Optimal features identified with strategy (5) are shown on individual subject brain renderings. For reference, optimal features identified with strategy (2) are also shown suggesting that both a combinatorics approach looking for the best smaller subgrid and a recursive feature elimination approach may provide overlapping results. Colored electrodes represent electrodes chosen by recursive feature elimination as optimal (color denotes the frequency range in which the electrode was chosen). Small black electrodes outline the overall electrode grid coverage.

2.1.b. *Presenter*: Richard Csaky, PhD (University of Oxford, United Kingdom)

Title: Inner speech decoding from electroencephalography and magnetoencephalography

Master: Christian Herff, PhD (Maastricht University, Netherlands)

Theme: Signal acquisition

Although inner speech is commonly experienced in daily life, there has been a scarcity of research focusing on imaged or covert speech, especially regarding non-invasive techniques [5]. This study seeks to address this gap by using electroencephalography (EEG) and magnetoencephalography (MEG) to collect data during three different inner speech paradigms, along with conducting an initial decoding analysis. Such research has the potential to lay the groundwork for word-level communication via brain-computer interfaces [6].

We conducted a study to examine the differences between silent reading, repetitive inner speech, and generative inner speech using five patient-relevant words (help, hungry, tired, pain, thirsty) in three healthy participants. Before and after each session, 5 minutes of resting state EEG and MEG data were collected. For all sessions, we additionally collected electrocardiography (ECG), electrooculogram (EOG), electromyography (EMG; on the jaw), and eye-tracking data. We collected a large number of inner speech trials (~200/word) in each session.

Although several methods were tried, no significant decoding was obtained using the MEG inner speech data. On the silent reading trials, we trained a 2-layer linear neural network using the entire 1-second epoch with 20-fold cross-validation. For one of the participants with six sessions, 30% validation accuracy was obtained, whereas 44% was achieved for the other participants (Figure 2 - example validation accuracy from one participant). Using a sliding-window linear discriminant analysis model, the peak accuracy was observed between 300 and 400 ms post-stimulus. In the EEG inner speech data, we found above-chance validation accuracy in only 3 sessions (out of 10), with an average of 25% in these 3 sessions. We tried various BCI decoding methods, e.g., wavelet features, Riemannian classification, and linear and nonlinear models, but nothing seemed to improve performance.

We explored the potential of decoding inner speech from a new MEG and EEG dataset through three paradigms across a few participants, but with a large number of trials. Our silent reading results demonstrate the feasibility of decoding visual representations of words from non-invasive recordings. The decoding appeared to be driven by early visual responses, with a later peak potentially reflecting higher-level language processing. This late component merits further investigation as a marker of semantic processing.

In contrast to silent reading, our extensive efforts to decode two types of inner speech were largely unsuccessful across EEG and MEG. While we explored various decoding algorithms and experimental designs, accuracy never substantially exceeded chance levels. This contrasts with more promising results from intracranial recordings in humans and suggests non-invasive signals may not adequately capture the subtle dynamics of inner speech.

Several factors could underlie the difficulty of decoding inner speech non-invasively. Inner speech lacks the external stimuli and muscle activations present during overt tasks, reducing the signal-to-noise ratio. There is also high inter-individual variability in inner speech strategies. Here we focused on collecting large trial counts from a few participants rather than a small sample across many subjects. Further limitations of our work include the small number of participants and the small set of words.

Future investigations could explore alternative paradigms more representative of natural speech, such as imagining longer phrases or reading whole sentences silently. Transfer learning and self-supervision may help extract robust inner speech representations amidst noise. Intracranial findings point to superior temporal, inferior frontal, and motor areas as promising decoding targets. For non-invasive BCIs, approaches beyond word-level decoding may be needed for inner speech-based communication, such as decoding phonemes, or imagined handwriting.

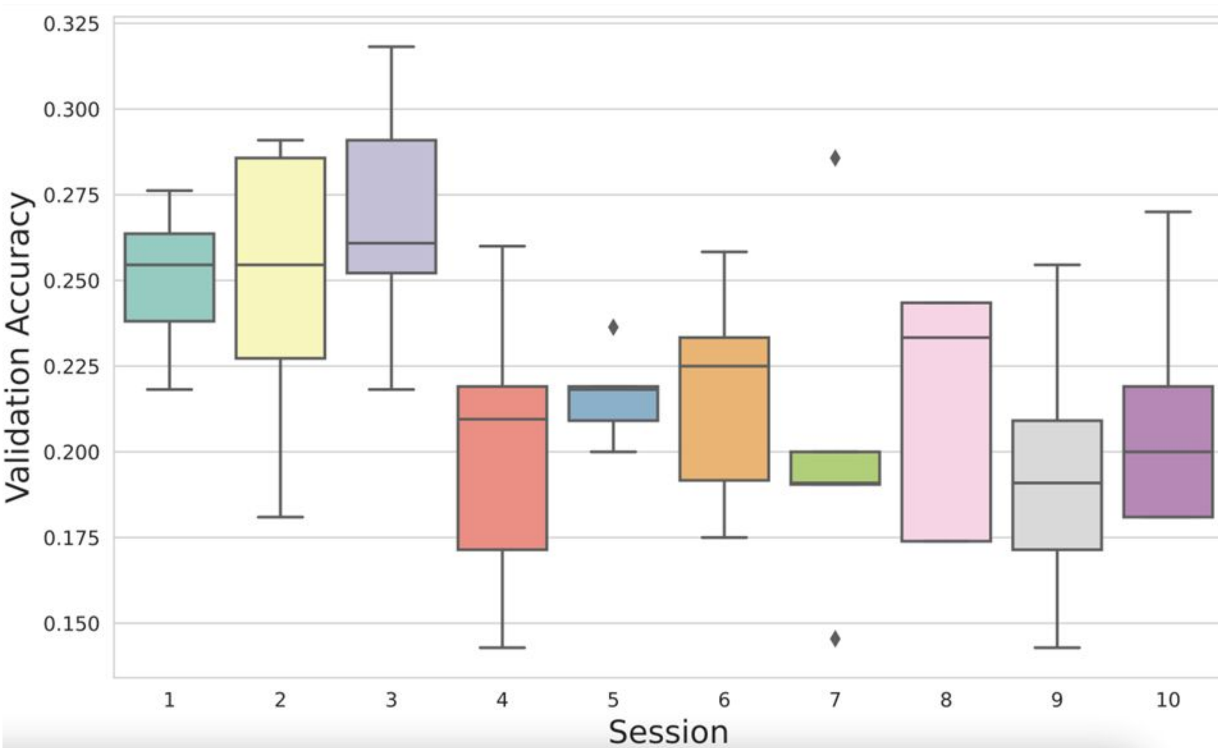


Figure 2. Validation accuracy distributions across the 5 folds of the 10 inner speech EEG sessions of one participant. Separate LDA models are trained and evaluated on each fold and session to decode which of the 5 words is being used in the 1-second inner speech trials. Chance level is 0.2.

2.1.c. *Presenter*: Maxime Verwoert (Maastricht University, Netherlands)

Title: Evaluating implant locations for a minimally invasive speech BCI

Master: Sergey Stavisky, PhD (University of California, Davis, USA)

Theme: Signal analysis

Speech BCIs present a promising avenue for restoring communication in individuals affected by a speech impairment, by converting neural signals into speech.

While conventional intracranial BCI technologies often necessitate craniotomies for implantation, stereo-electroencephalography (sEEG) offers a less invasive option, requiring only small burr holes [7]. This technology has the added benefit of sampling many cortical and subcortical regions at once. With the brain-wide coverage obtained through many recordings with epilepsy patients using sEEG electrodes, we sought to determine suitable electrode shaft locations for a speech BCI.

We recorded overt speech production data with 24 participants. Their acoustic and neural data were time-aligned before applying an electrode-shaft re-reference. A unit selection approach was used to reconstruct the neural signal directly into audio using a 10-fold cross-validation. Each individual shaft of each participant was analyzed separately to examine the spatial characteristics of decoding accuracy. We evaluated the audio reconstruction performance for each shaft by correlating the spectrogram of the original speech waveform to that of the reconstructed waveform.

Only a small number of shafts had a significant speech reconstruction performance and were mostly located near the lateral and central sulci (Figure 3). The prefrontal and occipital cortices did not appear to be informative. There was no difference in performance between the two hemispheres. We identified five cortical regions, in addition to many contacts in white matter, that were most involved in the significant shafts: the auditory cortex, the superior temporal cortex, the pre- and postcentral cortices and the insula. The insula, auditory cortex, other sulcal regions and contacts within white matter are particularly interesting, as these are not usually sampled with electrodes on the cortical surface. Identifying these target locations for a less invasive speech BCI may help in developing an advantageous solution to restore communication for individuals with speech impairments.

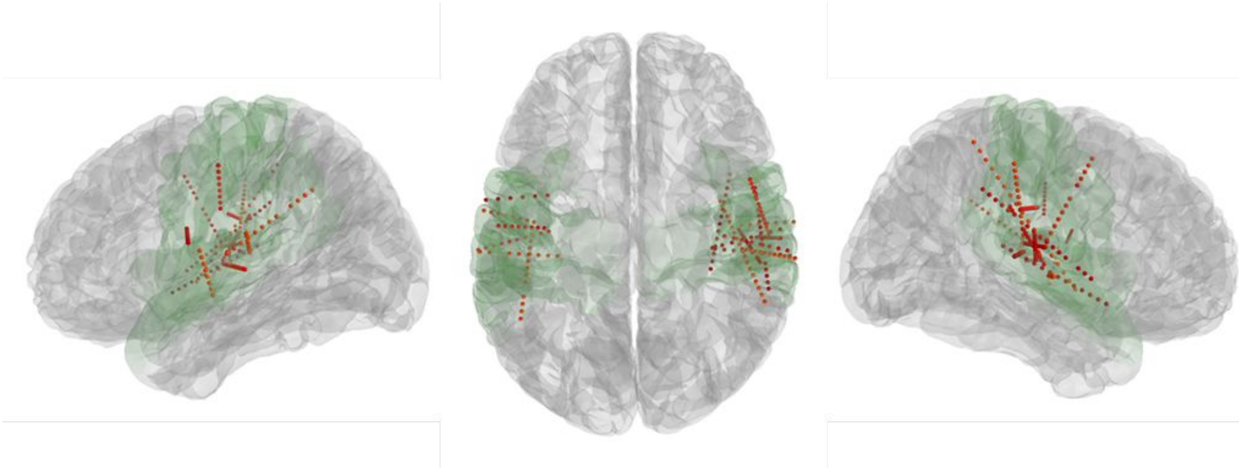


Figure 3. Electrode contacts belonging to significant shafts depicted in red, projected on an averaged brain. Highlighted in green are the most important regions (auditory cortex, superior temporal cortex, pre- and postcentral cortices, insula) in both hemispheres.

2.2 Motor imagery brain-computer interfaces

Motor imagery-based BCIs have been a common method throughout the history of BCI and are particularly popular for non-invasive approaches such as EEG [8]. Motor imagery has been convenient for a wide variety of patient populations and consumer applications alike, as it does not need external stimuli to perform and provides an intuitive mapping for control tasks. However, motor imagery often requires training for each user and can suffer from low accuracy when classifying multiple imagined movements. The recent work in this area pushes the boundaries of decoding by evaluating alternate features such as beta burst activity and novel motor network metrics to enhance classification. Researchers also attempt to reduce the data needed for motor imagery by applying domain adaptation, data augmentation techniques and transfer learning.

2.2.a. *Presenter*: Daniel Polyakov, PhD (Ben-Gurion University, Israel)

Title: Recruiting neural field theory for motor imagery data augmentation

Master: Christian Herff, PhD (Maastricht University, Netherlands)

Theme: BCI non-implanted - control

This study presents a new approach to enhance BCIs that rely on motor imagery (MI). A common challenge faced by MI-based BCIs is the scarcity of diverse training data, hindering their accuracy and practicality. To address this, we introduce a novel Data Augmentation (DA) method leveraging Neural Field Theory (NFT), a computational model inspired by the human brain's neural dynamics (Figure 4) [9].

The core innovation lies in using NFT to generate artificial EEG time series that mimic the ones recorded during an MI task, in order to expand the training dataset. To evaluate this approach, we employed the widely used '2a' dataset from BCI Competition IV [10]. For each subject in the dataset, we fitted an NFT model to common spatial patterns of each MI class, jittered the fitted parameters to enhance diversity, and generated time series for DA.

Our method resulted in a significant accuracy improvement of over 2% when classifying the "total power" feature, but it did not enhance classification for the "Higuchi fractal dimension" (HFD) feature. We compared our approach with a DA method that adds Gaussian noise to feature values, but the noise-based method failed to achieve statistically significant accuracy improvements.

The lack of improvement in HFD-based classification suggests that the NFT model was more effective at representing certain features, particularly those in the time domain. This could be because the NFT fitting process discards phase information, potentially limiting its effectiveness for features like HFD. Another finding was that user proficiency in MI tasks influenced the efficacy of the DA, with more proficient users benefiting more from the augmentation.

This study provides insights into the underlying mechanisms of the augmentation process by examining how NFT parameters impact the extracted features. Future research could explore the efficiency of this DA method for additional MI classification features, such as kurtosis or sample entropy, with a focus on parameter jittering. Additionally, assessing this method’s compatibility with other BCI paradigms could offer further valuable applications.

In conclusion, this research represents a significant advancement in the field of MI-based BCIs. By employing physiological models and innovative augmentation techniques, the study not only improves BCI performance but also offers valuable insights into the dynamics of neural field theory and its application in BCIs.

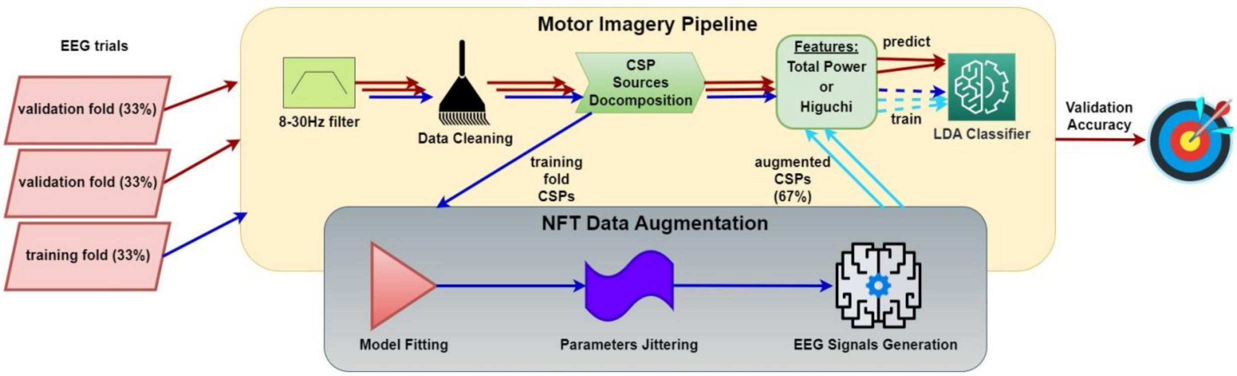


Figure 4. Evaluation workflow for MI data augmentation: A small dataset is created, and accuracy is tested using inverse cross-validation, with one-fold for training and the rest for testing. The motor imagery pipeline involves EEG preprocessing, common spatial pattern decomposition, feature extraction, and classification. NFT-based augmentation creates artificial CSP time series using a corticothalamic NFT model fitted to the original data. Reprinted from [11] with permission. EEG, electroencephalography; CSP, common spatial patterns; NFT, neural field theory; LDA, linear discriminant analysis

2.2.b. *Presenter*: Sotirios Papadopoulos (Université Claude Bernard Lyon 1, France)

Title: What is the exact relationship between beta band activity and hand motor imagery?

Master: Richard Andersen, PhD (California Institute of Technology, USA)

Theme: Signal analysis

Since the characterization of the event-related desynchronization (ERD) and synchronization (ERS) phenomena in the mu and beta frequency bands [12], the BCI community has heavily relied on band-limited power changes as the classification features of interest. Recent investigations in neuroscience have challenged the notion that signal power is the best descriptor of movement-related brain activity modulations, particularly in the beta frequency band (~13-30 Hz). Studies have demonstrated that on a single-trial level beta band activity occurs in short, transient events, termed “bursts”, rather than sustained oscillations [13]. This suggests that the ERD/S patterns only emerge when averaging across multiple trials, indicating that signal power may not fully capture all relevant brain activity modulations during motor-related tasks.

Analyzing beta bursts holds promise for accessing markers that may be as sensitive as beta power for classification, and that potentially capture more subtle condition-specific changes. To investigate this possibility, we used six EEG datasets [14] and examined the activity of channels C3 and C4 while the participants were performing “left” and “right” hand motor imagery (MI). Using a new burst detection and waveform analysis algorithm (Figure 5) [15], we demonstrated that classification features which describe the modulation of burst rate for beta bursts with distinct waveforms can be more informative than beta power alone. Furthermore, these features were more reliable than conventional burst activity representations (e.g., rate, amplitude, temporal and frequency spans). These results illuminate the non-linear relationship between beta burst activity and band power, underscoring the potential benefit for the BCI field from incorporating such recent neurophysiological findings [16].

In order to compute these waveform-specific burst rates, in this study we employed a nested cross-validation classification procedure. The computational complexity of this algorithm was a major limitation that needed to be circumvented so that a burst-based analysis of the beta band activity could be suitable for BCI applications. To address this, we took advantage of aforementioned results and in a follow-up study we introduced a new framework for analyzing beta burst activity. Briefly, we defined a metric to identify burst waveforms, recorded in channels C3 or C4, whose rate is expected to be maximally modulated during a MI task. Then, we used these waveforms as data-driven kernels and convolved the EEG recordings with each kernel. This allowed us to efficiently filter the signals of all recording channels and gave us access to state-of-the-art classification algorithms. We showed that beta burst waveforms, when used as data-driven filters, can improve classification accuracy and information transfer rate [17], while also minimizing the classification score loss in across-session transfer learning paradigms [18].

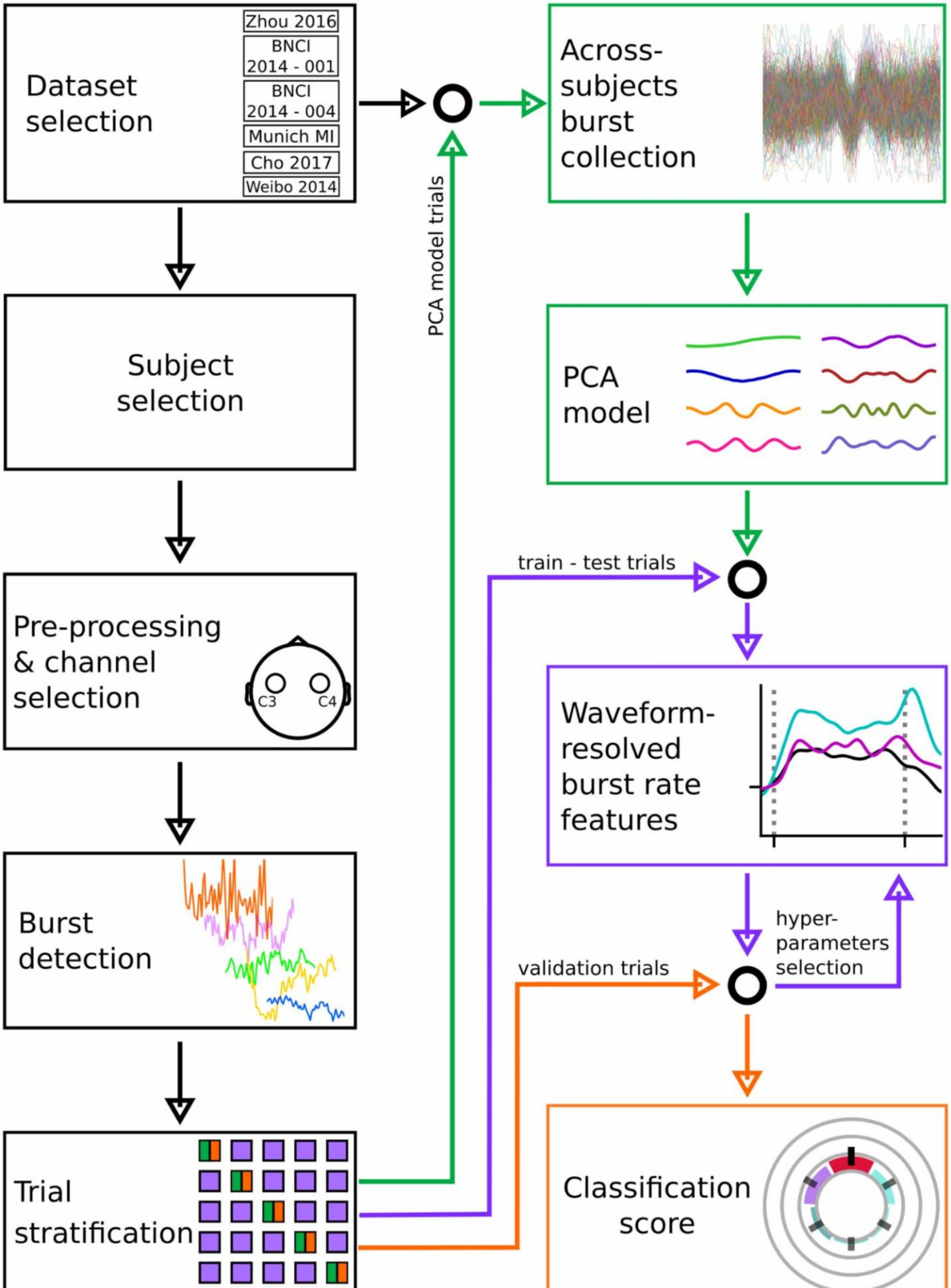

Dataset selection
Zhou 2016
BNCI 2014 - 001
BNCI 2014 - 004
Munich MI
Cho 2017
Weibo 2014
Subject selection
Pre-processing & channel selection
C3
C4
Burst detection
Trial stratification
PCA model trials
Across-subjects burst collection
PCA model
train - test trials
Waveform-resolved burst rate features
validation trials
hyper-parameters selection
Classification score

Figure 5. Flowchart of the waveform-resolved burst rate analysis: Each dataset was pre-processed by rejecting trials and keeping channels C3 and C4. A burst detection algorithm was applied to these raw signals. The remaining trials were split into three sets using nested 5-fold cross-validation. The first set, used to sample bursts and create a principal component analysis model (green boxes/arrows), combined data from all subjects. The second set, for training/testing (purple boxes/arrows), selected the best waveform-resolved features via repeated cross-validation. The third set (orange boxes/arrows) validated the model and computed classification scores. Reprinted from [16] with permission. PCA, principal component analysis.

2.2.c. *Presenter*: Valeria Spagnolo (Instituto de Matemática Aplicada del Litoral, IMAL, CONICET-UNL, Santa Fe, Argentina)

Title: Towards co-adaptive BCI based on supervised domain adaptation: results in motor imagery simulated data

Master: Ning Jiang, PhD (University of Waterloo, Canada)

Theme: BCI non-implanted - control

BCIs can be thought of as a two-learners system, in which the user learns how to control the computer and, simultaneously, the computer learns how to decode the user's brain activity [19]. When used across several sessions, the machine learning system employed to decode brain activity should adapt to changes in the EEG signal and help the user in the development of stable brain patterns. In this line, a backward formulation of optimal transport for domain adaptation (BOTDA) was proposed to avoid recalibration in cross-session MI-BCIs and to improve decoding performance [20]. Although BOTDA showed promising results in a supervised sample-wise scenario, it is interesting to elucidate the extent to which the success of the adaptation depends on the subject's ability to perform the MI task or on the adaptive capabilities of the model.

To investigate this, we simulated MI vs. rest EEG data to control MI alpha desynchronization (i.e. ERD) in the left hemisphere during MI. We conducted different cross-session scenarios, where a simulated session (S1) was used as a calibration dataset and a second session (S2) was utilized for testing. For each session, 100 trials of each class were generated. As a decoding algorithm, a common spatial pattern and a linear discriminant analysis were used [21]. Firstly, the model was trained at the ideal session (S1) and the performance of BOTDA was tested in sessions with decreasing %ERD. BOTDA showed successful adaptation when the provided EEG patterns matched the mental task, regardless of the %ERD in S2. On the contrary, experiments manipulating the percentage of erroneous MI trials indicated that BOTDA could not conduct a successful adaptation when there was a mismatch in between the provided EEG pattern and the intended mental task. Finally, we trained the decoding model with data from sessions with different ERD values. The decoder yielded chance-level performance when calibration data lacked discernible ERD patterns, highlighting BOTDA's efficacy only with discriminative calibration data. Results on these simulations suggest that BOTDA can be a valuable tool for developing co-adaptive MI-BCI systems.

2.2.d. *Presenter*: Juliana Gonzalez Astudillo, PhD (Paris Brain Institute, France)

Title: Network features for motor imagery-based brain-computer interfaces

Master: Richard Andersen, PhD (California Institute of Technology, Pasadena, USA)

Theme: Signal analysis

Exploring the complexities of the brain's motor cortex has been a central focus in neuroscience, particularly in advancing BCI technology. Traditionally, decoding MI has relied on understanding the spatial organization of the motor cortex [22], known for its principal involvement in controlling the contralateral side of the body. Moreover, recent advancements underscore that functional connectivity patterns not only unveil this lateralization during motor-related tasks but also offer a captivating window into modeling MI as a dynamic and intricate network, where brain regions or sensors serve as nodes and their statistical dependencies as links [23].

Here, we have investigated brain network topology and spatial organization's dual contribution to enhancing MI decoding through functional lateralization [24]. Introducing novel network metrics for *integration* (ω) and *segregation* (σ), we elucidate the contributions of within- and across-hemispheric connections in modeling MI states.
Using multiple open-access datasets of EEG signals from MI experiments focusing on left and right hand grasping motions [25], we construct spectral coherence-based

networks and calculate lateralization metrics for each electrode. Our analysis identifies discriminant electrodes predominantly located in motor-related areas such as the primary motor cortex, premotor area, supplementary motor area, and primary somatosensory cortex, which are crucial for movement planning and execution. Notably, ω highlights motor cortex involvement, while σ extends to frontal areas implicated in attention and motor planning.

In BCI classification, these network properties yield competitive accuracy and provide neurophysiological insights, contrasting with conventional approaches like common spatial pattern filters and Riemannian methods, which lack neurophysiological interpretation. However, the developed metrics are primarily suited for lateralized tasks, for instance bilateral motor cortex recruitment may result in similar features for both hands, limiting their discriminative power. Looking ahead, the precise detection of involved areas opens up the possibility of analyzing the temporal dynamics of these metrics to identify different stages of motor action. Combined with dynamic classification techniques, this could provide a more accurate and reliable solution for BCI.

2.2.e. *Presenters*: Satyam Kumar & Hussein Alawieh (The University of Texas at Austin, USA)

Title: Transfer Learning Promotes Acquisition of Individual BCI Skills

Master: Fabien Lotte, PhD (Inria Center at the University of Bordeaux, France)

Theme: BCI non-implanted - control

Motor imagery (MI) is one of the most commonly used modalities for controlling BCIs [26–28] due to its volitional nature, requiring no external stimuli. However, MI-based BCIs often necessitate tedious calibration sessions to record EEG data for building real-time machine learning decoders, which may suboptimally perform due to inherent EEG signal non-stationarity. Recent studies underlie the importance of longitudinal training with closed-loop feedback for robust MI-BCI control [29,30]. In this study [31] we show that a decoder trained on data from a single expert can provide consistent closed-loop feedback to naive subjects thus promoting MI skill acquisition. We propose two subject-independent real-time frameworks: a) Generic Recentering (GR) employing unsupervised domain adaptation, and b) Personally Assisted Recentering (PAR), an extension of GR that updates decoder parameters in real-time using a small amount of the naive subject data. These frameworks are founded on Riemannian Geometry Classifiers, leveraging affine invariant transforms to match covariate shifts on the Riemannian manifold [32,33], thereby reducing non-stationarities in real-time and providing contingent closed-loop feedback.

We tested our proposed framework on 18 BCI-naive volunteers, dividing them into PAR and GR groups. Over five consecutive online training sessions, participants controlled a standard binary class MI task with bar feedback [34] followed by a car racing task [35]. Experimental results show that participants in both groups exhibited increases in command delivery performance in the bar task (GR: $p<0.05$ and PAR: $p<0.01$). Moreover, subjects show a significantly increasing trend in command delivery performance over online sessions in both the frameworks. Race completion time values in the car racing task indicated that participants could finish the races significantly faster following the training sessions compared to their initial performance for both GR ($p<0.01$) and PAR ($p<0.05$). Furthermore, feature separability analysis [36] showed significant increasingly discriminant features for both frameworks and tasks. For both frameworks, the most contributing EEG channels for discriminating between the two MI classes were predominantly over the motor cortex. Despite using feedback from subject-independent decoders, participants developed their own enhanced individual MI features, distinct from the expert's data used for decoding. Finally, we demonstrate that unsupervised adaptation (GR) coupled with longitudinal training reached statistically similar performance to supervised recalibration (PAR) in a realistic setting.

Our proposed transfer learning frameworks promoted MI skill acquisition, removing the need for calibration sessions. Participants demonstrated improved BCI control and increased feature discriminability over multiple training days, crucial for mutual learning settings. Importantly, our frameworks enabled participants to modulate their task-specific individualized feature spaces for BCI control, diverging from the expert's patterns.

A limitation of the current work is that users operated the BCIs in binary class settings. Future work should aim towards validating the proposed frameworks in multiclass BCI settings to enhance the degree of freedom for controlling external devices and applications. Moreover, the current study used data from a single expert subject for online feedback. In the future, data from multiple experts could be pooled together to train data-driven deep learning models like EEGNet [37] and TSMnet [38] for improving online BCI feedback. Finally, these expert-based decoding frameworks could be used to provide online feedback to stroke patients for longitudinal MI-BCI training who may struggle to generate distinctive calibration data due to their reduced ability to modulate sensorimotor rhythm [39].

2.3 Brain-computer interfaces for pediatric populations

BCIs hold promise for enhancing the interaction and communication abilities of individuals with motor impairments. However, there has been limited exploration of BCI research involving pediatric and young adult populations [40]. Existing studies in these demographics have yielded conflicting results, underscoring the need for the BCI community to focus on enhancing the design, implementation, and user experience specifically tailored for pediatric and young adult populations. This emphasis is especially crucial for individuals with neurodevelopmental disorders, neurodegenerative disorders, or severe motor disabilities.

2.3.a. *Presenter*: Dion Kelly, PhD (University of Calgary, Canada)

Title: The effect of gamified calibration environments on P300 and MI BCI performance in children

Master: Camille Jeunet, PhD (Aquitaine Institute for Cognitive and Integrative Neuroscience, Bordeaux, France)

Theme: User aspects: experience, ethics, target population

This study explored the potential of gamification to improve BCI calibration in children, aiming to address longstanding calibration challenges such as monotony and lack of engagement, which are exacerbated by children’s limited attention and motivation

[41]. Incorporating scoring and rewards into calibration tasks, this randomized, cross-over study compared gamified and non-gamified environments to assess their impact on classification accuracy and task performance.

Thirty-two typically developing children (mean age 11.9 years) participated in two sessions, performing utility-driven tasks following gamified and non-gamified calibration. The tasks included spelling via visual P300 event-related potentials (Figure 6) and controlling a cursor via sensorimotor rhythm (SMR) modulation (Figure 7). Gamification elements like stories, quests, points, and sounds were integrated into the gamified calibration environments to enrich engagement. We evaluated BCI performance, including classification accuracy and online accuracy, as well as motivation, tolerability, and mental workload. For the P300 paradigm, classification accuracy was high in both gamified and non-gamified conditions, exceeding 96%. However, online performance during the spelling task was significantly lower following gamified calibration (71.47%) compared to non-gamified calibration (80.47%, $p < 0.01$). In the SMR paradigm, classification accuracy was 61.81% in the gamified condition versus 59.84% in the non-gamified condition, with no significant differences between conditions for classification or online cursor control performance. Furthermore, gamification did not significantly impact participants' motivation, tolerability, or workload perceptions.

This study highlights the capability of children to effectively use advanced BCI systems, achieving performance comparable to adults. However, the results suggest that the gamified elements employed may not have been sufficiently engaging. Several limitations should be noted, including the potential introduction of an auditory P300 component due to auditory stimuli in the gamified calibration task, which was absent in the utility-driven tasks and may have affected classification performance. Additionally, a ceiling effect in the P300 paradigm, where performance was already high in the non-gamified condition, may have limited the ability to observe the true impact of gamification on BCI performance.

Future investigations should focus on optimizing gamified calibration environments tailored to individual preferences and abilities. There is also a need to explore alternative gamification designs, potentially incorporating user feedback to enhance engagement and motivation, especially for younger children or those with disabilities. Further research is also necessary to examine the long-term effects of repeated practice on BCI performance and to investigate how these results translate to clinical populations with motor impairments or communication challenges.

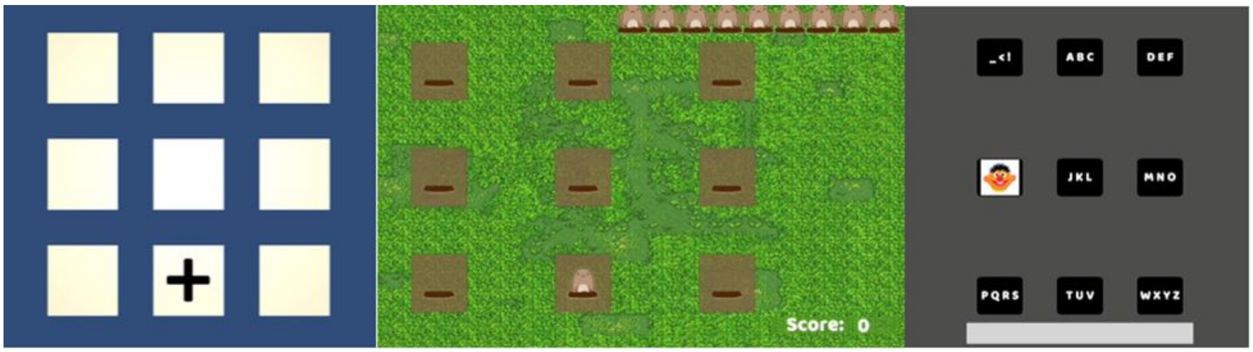


Figure 6. P300 scenes: standard calibration scene (left), gamified calibration scene (Mole Patrol game, middle), two-stage T9 speller scene for spelling task (right).

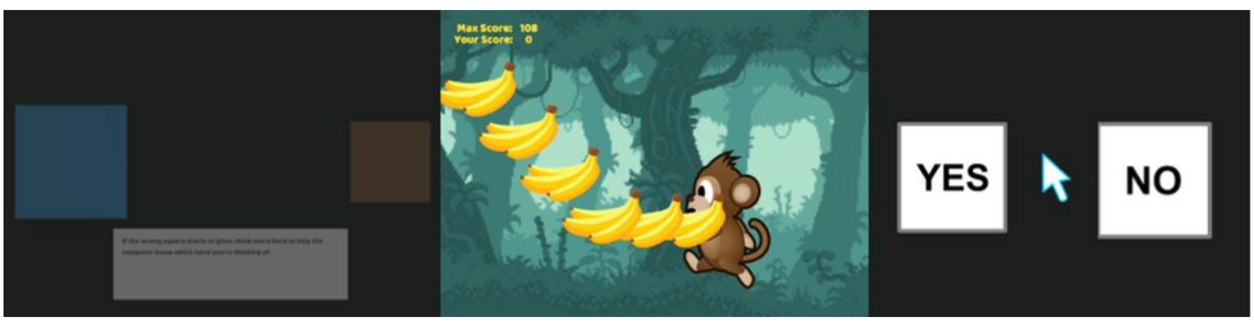


Figure 7. SMR scenes: standard calibration scene (left), gamified calibration scene (Banana Dash game, middle), cursor control scene for yes/no response task (right). Calibration consisted of 20 segments of six 1.5s-epochs for a total time of 5.67 minutes.

2.3.b. *Presenter*: Joanna R.G. Keough, MSc (University of Calgary, Canada)

Title: Mechanisms and Impacts of Brain-Computer Interface Fatigue in Children

Master: Camille Jeunet, PhD (Aquitaine Institute for Cognitive and Integrative Neuroscience, France)

Theme: User aspects: experience, ethics, target population

BCIs can assist children with disabilities in communication, environmental exploration, and gameplay [42]. BCI research is rapidly developing but has neglected pediatric populations. Like many cognitively demanding tasks, fatigue is a critical factor to consider for BCI performance and enjoyment [40] and has often been reported by patients and families within our pediatric clinical BCI program. BCI fatigue has been studied in adult populations, but there are no pediatric studies to date. This prospective, cross over study assessed the effects of two BCI paradigms and a control condition on self-reported fatigue and EEG biomarker of fatigue – alpha band power.

Thirty-two typically developing children aged 7-16 years participated in three sessions: motor imagery-BCI, P300-BCI, and film viewing (control) (Figure 8). The DSI-24C headset was utilized for BCI operation and EEG collection. Self-reported fatigue and resting-state EEG alpha band power significantly increased across all sessions (p<0.001; p=0.047 respectively). The increase in self-reported fatigue observed was greater in the younger half of participants. These two measures of fatigue were uncorrelated to one another. No differences in fatigue development between sessions were observed. This project provides a baseline understanding of pediatric BCI fatigue. Short periods (30-minutes) of BCI use can increase self-reported fatigue and an EEG biomarker of fatigue. Performance was stable across BCI sessions and not associated with our measures of fatigue.

The clinical implications and impact of fatigue on useability and enjoyment are unclear and point to limitations of this study. These include a modest sample size and large age range complicating age-based analysis. An additional unexpected challenge was the tolerability of the DSI headset. Many participants found it uncomfortable and 25% of participants requested to stop at least one of the three sessions early due to discomfort. Despite these limitations, our results support the variability of fatigue and the overall BCI experience in children that warrant future investigation to inform the design of pediatric BCI systems to meet the unique goals of children and families. These investigations should include longer BCI sessions with a more tolerable headset. Not all children had adequate control of the BCI, and future work should uncover predictors of performance particularly in children. Strategies should be identified to promote BCI learning.

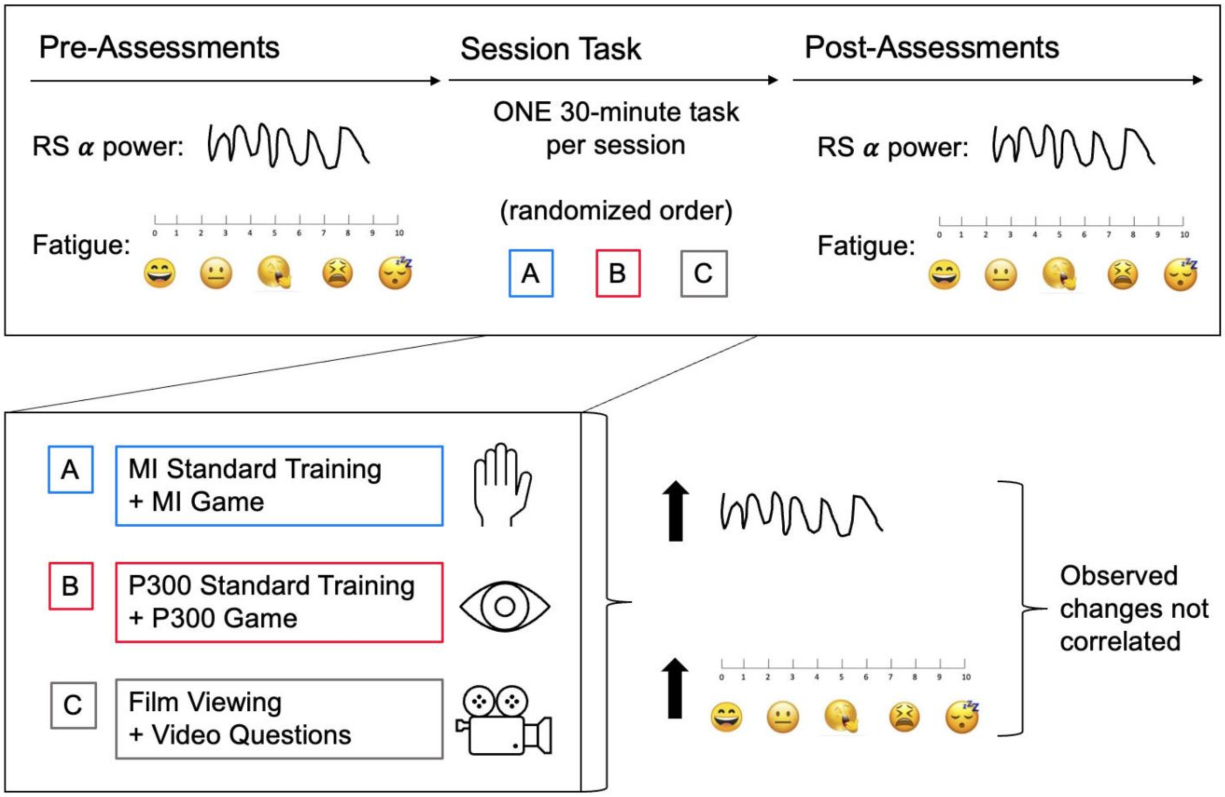


Figure 8. Protocol Schematic for All Three Sessions. Session tasks were balanced using a Latin square design. Sessions lasted 60 to 90 min. MI, motor imagery; RS, resting state. Adapted with permission from figures originally published in [43].

2.3.c. *Presenter*: Araz Minhas (University of Calgary, Canada)

Title: Does my Child Know I'm Here? EEG Signatures of Parental Comfort for Disorders of Consciousness in a Critically Ill Child

Master: David E. Thompson, PhD (Kansas State University, USA)

Theme: BCI non-implanted - other

Each day in the Pediatric Intensive Care Unit (PICU), there are unconscious and comatose children afflicted with severe brain diseases, whose parents lie beside them, desperately wondering if their child will ever awaken. Up to 20% of adult patients with such disorders of consciousness (DoC) exhibit signs of cognitive-motor dissociation

(CMD) [44], wherein patients' willful modulation of brain activity may be observed via EEG when given motor commands— indicating some intact cognition, despite behavioral unresponsiveness. CMD is a promising early positive prognostic marker and may enable some simple communication ("Yes"/ "No") via BCIs for such patients. Unfortunately, children have been largely neglected in CMD and BCI research [45]. However, much potential for revealing CMD may lie in their developing brain networks' heightened receptivity to social stimuli like parental comfort and affection. Detecting such networks' activation in comatose children whose parents are constantly caring for them in the PICU could reveal new brain activity markers that may help predict outcomes early and allow families to communicate with their children in critical circumstances.

To explore this possibility, a 13-year-old female post-anoxic coma patient's 20-channel EEG was analyzed with synchronized 17-hour PICU video footage. Highcuhi Fractal Dimension values (HFD; indexing EEG complexity) were compared across video-derived timestamps of parental comfort (physical contact / talking to children), presence (in room), and absence. Shifts in child EEG complexity (mean HFD) positively correlated with parental comfort ($r \approx 0.26$). HFD values formed two clusters (K-means; Silhouette=0.54)— a higher HFD cluster (1.40±0.11) coinciding mainly with parental presence (74% of clustered time points), and one with lower HFD (1.24±0.05) primarily during parental absence (61%, $p<0.01$). These preliminary results, summarized in Figure 9, suggest that parental comfort may elicit discernible EEG changes in pediatric DoC – encouraging future investigations of such indicators for assisting prognosis or communicative BCIs. As the generalizability of these results is limited by the single-patient case design, future research involving larger cohorts will also be needed to validate these findings, and more extensively explore the integration of such complexity measures into prognostic models and potential BCI tools for pediatric coma.

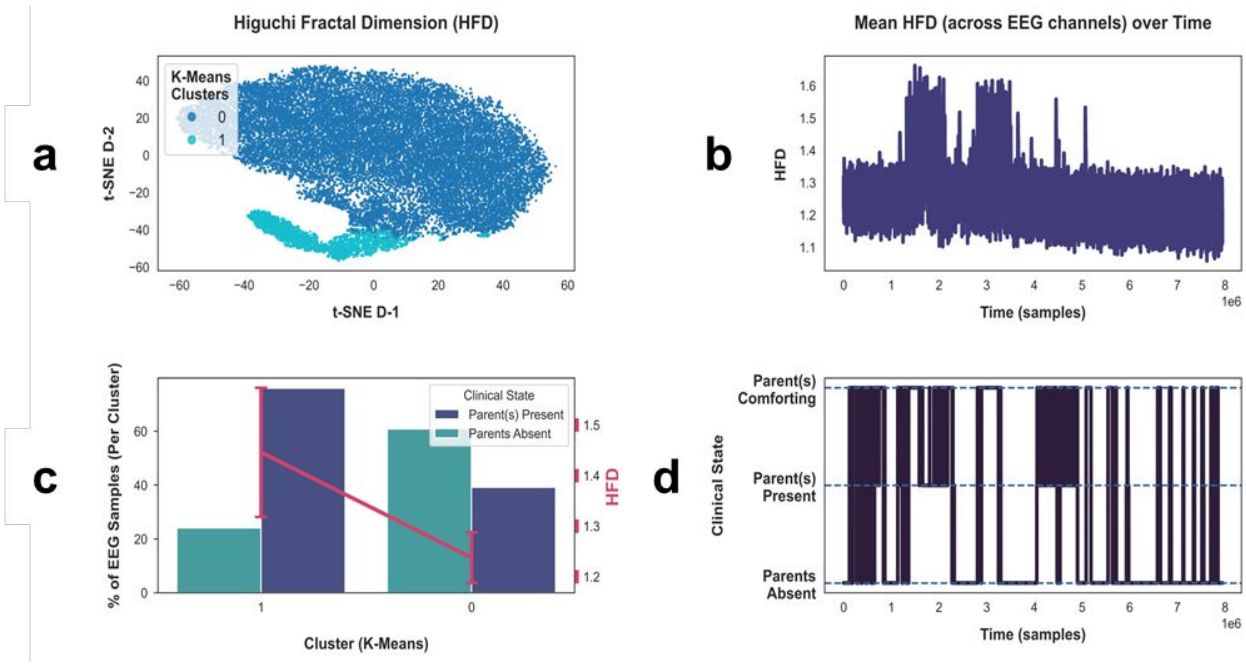


Figure 9. (**a**) K-means clustering of Higuchi Fractal Dimension (HFD) values from continuously recorded EEG (cEEG) data of a pediatric post-anoxic coma patient, revealing two distinct clusters. (**b/d**) Mean HFD values across channels over time, indicating fluctuations in EEG complexity. Temporal alignment of parental state with cEEG suggests a correlation between parental comfort and increased EEG complexity. (**c**) Distribution of EEG samples per cluster found higher HFD values associated with parental presence/comfort, and lower HFD during parental absence. Reprinted from [46] with permission.

2.4 Platforms for closed-loop brain-computer interface research

Closed-loop BCI applications encompass a diverse array of functionalities, extending from delivering precisely timed brain stimulation [47,48] to offering instantaneous feedback to users and facilitating the control of various end effectors [49]. This multifaceted scope enables closed-loop BCIs to cater to a wide spectrum of needs and scenarios, including therapeutic interventions, neurorehabilitation programs, and assistive technologies aimed at enhancing users' autonomy and quality of life. Developing platforms that can easily perform or integrate closed-loop applications may enable the generalizability and translation of these applications.

2.4.a. *Presenter*: Matthias Dold (Radboud University, Netherlands)

Title: Platform for closed-loop deep brain stimulation research: DAREPLANE

Masters: Aysegul Gunduz, PhD (University of Florida, USA) & Andreea Ioana Sburlea, PhD (University of Groningen, Netherlands)

Theme: BCI implant - control

BCIs continuously decode the brain state, a highly relevant building block for adaptive neurostimulation. The **DA**ta driven **RE**search **PL**atform for **NE**urotechnology (DAREPLANE) [50] project creates a modular open source platform to enable BCI methods for adaptive closed-loop deep brain stimulation (aDBS). Current research on aDBS is either conducted with custom soft- and hardware setups [51–53], or is fully embedded in a single vendor's systems [54–56]. DAREPLANE supports customized setups by providing a platform of open-source single responsibility modules for tasks involved in closed-loop setups. Examples of such tasks related to aDBS are controlling the stimulation parameters, decoding multi-modal recordings, exploring control strategies, rendering of different user tasks, a thorough logging, and real time data monitoring. An abstract high-level overview of such a setup with DAREPLANE is shown in Figure 10.

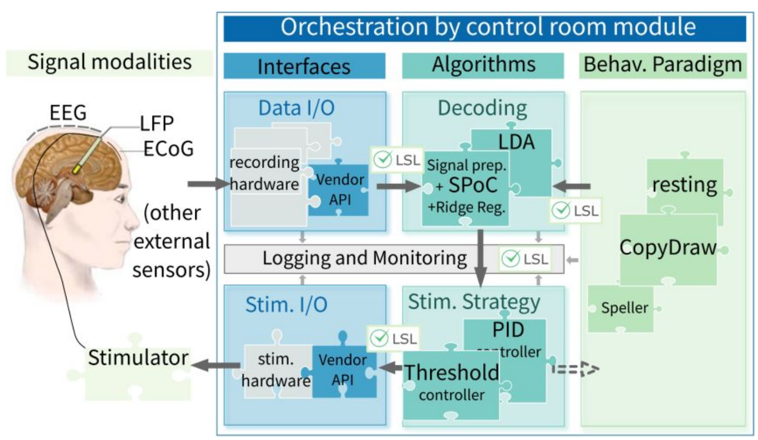


Figure 10. Schematic of a closed-loop DBS experiment and involved DAREPLANE modules. The jigsaw puzzle pieces represent different modules that can be combined to an aDBS setup. Different modules for the same type of task can be switched in place. Adapted with permission from [50]. EEG, electroencephalography; LFP, local field potential; ECoG, electrocorticography; I/O, input/output; API, application programming interface; PID, proportional - integral - derivative

The platform is built with the experience of our previous work on decoding of neural markers for deep brain stimulation (DBS) [53]. It relies on socket communication and uses the lab streaming layer [57] protocol for data streaming. This choice makes it mostly technology agnostic, with the exception of the central orchestration which is implemented in Python. The modules can still be used standalone, relaxing the requirements to the programming language the modules are implemented in.

An early stage version of the platform has already been used during a single aDBS session and various open-loop DBS [50] in patients with Parkinson's disease (PD) while they are performing a motor task [58]. Although targeted for aDBS experiments, DAREPLANE can also be used to implement classical BCI applications like spellers or motor-imagery controls. Due to the use of network communication, the bandwidth of the involved network hardware can limit the throughput of the platform. This can be relevant for high channel counts, with high sampling rates and depends on how much data is shared between modules. Further work will investigate and quantify these limits in more detail.

2.5 Deep learning in brain-computer interfaces

As the availability of large-scale datasets continues to grow, leveraging deep learning techniques for feature extraction and decoding brain states within BCI systems holds the potential to significantly enhance performance [59]. This advancement could lead to more accurate and reliable outcomes, ultimately empowering BCI technology to better serve individuals with diverse neurological conditions and needs.

2.5.a. *Presenter*: Yiyuan Han, PhD (University of Essex, United Kingdom)

Title: Offline Prediction of Prolonged Acute Pain by means of Convolutional Neural Network Model applied to Electroencephalographic Oscillatory Connectivity

Master: Christian Herff, PhD (Maastricht University, Netherlands)

Theme: Signal analysis

Unresponsive patients, e.g., ones with disorder of consciousness, face challenges in communicating their pain, making pain assessment difficult for caretakers. EEG signals offer a potential avenue for pain assessment at the bedside. However, due to individual variation, building accurate pain assessment models necessitates labeled data, which cannot be obtained from unresponsive patients. To address this gap, we aimed to develop a model capable of generalizing to new individuals without labeled data. For this purpose, we trained a convolutional neural network (CNN) to classify pain and non-pain conditions from EEG signals across individuals.

Forty-three healthy individuals participated in the experiment, with data from thirty-six participants included for analysis after exclusions. We focused on two conditions: pain induced by hot water (H) and resting states with eyes open (O) or closed (C). EEG signals were segmented into 5-second trials with a 50% overlap. Inter-site phase clustering (ISPC) was computed to measure functional connectivity between 32 EEG channels [60]. The ISPCs were reorganized into a 32x32 matrix as input features for the CNN model. Leave-one-out tests were conducted for each participant, with one participant excluded from model training. Cumulative evidence (CE) was computed to evaluate the effect of the number of consecutive trials. In the binary classifications between pain condition (H) and resting states (O or C), the accuracy of CE was significantly higher than the tests without cumulative evidence within one minute (Figure 11a). For H vs O, the maximum CE accuracy was 69.26%±14.72%, while the original accuracy was 63.99%±13.11%. For H vs C, the maximum CE accuracy was 81.93%±14.73% and the original accuracy was 76.80%±15.28%.

For interpreting the model's generalization, we used Gradient-weighted Class Activation Mapping (Grad-CAM) to generate the activation patterns of the functional connectivity in binary classification (Figure 11b). Comparing the patterns for the binary classification between H and O/C conditions, the functional connectivity between frontal and central regions was specific to pain. The neurophysiology of somatic pain involves the integration between frontal and central lobes, which might be the origin of such specificity [61].

Individual variation in neural responses to pain poses challenges for pain assessment model generalization. Transfer learning models are rare due to this variability

[62]. Recent research suggests that slow alpha frequency and alpha band functional connectivity correlate with individual pain sensitivity, offering potential neural markers for pain prediction [60,63]. Our study demonstrates the potential of alpha band functional connectivity to mitigate individual differences in pain prediction, indicating a promising avenue for future research in pain assessment using EEG signals. The analysis of activation patterns suggested the interpretation of the obstacle in generalization, Salomons revealed that prefrontal cortex activation is associated with individual differences of pain perception [64]. Hence, the overlap of the frontal region in both pain-related and individual-related specificity could harden the generalization.

This research did not effectively involve processing individual differences of neural responses to pain, for example, transfer learning frameworks taking the individual-specific feature into account. In the following study, we will develop transfer learning models to improve the generalisability of the pain prediction model. Another limitation is that this study did not consider the influences of thermoception, for which the innocuous thermal stimulation can help declare its effects in the future.

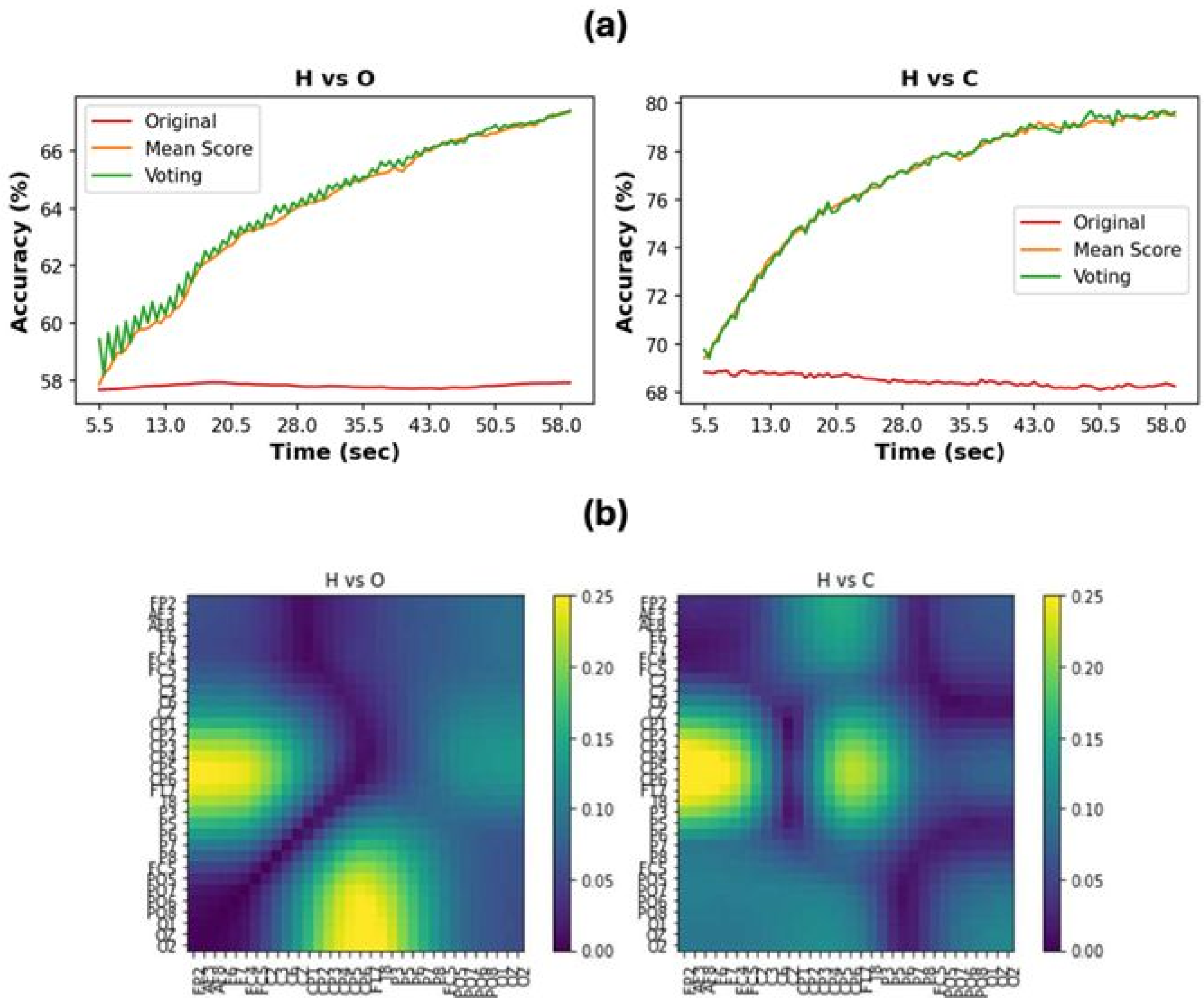


Figure 11. (**a**) The effect of time length to classification accuracy. The ‘original’ model represents the general evaluation without cumulative evidence, ‘mean score’ was based on the mean prediction score to predict the labels, and ‘voting’ mode predicted the labels according to the most frequency prediction in the cumulation range. Adapted from [65] with permission. (**b**) Activation patterns of functional connectivity out of Grad-CAM. The highlighted regions represent the connectivity with higher weights in the classification. Adapted from [60] with permission.

2.5.b. *Presenter*: Alexander McClanahan, MD (University of Arkansas for Medical Sciences, USA)

Title: Decoding Visual Scenes from Visual Cortex Spikes Using Deep Learning

Master: Xing Chen, PhD (University of Pittsburgh, USA)

Theme: Signal analysis

Recent advancements in machine learning have revolutionized neural decoding, showcasing remarkable achievements such as decoding rodent spatial coordinates via hippocampal place cells, and motor activity [66,67]. We investigated the potential of deep learning in decoding visual image stimuli from neural spikes across various time bins and brain regions of the rodent brain.

Electrophysiology recordings and stimulus presentations were obtained from the Allen Institute for Brain Sciences Visual Coding Neuropixels Dataset using the AllenSDK. Three deep learning models were trained on spike counts across thousands of cortical and subcortical neurons and over 5,000 natural scene stimulus presentations. Models were tested on held-out test spikes and evaluated for image decoding accuracy.

Three machine learning models were trained to decode and classify which image was shown to the animal solely from visual neural spiking activity, with results summarized in FIgure 12. Each model's decoding accuracies were subsequently compared across various time bin durations and anatomical regions of the mouse visual system. In our analysis, time bin durations of 50 ms and greater appeared to capture neural information in the most robust way for decoding. Deep neural networks outperformed shallow neural networks and linear support vector machines across nearly all conditions (aside from small time bin durations, which was felt to be secondary to overfitting) and within individual brain regions. VISp (primary visual cortex) outperformed all other discrete brain regions in decoding accuracy, with VISal (anterolateral visual cortex) and LGN (thalamic) closely behind, and CA1 and CA3 (hippocampal regions) performing at chance, effectively serving as controls (Figure 12c). These findings suggest possible avenues for future visual neural decoding efforts and offer insights into optimal neural decoding algorithm design.

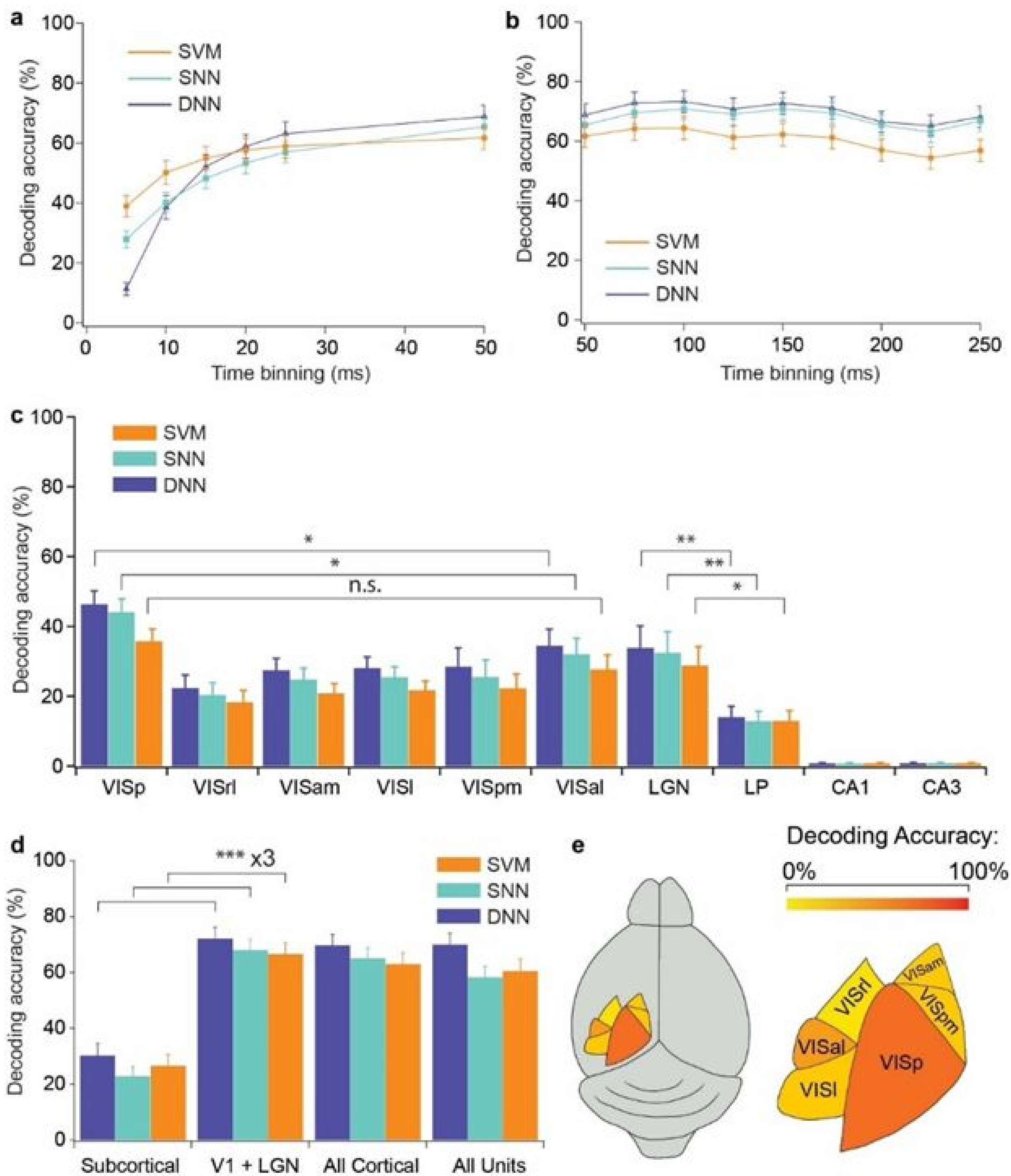


Figure 12. Neural Decoding Analysis. (**a-b**) Results of time binning analysis. Mean decoding accuracies of each time bin condition and machine learning model plotted and reported in the underlying table. (**c**) Individual brain region decoding analysis. Mean decoding accuracies across all sessions reported for each brain region and machine learning model, superimposed

on top of a table of values. (**d**) Grouped brain region decoding analysis. Graphical comparison between mean decoding accuracies of various grouped brain regions for each machine learning model, along with mean values. (e) Anatomical heatmap of decoding accuracies of six visual cortex subregions decoded from, overlayed on mouse brain.

Several limitations exist, however. Data were obtained from an open dataset provided by the Allen Institute, which may aid in reproducibility but inherently limited our ability to acquire raw spiking data. Our deep learning and data analysis therefore relied on data obtained by another institution. The interpretability of this work may be partially limited given the unpredictable nature of the representations learned by deep neural networks as evidenced by signs of overfitting described above. While our decoding networks were validated, trained, and tested within each individual subject, it remains unclear how well the models would generalize across subjects.

While conventional neural decoding algorithms make assumptions about the encoding of neural representations, deep learning-based neural decoding makes few assumptions. However, most deep learning-based neural decoding work has been done in motor cortex decoding. Accurate decoding of electrophysiology signals from brain structures involved in visual processing hold great promise in better informing our understanding of sensory processing, artificial intelligence, and BCIs for visual prosthetics. Taking a page from the motor decoding literature, future directions of this work involve implementing a neural population dynamics approach given the richness of spiking data in this open dataset. For example, characterizing the distinct neural trajectories that visual scene stimuli produce, as has been described with movement patterns in the motor cortex. Lastly, while our initial focus was decoding static visual stimuli, reconstruction of both static and dynamic (movies) visual stimuli from action potential spikes would represent a significant breakthrough, as has been explored in recent years largely with fMRI.

2.5.c. *Presenter*: Mousa Mustafa (Technische Universität Berlin, Germany)

Title: Decoding Invasive Brain Signals Using Deep Learning

Master: Marianna Semprini, PhD (Italian Institute of Technology, Genoa, Italy)

Theme: Brain implant - other

This research explores the use of deep learning and classical machine learning models to predict self-paced hand movements in patients with PD using ECoG recordings. Deep learning has advanced the decoding of ECoG data [68], providing insights into precise hand movements. Adaptive bidirectional neuromodulation, which combines neurostimulation with real-time brain activity feedback, offers the potential for more accurate symptom management for patients with PD [69]. Merk et al. [70] conducted a comprehensive review on the current state of machine learning use for DBS, and these developments underscore the promise of deep learning in neurology, including applications in brain-computer interfaces and neuroprosthetics. The study's objective is to compare the accuracy and precision of predictions made by these models and evaluate their potential for use in closed-loop deep brain stimulation treatment for PD.

A variety of classical machine learning models (Logistic Regression, XGBoost Classifiers, support vector machine, K-neighbor classifier, Random Forests, and Gradient Boosting) and deep learning model architectures (CNN, ResNet, HTNet, and multilayer perceptron) were used in this study. The models were trained on data recorded from intracranial electrodes placed at the sensorimotor and parietal cortex of patients. Preprocessing and frequency band variance features were extracted for the classical machine learning models using the py_neuromodulation toolbox, while continuous normalized ECoG data were used to train the deep learning architectures. After training the models, validating them via 3-fold cross-validation, and evaluating them on the balanced accuracy metric, it was observed that the best deep learning model outperformed the classical machine learning models on most subjects in balanced accuracy and in all subjects on the F1 score. A visualization of the processing pipeline may be found in Figure 13a.

The results of this study demonstrate the potential of deep learning models in accurately predicting self-paced hand movements using ECoG recordings from patients with PD. The deep learning models outperformed the traditional machine learning models in accuracy and precision. Specifically, the deep learning models achieved a balanced accuracy with a mean of 0.8808 and a standard deviation of 0.0532, and an F1 score with a mean of 0.7378 and a standard deviation of 0.0799. In comparison, the classical machine learning models had a balanced accuracy with a mean of 0.7875 and a standard deviation of 0.1071, and an F1 score with a mean of 0.5330 and a standard deviation of 0.1948 (Figure 13b). These findings suggest that deep learning models have the potential to be a valuable tool in the treatment of Parkinson's disease.

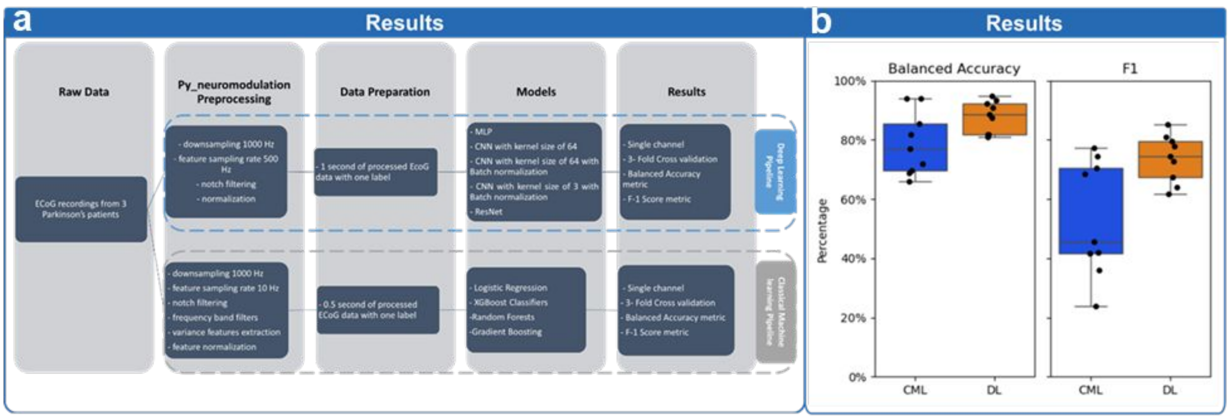


Figure 13. (**a**) Overview of the pipeline used for each model group. (**b**) comparison of the results on both the balanced accuracy score and F1 metrics between the classical machine learning (CML) group and deep learning (DL) group.

The study's limitations include a small sample size, data variability among patients and lack of model interpretability. Future research should focus on larger and more diverse cohorts, longitudinal studies, improving model interpretability, and exploring the effect of data size on training the deep learning models. Additionally, exploring real-world implementation in clinical settings is crucial. Addressing these aspects will help fully realize the potential of deep learning models in treating Parkinson's disease.

2.6 Exploring brain-computer interfaces for neurorehabilitation

For neurorehabilitation, BCIs serve as invaluable tools by translating neural signals into tangible feedback, thereby aiding patients in various situations, such as post-stroke rehabilitation or mental health improvement. By continually refining the design, enhancing feedback mechanisms, and broadening the clinical applications of BCIs in neurorehabilitation settings, we can effectively customize these systems to meet the unique needs and preferences of each user.

2.6.a. Presenter: Jose Gonzalez-Espana (University of Houston, USA)

Title: NeuroExo: A Low cost Non Invasive Brain Computer Interface for upper-limb stroke neurorehabilitation at home

Master: Ning Jiang, PhD (University of Waterloo, Canada)

Theme: Brain non-implanted - control

EEG-based BCIs for real-time control of end effectors in at-home neurorehabilitation demand robust software and hardware solutions. However, the high cost of quality EEG amplifiers hinders their commercial viability. In the NeuroExo BCI System, it addressed these challenges by developing a low-cost BCI system with a focus on democratized access. Specifically designed for upper-limb stroke rehabilitation, the NeuroExo BCI System serves as a groundbreaking proof of concept.

The system comprises key components, including a versatile EEG headset with five dry-comb electrodes for a form-fitting, universally adaptable solution. Using cost-effective devices such as the BeagleBone Black Wireless, ADS1299, and ICM-20948 for processing and data collection, we ensured affordability. LabVIEW facilitated seamless integration as the primary coding language. The NeuroExo BCI system has real-time capabilities in both open and closed-loops modes. In open loop mode, raw EEG and inertial measurement unit data were collected at an 80 Hz rate, while in the closed loop mode, a WiFi-enabled robotic arm served as the end effector for upper-limb rehabilitation at a 40 Hz rate.

To validate the system's clinical utility for at-home neurorehabilitation, stroke survivors enrolled at TIRR Memorial Hermann participated in a comprehensive program. This included one week of clinic training followed by six weeks of home therapy with the NeuroExo BCI system, with progress assessed by a physical therapist before and after sessions. The goal of the NeuroExo system is to enhance the feasibility of at-home neurorehabilitation for chronic stroke patients, offering a low-cost, portable, reliable, and user-friendly solution.

In future work, the results of at-home use by stroke survivors and healthy participants will be presented. A user-centered analysis of the system will also be included. Improvements in the hardware, firmware, and both the back-end and front-end software are expected to be implemented based on the user-centered experience.

2.6.b. *Presenter*: Florencia Garro, PhD (Italian Institute of Technology, Genoa, Italy)

Title: Effects of Robotic Assistance in ERP Modulation for Upper-limb Exoskeleton Control

Master: Ning Jiang, PhD (University of Waterloo, Canada)

Theme: Brain non-implanted - control

Event-related potential (ERP)-based BCIs are investigated in robotic neurorehabilitation to potentially boost brain plasticity and motor learning by engaging patients in the control loop [71]. Exoskeletons offer assistance levels (ALs) that could be fine-tuned using ERP-based BCI [72]. However, it remains unclear if and how brain activity is affected by varying ALs. We analyze ERP modulation during a standardized task with different ALs provided by FLOAT, a novel upper limb exoskeleton [73], to explore the relationship between brain activity and ALs.

We collected high-density EEG from 10 healthy right-handed individuals while performing a standardized reaching task under three distinct conditions: unassisted free movement (No_Exo) and two levels of FLOAT-assisted movements: low and high AL (Exo_AL1 and Exo_AL2). Between 100-350 ms after the Go cue, a cluster-based permutation test using the Monte Carlo method shows differences in both **Exo_AL1** and **Exo_AL2** vs **No_Exo** conditions (p<0.05). The difference is most pronounced over central, centroparietal, and left parietal-occipital sensors, including the frontocentral area for **Exo_AL2** (Figure 14a). Between -250-250 ms centered on target reach, we found differences between the **Exo_AL2** and **No_Exo** condition, most pronounced over central and left parietal-occipital sensors (Fig. 14b). The lack of difference between Exo_AL1 and No_Exo suggests that the motor scheme is unchanged, and thus, the two conditions are perceived similarly in that movement phase.

Comprehending the impact of ALs on brain activity may boost BCI design, aiding in the enhancement of human-in-the-loop optimization strategies for neurorehabilitation. Specifically, future research aims to support the development of novel metrics based on standardized neuromechanical data for assessing the performance of both robotics and patients. Limitations of this study include the self-paced nature of the task, which may introduce asynchrony in ERPs, and the small sample size. Future work will address these limitations by expanding the sample size to enable more robust statistical analyses, and by exploring additional analyses, such as frequency domain approaches.

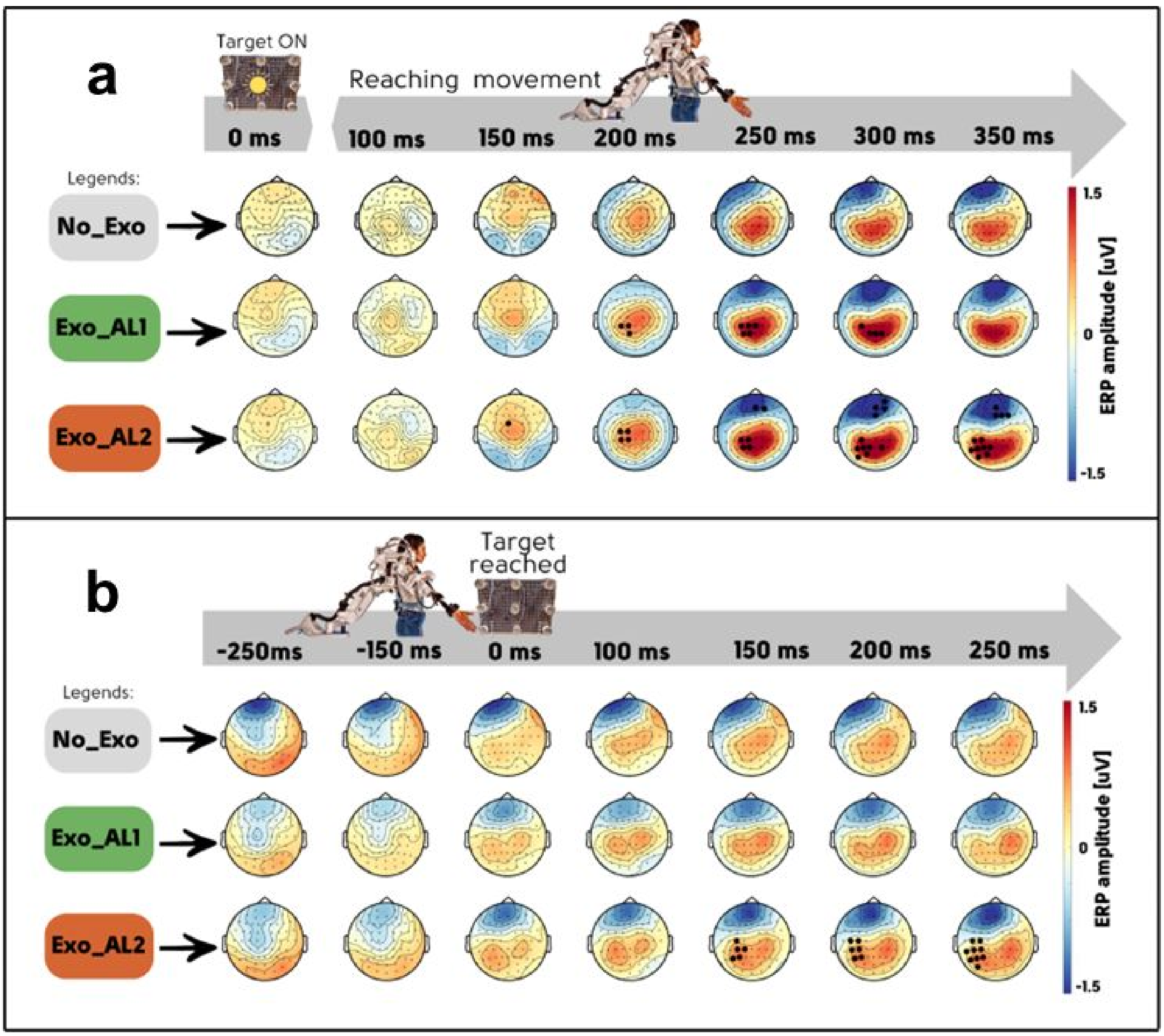


Figure 14. ERP amplitudes for No_Exo (gray), Exo_AL1 (green), and Exo_AL2 (red) across various time intervals centered on the Go cue (**a**) and target reach (**b**) conditions. Adapted from [74] with permission.

2.6.c. *Presenter*: Angela Vujic, PhD (Massachusetts Institute of Technology, Boston, USA)

Title: Joie: An Affective Brain-computer Interface for Learning Mental Strategies for Positive Affect

Master: David E. Thompson, PhD (Kansas State University, USA)

Theme: BCI non-implanted - other

Training to enhance left prefrontal brain activity via neurofeedback may alleviate symptoms of anxiety and depression [75,76]. To impart users with positive mental strategies, we developed Joie, a joy-based EEG BCI [77,78]. Joie utilizes prefrontal alpha asymmetries linked to joyful thoughts as input to control a character's movement in a neurofeedback video game (Figure 15). The video game is designed as an endless runner where users are rewarded and receive a score based on how long they sustained left prefrontal asymmetry. Joyful thoughts during gameplay induce left prefrontal asymmetry, resulting in positive feedback in-game, whereas right prefrontal asymmetry results in negative feedback. In a lab study involving 20 participants undergoing 15 training sessions each over two weeks, our experimental group, instructed to imagine positive music, winning awards, and other strategies associated with approach and withdrawal motivation behavior, exhibited a significantly improved ability to activate alpha asymmetry compared to placebo and control groups. Joie highlights the potential of prefrontal asymmetries, or applying the approach and withdrawal motivation model, as input for affective BCIs. Training these asymmetries via neurofeedback can impart mental strategies with potential applications in mental health for reducing anxious or depressive symptoms.

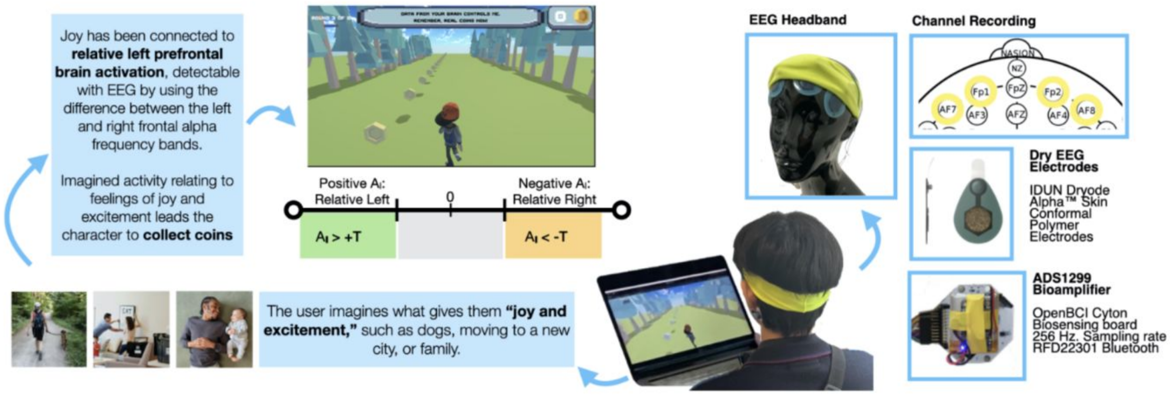


Figure 15. Joie's neurofeedback design with a wearable, dry electrode headband. The user imagines joyous thoughts activate prefrontal left asymmetries that cause their character to collect coins as a reward. Reprinted from [75] with permission.

2.7 Advancements in sampling the sensorimotor cortex

Recordings obtained from the sensorimotor cortex have played a pivotal role in advancing BCIs and their practical applications. Recent innovations in neural interface technology, such as endovascular electrode arrays, advancements in sampling techniques, such as ultra-high-density ECoG recordings, offer new avenues for capturing neural signals and extracting information. Despite these technological strides, there remains a crucial need to thoroughly characterize the information encoded within these novel signals and datasets to understand their applicability.

2.7.a. *Presenter*: Kriti Kacker (Carnegie Mellon University, USA)

Title: Spectral features of endovascular ECoG signals recorded from a Stentrode in human motor cortex

Master: Richard Andersen, PhD (California Institute of Technology, USA)

Theme: Brain implant - control

The Stentrode^{TM} is a novel endovascular BCI technology implanted within the superior sagittal sinus to measure field potentials, similar to ECoG, from the primary motor cortex, enabling communication for individuals with severe paralysis [79]. However, the features of these vascular ECoG (VECoG) signals have not been fully characterized in humans. Participants with severe paralysis due to amyotrophic lateral sclerosis and brainstem stroke have been implanted in pilot clinical trials in Australia (n=4) and in an Early Feasibility study in the United States (n=6).

We examined the VECoG signals from one US participant to identify spectral features associated with volitional motor intent (Figure 16). The recorded field potentials were filtered into standard frequency bands: alpha (8-13 Hz), beta (13-30 Hz), low gamma (30-80 Hz), and high gamma (80-200 Hz). For each band-limited signal, we calculated the change in root-mean-square voltage (Vrms) between rest and movement epochs, quantifying the percentage change of Vrms movement from rest (termed as modulation depth) for each trial.

We investigated the features of the Stentrode signals and identified the spectral characteristics that exhibited strong and consistent changes in amplitude between rest and attempted movement conditions. The average modulation depth across all channels was 22.77 ± 6.34% in the low gamma band and 40.20 ± 6.00% in the high gamma band during right hand movement. The classifier performance for both the gamma bands remained stable, with the low gamma classifier achieving a mean accuracy of 93 ± 3% and the high gamma classifier achieving a mean accuracy of 96 ± 3%. These results suggest that the Stentrode reliably detects volitional motor signals and maintains long-term stability for up to 10 months post-implantation. Our preliminary analysis indicates that these endovascular neural signals exhibit properties similar to those reported for ECoG-based measures of motor intent. Future research should explore VECoG signals over a longer time period and across more participants to confirm that the BCI can operate reliably and effectively over the course of several years.

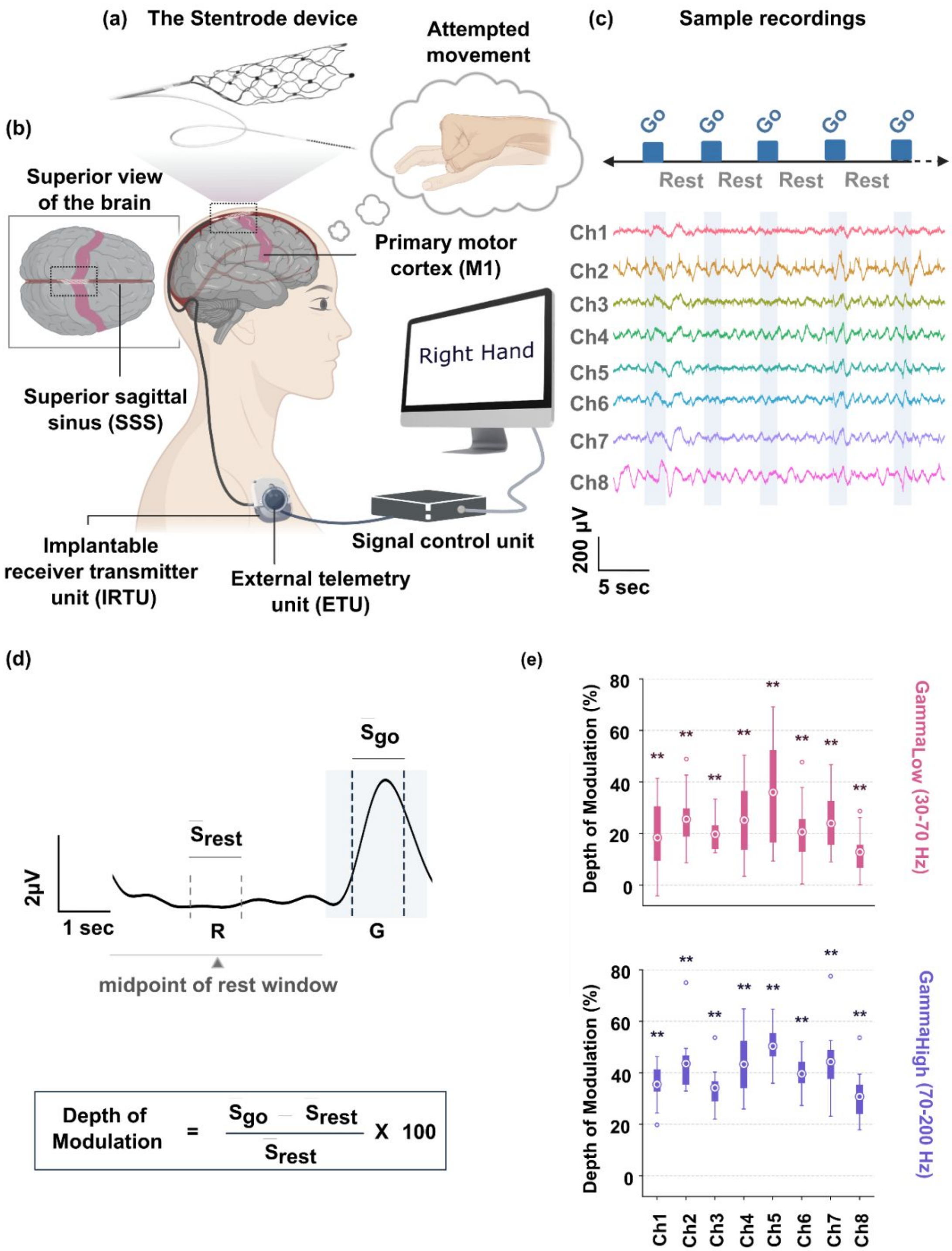


Figure 16. (**a**) The Stentrode device with 16 electrodes. (**b**) The Stentrode is a flexible electrode array implanted in the superior sagittal sinus using stent technology and sits adjacent to the primary motor cortex. The participants are instructed to attempt movement of specific body segments based on the cues on the screen. The data recorded by the Stentrode is sent

wirelessly to the external telemetry unit by the implantable receiver transmitted unit. The signal control unit sends the data further to the computer. (**c**) Sample VECoG recorded from eight channels during alternating cues of rest and go. (**d**) Modulation depth is calculated as the percentage change in the average amplitude during attempted movement window (Sgo) with respect to the average amplitude during the rest window (Srest). (**e**) Modulation depth for VECoG signals across all channels in the low gamma and high gamma bands while the participant attempted to move their right hand. ** Indicates t-test was significant at $p < 0.01$.

2.7.b. *Presenter*: Christoph Kapeller, PhD (g.tec medical engineering GmbH, Austria)

Title: Increased spatial resolution reveals separated EEG activation of individual finger movements

Master: Christian Herff, PhD (Maastricht University, Netherlands)

Theme: Signal acquisition

The study of high-density EEG electrodes is currently of great interest in BCI research. The 10-20 system, proposed by Jasper in 1958 [80], and the 10-10 extension by Chatrian et al. in 1985 [81], are the established standards by the American EEG society. In 2001, Oostenveld introduced the 5% system positions [82]. Our proposed setup with active ultra-high-density electrode (uHD) records EEG via scalp grids with an electrode spacing of 8.6mm, compared to a median Euclidean distance of 35.4mm in the 10-10 system (Figure 17). This represents a four times higher spatial sampling, combined with an increased R^2 of the cross-channel EEG from 0.18 to 0.44, indicating a net increase of information content over all EEG signals [83]. Studies have shown that biomarkers for individual finger extensions achieved classification accuracy for two fingers by +6-7% from 10-10 EEG to uHD EEG [84,85]. Specifically, with a grand average accuracy of 64.8% and a maximum of 79.2% for index versus ring finger [83]. A within-subject analysis of the uHD EEG vs 10-10 EEG showed a clear reduction of channels with multi-finger activation with more focused single finger sites over the motor cortex. Moreover, it is possible to discriminate between hand gestures and their imagination, namely, rock-paper-scissors, with 72.7% and 71.3%, respectively, in a pair-wise classification [86], demonstrating the utility of a uHD EEG.

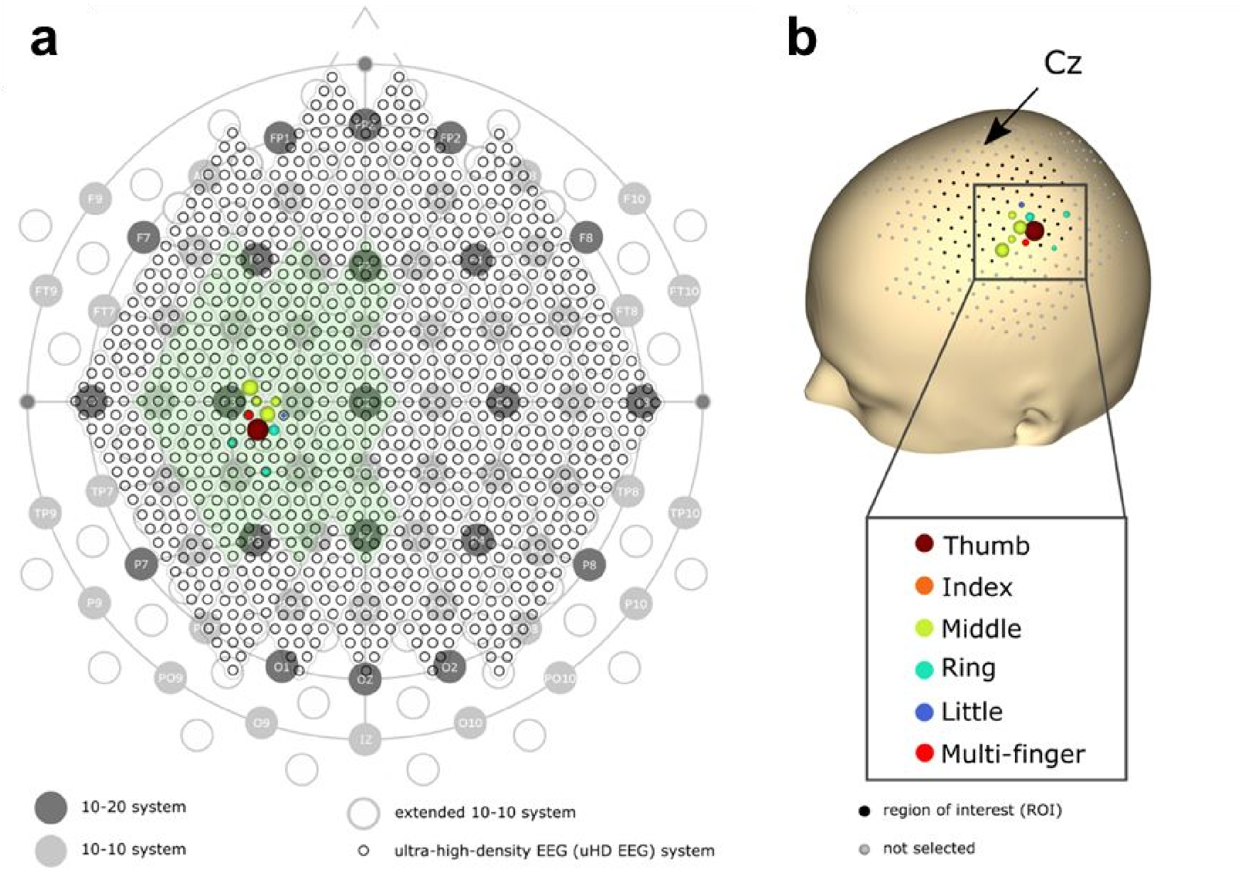
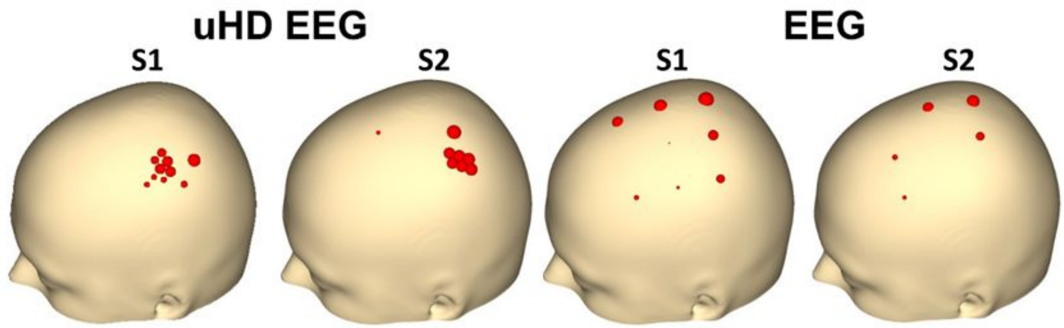


Figure 17. A focal point overlying the sensorimotor cortex around the 10-20 position C3 shows the highest activation. Ten electrodes were color-coded according to the finger with the greatest significance in ERD/S change, one finger includes information from several fingers (Mult-finger).

A subject specific example is provided in Figure 18, which represents the superimposed finger activity from Subject 1 on the electrode distribution comparison plot (a) and the MNI head (b). Results show the analysis of the beta band (13-30 Hz), which was used for feature extraction. After calculating the Event-related synchronization/desynchronization (ERD/S), a Wilcoxon signed-rank test was used to find significant channels with movement-related beta band changes. Significant channels are colored respectively for each finger and multi-finger channels, which were found to be active for several individual fingers. Figure 2 shows that ultra-high density / 10-10 beta power revealed 11% / 11% single-finger, 1% / 61% multi-finger and 88% / 28% no-finger sites, respectively. ERD/S bubble plots reflect the radius from the active channels' ERD/S amplitude.



Subject	S1 (uHD EEG)	S2 (uHD EEG)	Merged (uHD EEG)	S1 (EEG)	S2 (EEG)	Merged (EEG)
ROI (channels)	73	73	**146**	9	9	**18**
Significant channels	10	8	**18**	8	5	**13**
Single-finger	12%	10%	**11%**	11%	11%	**11%**
Multi-finger	1%	1%	**1%**	78%	44%	**61%**
no-finger	86%	89%	**88%**	11%	44%	**28%**

Figure 18. Significant channels marked in red from the single finger movement paradigm comparing the uHD EEG and 10-10 EEG system. The bubble radius reflects the ERD/S amplitude. The table states the region of interest selected, the number of significant channels and the ratio of single and multi-finger activation.

As our study included only two subjects, the results are not generalizable. A larger cohort, encompassing both male and female participants, as well as varying preferred hand dominance, is necessary to improve the robustness and applicability of the findings. For optimal system performance of the ultra-high-density EEG system, hair removal is essential, as effectiveness diminishes with increased hair length. Comprehensive testing across various hair types is necessary to identify potential limitations. Additionally, as the number of electrode grids increases, the system's form factor becomes more complex, leading to extended setup times and reduced user comfort. Future research should integrate uHD EEG with source reconstruction techniques to further refine high-resolution neurophysiological localization through non-invasive recordings.

2.7.c. *Presenter*: Simon Geukes (UMC Utrecht Brain Center, Netherlands)

Title: Ultra-high-density electrocorticography recordings of the human sensorimotor cortex

Master: Victoria Peterson, PhD (Instituto de Matemática Aplicada del Litoral, Santa Fe, Argentina)

Theme: Signal analysis

ECoG is a popular recording method for clinical and research purposes, including brain-computer interfaces [87]. Clinical ECoG grids have 10 mm inter-electrode distance (IED), while high-density (HD) ECoG grids have 3-4 mm IED. Both clinical and HD ECoG may spatially undersample the cortex, as the cortical resolution is higher than the resolution offered by these grids [88,89]. Ultra-high-density (uHD) ECoG, which offers submillimeter resolution, may resolve this. However, whether uHD ECoG can record distinct neural signals without considerable spatial oversampling remains unclear.

To investigate this, we simultaneously recorded intraoperative HD and uHD ECoG (Figure 19a-b) from the sensorimotor cortex while participants were awake (n=3) or under general anesthesia (n=1). During awake surgeries, the participants performed motor mouth or hand tasks. To verify signal quality, we computed the power spectra of the recorded signals. To investigate overlap between electrodes as a function of IED, we calculated the distance-averaged correlation: the average correlation coefficient between equidistant electrode pairs, for different frequency bands. Lastly, to quantify functional responses, we regressed the mean high-frequency band power (64-128 Hz) to the tasks.

We found that: 1) In all participants, the 1/f decay and noise peaks were similar in the power spectra of HD and uHD grids; 2) In three participants, HFB power overlapped only moderately (r: 0.35-0.65) between electrodes at 0.9 mm IED. This is illustrated in Figure 19c, which shows the distance-averaged correlation for the HD and uHD grid of one participant. 3) In one participant, 70% of the uHD electrodes significantly responded to the task, revealing a distinct spatial pattern where certain electrodes responded significantly while adjacent ones did not. Taken together, we conclude that uHD ECoG does not spatially oversample the sensorimotor cortex. Further investigation into optimal recording procedures, re-referencing methods and analytical methods to quantify single electrode responses are needed to fully leverage the potential of uHD ECoG.

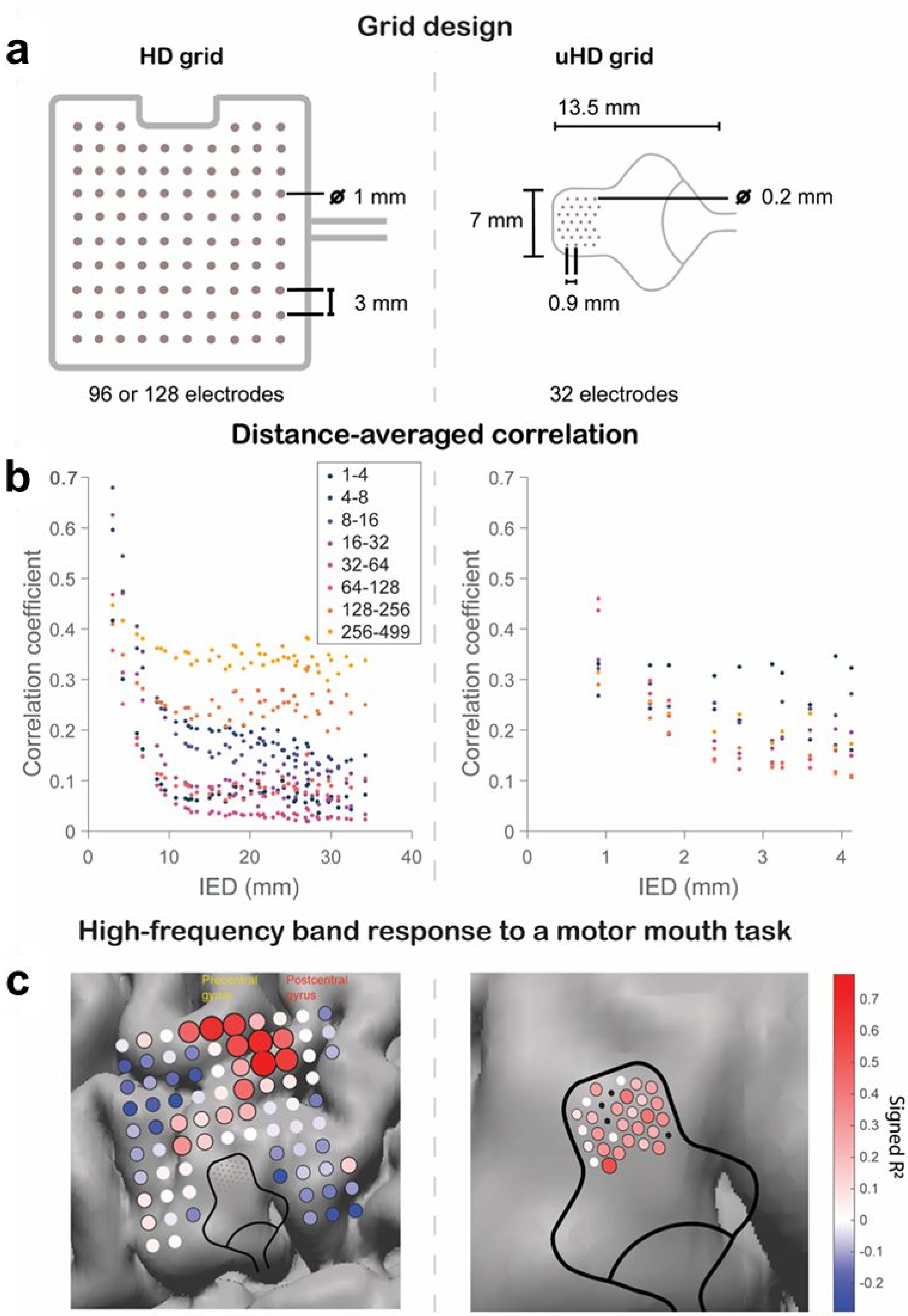

Grid design
a
HD grid
uHD grid
ø 1 mm
3 mm
96 or 128 electrodes
13.5 mm
7 mm
ø 0.2 mm
0.9 mm
32 electrodes
Distance-averaged correlation
b
1-4
4-8
8-16
16-32
32-64
64-128
128-256
256-499
Correlation coefficient
IED (mm)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10
20
30
40
1
2
3
4
High-frequency band response to a motor mouth task
c
Precentral gyrus
Postcentral gyrus
Signed R²
-0.2
-0.1
0.1
0.2
0.3
0.4
0.5
0.6
0.7

Figure 19. (**a**) Left panel: illustration of the 96-channel HD grid (Ad-Tech Medical, Oak Creek, USA). A 128-channel grid (PMT Corporation, Chanhassen, USA) with the same IED and exposed diameter was used as well. Right panel: illustration of the uHD grid (CorTec Neuro, Freiburg, Germany). (**b**) Distance-averaged correlation for the HD grid (left panel) and uHD grid (right panel) of one participant. The frequency bands (in Hz) are denoted by the color coding. (**c**) High-frequency band response (64-128 Hz) to a motor mouth task for the HD grid (left panel) and uHD grid (right panel) of one participant. HD electrodes overlaying the uHD grid are not shown. Excluded electrodes are colored black. Electrode radius increases with the R2 value. Circumvented electrodes responded significantly to the task. (**a**) and (**c**) are adapted, with permission, from[90].

2.8 Novel techniques for advancing brain-computer interface performance

Integrating multiple modalities, such as incorporating both brain signals and other physiological signals as input, merging brain recordings with stimulation techniques, or exploring new analytic techniques hold promise for advancing BCI control and decoding capabilities. By harnessing the complementary strengths of diverse signals, BCI systems stand to benefit from heightened efficacy and enhanced accuracy, thereby amplifying their use in real-world applications. Moreover, developing innovative strategies for encoding movement patterns, optimizing dynamic stopping methods for diverse applications, and augmenting motor skill acquisition may unlock new dimensions of BCI functionality.

2.8.a. *Presenter*: Tan Gemicioglu (Cornell University, USA)

Title: Transitional Gestures for Enhancing ITR and Accuracy in Movement-based BCIs

Master: Ning Jiang, PhD (University of Waterloo, Canada)

Theme: BCI non-implanted - control

Motor imagery and motor attempt-based BCIs enable users to communicate by sequentially performing different actions. Conventional interaction methods use a set of body parts or motions with a one-to-one mapping to commands. However, this mapping makes it challenging to use movement for high-speed spellers due to constraints in the number of possible commands. A recent interaction method, BrainBraille, uses a pseudobinary encoding where up to six body parts can be tensed simultaneously and mapped onto a Braille character for language-independent alphabetic encoding. However, non-invasive BCI modalities such as EEG and functional-near infrared spectroscopy (fNIRS) have limited spatial specificity and often struggle to distinguish simultaneous movements.

We propose a new method encoding transitions between gestures in different body parts to combinatorially increase the size of the command set by using transitional gestures where information is extracted from transitions between different movements to improve accuracy, number of possible commands, and information transfer rate (ITR). In a pilot study using the NIRx NIRSport, participants tensed the left hand and right hand in transitional patterns in a random order for 40 trials each. We applied a 0.09Hz low-pass Butterworth filter and performed independent component analysis. A support vector machine obtained 81% accuracy in left vs. right classification while obtaining 92% accuracy in left-to-right vs right-to-left classification, demonstrating the accuracy benefits of transitional gestures.

Then, we adapted the BrainBraille encoding scheme with a transitional encoding. BrainBraille is currently limited to a maximum of three simultaneous movements and uses 27 out of 37 possible commands. Our transitional BrainBraille encoding would allow P(6,3)=120 commands, allowing a wider range of characters while maintaining the same constraints and potentially increasing ITR from BrainBraille's current ITR of 143 bits per minute to 218 bits per minute. Our findings suggest that a transitional encoding can make a movement-based speller more feasible by increasing accuracy, speed, and flexibility in modalities with limited spatial specificity.

2.8.b. *Presenter*: Ceci Verbaarschot, PhD (University of Pittsburgh, USA)

Title: The effect of artificially created sensory feedback on motor cortex activity during task performance

Master: Marianna Semprini, PhD (Italian Institute of Technology, Genoa, Italy)

Theme: BCI implant - other

Intracortical microstimulation (ICMS) of the human somatosensory cortex induces localized sensations on an individual's paralyzed hand and can enhance control of a brain-controlled prosthetic arm [91,92]. Typically, there exists a direct interaction between naturally occurring tactile sensations and motor function. Ongoing sensory input influences the activity of the motor cortex, leading to intricate patterns of both inhibitory and excitatory responses. We investigated whether artificial touch (created via ICMS) could have a similar effect on motor cortex activity.

Two participants with tetraplegia with implanted intracortical microelectrode arrays in their somatosensory and motor cortices (Figure 20a) underwent ICMS trains of various amplitudes (40, 60, 80 μA) and frequencies (50, 100, 200 Hz), while they passively watched a movie. Next, we investigated the effect of ICMS (50 Hz, 60 μA) while they attempted (full hand grasp or individual finger) movements during an engaging Guitar Hero-like game (Figure 20b). We found that higher stimulation amplitudes linearly increased the global population activity in the motor cortex (Figure 20c). Meanwhile, frequency had varying effects in which stimulation at 50 Hz had a largely excitatory effect, 200 Hz had a predominantly inhibitory effect, and lastly 100 Hz had mixed effects depending on the electrode (Figure 20c). Despite prominent effects on motor cortex activity, offline decoding of three individual fingers showed promise (89% accuracy) during 50 Hz ICMS.

Our findings suggest that ICMS not only creates an artificial sense of touch during motor control but also modulates motor cortex activity in a stimulus-dependent manner. Under normal circumstances, dynamically evolving sensory input likely modulates motor cortex activity, enabling us to, e.g., tighten our grip when we sense that an object is slipping from our hands. In future research, we investigate whether ICMS could play a similar functional role during motor control. To do so, we will manipulate the congruency of the ICMS-evoked sensation location and the ongoing motor task. Often, participants will feel a sensation on the same finger that they attempt to move during the Guitar-Hero like game. Occasionally, we will evoke a sensation on a different finger, one that is incongruent with the ongoing motor task. If we find the motor cortex to encode the congruency of the sensory signal with the motor task, this will provide credence that ICMS can serve as a functional source of information during motor control.

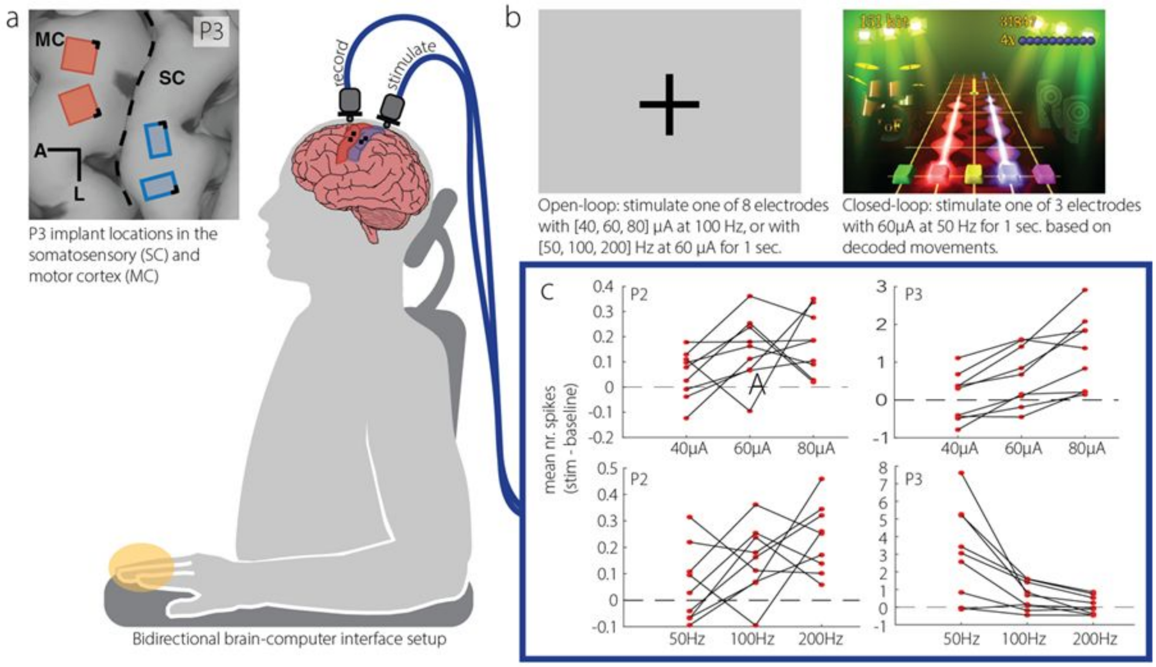


Figure 20. Overview of study design and results. (**a**) Schematic illustration of the BCI setup. (**b**) Experimental design using either open-loop (left) or closed-loop (right) stimulation. (**c**) Main results of intracortical microstimulation in the somatosensory cortex on the motor cortex for different amplitudes (top) and frequencies (bottom).

2.8.c. *Presenter*: Michael Wimmer (Know Center Research GmbH, Austria)

Title: Toward Hybrid BCI: EEG and Pupillometric Signatures of Error Perception in an Immersive Navigation Task in VR

Master: Marianna Semprini, PhD (Italian Institute of Technology, Genoa, Italy)

Theme: BCI non-implanted - other

The latest wearable devices used to visualize virtual reality (VR) content are equipped with built-in sensors and cameras to acquire user-specific physiological data, such as gaze or pupil size. Interactions with virtual environments may sometimes seem erroneous to users, as the behavior of the VR might not align with the user's intentions or expectations. Previous research has shown that EEG responses to errors, i.e., error-related potentials (ErrPs), can enhance the performance of BCIs [93]. The successful decoding of errors allows systems to take corrective actions, e.g., to stop unwanted commands or provide visual aids. Since most error classifiers rely on brain signals, this study explores the potential of pupillometric signals for hybrid error decoding approaches.

For this purpose, we designed an interactive VR flight simulation in which 19 participants navigated a glider through a series of targets (Figure 21). At random intervals, participants encountered unexpected behaviors or changes in the simulation, such as sudden displacements of the target locations and unintended glider movements.

The grand average responses revealed pupil dilations peaking approximately 600 ms after the error events. ErrPs were consistent with the existing literature [94]. The pupil dilations exhibited considerable variability across participants, which affects the performance and generalizability of classifiers. However, hybrid decoding approaches could significantly improve the accuracy in reduced EEG setups, i.e., using only one or three electrodes, by up to 3 to 4% on average and up to 8% at the participant level [95]. Studying the impact of such setup reductions has practical relevance, as they increase the BCI's usability in real-world applications. Further analysis of the behavioral data showed that participants took on average more than 400 ms to react to error events. The offline error decoders we implemented could detect errors up to 50 ms faster than participants responded to them [96].

The results of this work suggest that error-related pupillometric responses have the potential to improve existing error decoding approaches and hence, the design of hybrid BCIs [95]. Next steps in advancing hybrid classifiers should include research on suitable features derived from pupil signals. Similarly, investigations into the impact of different data fusion approaches could further enhance the decoding performance. Finally, these contributions should be tested in real-time scenarios where the VR adapts dynamically to errors.

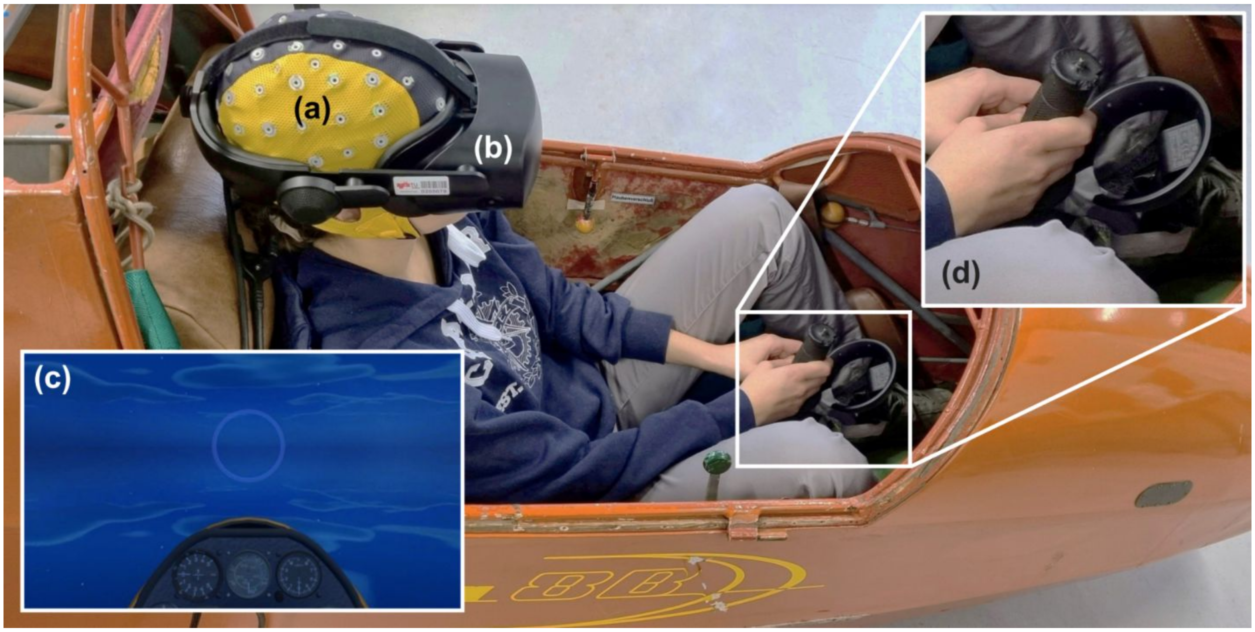


Figure 21. Overview of the experimental setup. The participant is seated in a glider, wearing an EEG cap (**a**) and an HMD (**b**) to interact with the virtual environment (**c**). The joystick of the HMD (**d**), used to navigate the virtual glider, is attached to the physical glider's control stick. Figure adapted from [95] with author consent.

2.8.d. *Presenter*: Mushfika Sultana (University of Essex, United Kingdom)

Title: Assessing the impact of transcranial Direct Current Stimulation on the enhancement of race driving skills

Master: Eli Kinney-Lang, PhD (University of Calgary, Canada)

Theme: BCI non-implanted - other

Recently, non-invasive brain stimulation like transcranial direct current stimulation (tDCS) has become popular and has been applied to focally change neuronal activation [97]. Although tDCS seems to be a promising approach for enhancing complex motor skill acquisition, very few studies have investigated the potential role of brain stimulation on race driving [98]. We have attempted an initial evaluation of the impact of anodal tDCS on race training. Toward this goal, we have analyzed multimodal experimental data consisting of EEG and telemetry from a driving simulator of 11 novice participants.

Twenty minutes of active or sham tDCS (PlatoWork by PlatoScience, Copenhagen, Denmark) was applied before a race driving task. Subjects were randomly and blindly assigned to one of two tDCS groups (6 active, 5 sham) balancing potential confounding factors (age, gender, driving proficiency, corrected vision). Each participant went through 10 experimental sessions (20 laps per session). The tDCS effect was evaluated through a mixed-design ANOVA where the lap time gain as a result of training was the response variable, the tDCS group was the between-subjects factor and the session index was the within-subjects factor. Furthermore, we assessed the average, standard deviation, and significance (with unpaired, two-sided Wilcoxon rank sum tests) of the lap times per group and session. Although no significant effect of tDCS on lap time gain can be established (F=0.63, p=0.76), additional post-hoc analysis showed that subjects in the active tDCS group exhibited better outcomes in sessions where intense learning takes place. Specifically, active-tDCS subjects performed in the last session significantly better (by almost 3 s on average) than sham-tDCS (active: 89.4±9.5, sham: 92.0±10.5, $p<10{-}17$), although performance was balanced (no statistically significant difference between the two groups) in the first session.

These preliminary results suggest that tDCS may be effective in supporting the learning of race driving, although the impact is not strong enough to be clearly observed in a session-wise, mixed-design ANOVA. It is important to note that the small sample size may account for the absence of a pronounced effect. Our findings indicate that tDCS can help novice users learn race driving more quickly, but the effect was modest and requires confirmation in future research. Further studies with larger populations will seek to clarify and validate these results.

2.8.e. *Presenter*: Sara Ahmadi, PhD (Radboud University, Netherlands)

Title: A model-based dynamic stopping method for code-modulated visual evoked potentials BCI

Master: Xing Chen, PhD (University of Pittsburgh, USA)

Theme: Signal analysis

BCIs are evolving beyond mere assistive technology, with dynamic stopping methods offering a means to expedite their speed [99]. These methods allow for decisions to be made regarding symbol ejection or further information acquisition based on the decoder's confidence level, thereby leveraging trial variance to enhance speed without compromising overall accuracy. However, conventional optimization metrics like symbols per minute and ITR may not adequately reflect system performance for specific applications or user types.

In our proposal, we advocate for a model-based approach harnessing analytical insights into the underlying classifier model. By establishing that similarity scores between observed and predicted responses for both target and non-target classes follow Gaussian distributions, we frame the dynamic stopping as a binary hypothesis decision problem. Here, different costs are assigned to various courses of action, with the cost ratio (*CR)* representing the ratio between the cost of False Alarm and Miss. Using a likelihood ratio test based on Bayes criterion, we determine the decision region where the total risk, calculated as the sum of costs weighted by the likelihood of each action, is minimized [100].

Preliminary findings on a code-modulated visual evoked potential dataset [101] demonstrate the efficacy of our approach. By adjusting the cost ratio, we observed varying trade-offs between speed and accuracy. For instance, with a small cost ratio, the system exhibits rapid response times (average time = 318*ms* for *CR*=1) but relatively high error rates (*Err*=81.9% for a 36-class problem), which may suit applications where post-processing, such as employing a language model, can compensate for lower accuracy. Conversely, increasing the cost ratio to *CR*=10^6 extends response time (average time = 2.32 seconds) while substantially reducing error rates (*Err*=22.9%), rendering the system more suitable for error-sensitive applications.

3. Conclusions

The Tenth International BCI Meeting provided a platform for trainees to showcase their research and engage in meaningful discussion with experts and the BCI community through master classes. The sessions, organized by the Postdoc & Student Committee of the BCI Society, were designed to foster interactions between trainees and established researchers and encourage a conducive environment for learning and collaboration. The master classes are a unique way to showcase the breadth of BCI research, illuminating both the challenges and breakthroughs encountered across various fields.

The selected summaries featured in this paper offer insights into the multifaceted topics explored in BCI research, reflecting the ongoing efforts of researchers to advance technology. Divided into eight specific themes, including speech decoding, motor imagery, and closed-loop BCIs, each summary presents the presenter's work, preliminary findings, and conclusions. Notably, the inclusion of trainees and senior researchers as co-authors emphasizes collaboration and mentorship within the BCI community. The master classes will continue to highlight the remarkable contributions of BCI trainees at the upcoming Eleventh International BCI Meeting.

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Abbreviations

aDBS - adaptive deep brain stimulation

AL - assistance level

ANN - artificial neural network

BRAND - Backend for Realtime Asynchronous Neural Decoding

BCI - brain-computer interface

BOTDA - backward formulation of optimal transport for domain adaptation

CMD - cognitive-motor dissociation

CNN - convolutional neural network

DA - data augmentation

DAREPLANE **- DA**ta driven **RE**search **PL**atform for **NE**urotechnology

DBS - deep brain stimulation

DoC - disorders of consciousness

ECG - electrocardiography

ECoG - electrocorticography

EEG - electroencephalography

EMG - electromyography

EOG - electrooculogram

ERD - event-related desynchronization

ERP - Event-related potential

ErrPs - error-related potentials

ERS - event-related synchronization

VECoG - endovascular electrocorticography

fNIRS - functional-near infrared spectroscopy

GR - Generic Recentering

HD - high density

HFB - high frequency band

HFD - Higuchi Fractal Dimension

ISPC - Inter-site phase clustering

ITR - information transfer rate

ICMS - Intracortical microstimulation

MEG - magnetoencephalography

MI - motor imagery

NFT - neural field theory

PAR - Personally Assisted Recentering

PD - Parkinson’s disease

PICU - Pediatric Intensive Care Unit

RNN - recurrent neural network

sEEG - stereo-electroencephalography

SMR - sensorimotor rhythm

tDCS - transcranial Direct Current Stimulation

uHD - ultra-high density

VR - virtual reality

References

[1] Metzger S L, Littlejohn K T, Silva A B, Moses D A, Seaton M P, Wang R, Dougherty M E, Liu J R, Wu P, Berger M A, Zhuravleva I, Tu-Chan A, Ganguly K, Anumanchipalli G K and Chang E F 2023 A high-performance neuroprosthesis for speech decoding and avatar control *Nature* **620** 1037–46

[2] Willett F R, Kunz E M, Fan C, Avansino D T, Wilson G H, Choi E Y, Kamdar F, Glasser M F, Hochberg L R, Druckmann S, Shenoy K V and Henderson J M 2023 A high-performance speech neuroprosthesis *Nature* **620** 1031–6

[3] Luo S, Rabbani Q and Crone N E 2022 Brain-Computer Interface: Applications to Speech Decoding and Synthesis to Augment Communication *Neurotherapeutics* **19** 263–73

[4] Berezutskaya J, Freudenburg Z V, Vansteensel M J, Aarnoutse E J, Ramsey N F and van Gerven M A J 2023 Direct speech reconstruction from sensorimotor brain activity with optimized deep learning models *J. Neural Eng.* **20** 056010

[5] Panachakel J T and Ramakrishnan A G 2021 Decoding Covert Speech From EEG-A Comprehensive Review *Front. Neurosci.* **15**

[6] Metzger S L, Liu J R, Moses D A, Dougherty M E, Seaton M P, Littlejohn K T, Chartier J, Anumanchipalli G K, Tu-Chan A, Ganguly K and Chang E F 2022 Generalizable spelling using a speech neuroprosthesis in an individual with severe limb and vocal paralysis *Nat. Commun.* **13** 6510

[7] Verwoert M, Ottenhoff M C, Goulis S, Colon A J, Wagner L, Tousseyn S, van Dijk J P, Kubben P L and Herff C 2022 Dataset of Speech Production in intracranial Electroencephalography *Sci. Data* **9** 434

[8] Singh A, Hussain A A, Lal S and Guesgen H W 2021 A Comprehensive Review on Critical Issues and Possible Solutions of Motor Imagery Based Electroencephalography Brain-Computer Interface *Sensors* **21** 2173

[9] Robinson P A, Rennie C J, Rowe D L, O'Connor S C and Gordon E 2005 Multiscale brain modelling *Philos. Trans. R. Soc. B Biol. Sci.* **360** 1043–50

[10] Tangermann M, Müller K-R, Aertsen A, Birbaumer N, Braun C, Brunner C, Leeb R, Mehring C, Miller K J, Müller-Putz G R, Nolte G, Pfurtscheller G, Preissl H, Schalk G, Schlögl A, Vidaurre C, Waldert S and Blankertz B 2012 Review of the BCI Competition IV *Front. Neurosci.* **6** 55

[11] Polyakov D, Robinson P A, Muller E J and Shriki O 2024 Recruiting neural field theory for data augmentation in a motor imagery brain-computer interface *Front. Robot. AI* **11** 1362735

[12] Pfurtscheller G and Neuper C 2001 Motor imagery and direct brain-computer communication *Proc. IEEE* **89** 1123–34

[13] Little S, Bonaiuto J, Barnes G and Bestmann S 2019 Human motor cortical beta bursts relate to movement planning and response errors *PLoS Biol.* **17** e3000479

[14] Aristimunha B, Carrara I, Guetschel P, Sedlar S, Rodrigues P, Sosulski J, Narayanan D, Bjareholt E, Barthelemy Q, Schirrmeister R T, Kobler R, Kalunga E, Darmet L, Gregoire C, Abdul Hussain A, Gatti R,

Goncharenko V, Thielen J, Moreau T, Roy Y, Jayaram V, Barachant A and Chevallier S 2024 Mother of all BCI Benchmarks

[15] Szul M J, Papadopoulos S, Alavizadeh S, Daligaut S, Schwartz D, Mattout J and Bonaiuto J J 2023 Diverse beta burst waveform motifs characterize movement-related cortical dynamics *Prog. Neurobiol.* **228** 102490

[16] Papadopoulos S, Szul M J, Congedo M, Bonaiuto J J and Mattout J 2024 Beta bursts question the ruling power for brain-computer interfaces *J. Neural Eng.* **21**

[17] Papadopoulos S, Darmet L, Szul M J, Congedo M, Bonaiuto J J and Mattout J 2024 Surfing beta burst waveforms to improve motor imagery-based BCI 2024.07.18.604064

[18] Papadopoulos S, Darmet L, Szul M J, Congedo M, Bonaiuto J and Mattout J 2024 Improved motor imagery decoding with spatiotemporal filtering based on beta burst kernels *9th Graz Brain-Computer Interface Conference 2024* (Graz, Austria: Verlag der Technischen Universität Graz)

[19] Singh A, Lal S and Guesgen H W 2017 Architectural Review of Co-Adaptive Brain Computer Interface *2017 4th Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE)* 2017 4th Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE) pp 200–7

[20] Peterson V, Nieto N, Wyser D, Lambercy O, Gassert R, Milone D H and Spies R D 2022 Transfer Learning Based on Optimal Transport for Motor Imagery Brain-Computer Interfaces *IEEE Trans. Biomed. Eng.* **69** 807–17

[21] Lotte F and Guan C 2011 Regularizing Common Spatial Patterns to Improve BCI Designs: Unified Theory and New Algorithms *IEEE Trans. Biomed. Eng.* **58** 355–62

[22] Pfurtscheller G and Lopes da Silva F H 1999 Event-related EEG/MEG synchronization and desynchronization: basic principles *Clin. Neurophysiol. Off. J. Int. Fed. Clin. Neurophysiol.* **110** 1842–57

[23] Cattai T, Colonnese S, Corsi M-C, Bassett D S, Scarano G and De Vico Fallani F 2021 Phase/Amplitude Synchronization of Brain Signals During Motor Imagery BCI Tasks *IEEE Trans. Neural Syst. Rehabil. Eng. Publ. IEEE Eng. Med. Biol. Soc.* **29** 1168–77

[24] Gotts S J, Jo H J, Wallace G L, Saad Z S, Cox R W and Martin A 2013 Two distinct forms of functional lateralization in the human brain *Proc. Natl. Acad. Sci.* **110** E3435–44

[25] Jayaram V and Barachant A 2018 MOABB: trustworthy algorithm benchmarking for BCIs *J. Neural Eng.* **15** 066011

[26] Millán J d. R, Rupp R, Müller-Putz G R, Murray-Smith R, Giugliemma C, Tangermann M, Vidaurre C, Cincotti F, Kübler A, Leeb R, Neuper C, Müller K-R and Mattia D 2010 Combining Brain–Computer Interfaces and Assistive Technologies: State-of-the-Art and Challenges *Front. Neurosci.* **4** 161

[27] Biasiucci A, Leeb R, Iturrate I, Perdikis S, Al-Khodairy A, Corbet T, Schnider A, Schmidlin T, Zhang H, Bassolino M, Viceic D, Vuadens P, Guggisberg A G and Millán J d R 2018 Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke *Nat. Commun.* **9** 2421

[28] Tonin L, Perdikis S, Kuzu T D, Pardo J, Orset B, Lee K, Aach M, Schildhauer T A, Martínez-Olivera R and Millán J D R 2022 Learning to control a BMI-driven wheelchair for people with severe tetraplegia *iScience* **25** 105418

[29] Perdikis S, Tonin L, Saeedi S, Schneider C and Millán J D R 2018 The Cybathlon BCI race: Successful longitudinal mutual learning with two tetraplegic users *PLoS Biol.* **16** e2003787

[30] Perdikis S and Millan J del R 2020 Brain-Machine Interfaces: A Tale of Two Learners *IEEE Syst. Man Cybern. Mag.* **6** 12–9

[31] Kumar S, Alawieh H, Racz F S, Fakhreddine R and Millán J D R 2024 Transfer learning promotes acquisition of individual BCI skills *PNAS Nexus* **3** pgae076

[32] Zanini P, Congedo M, Jutten C, Said S and Berthoumieu Y 2018 Transfer Learning: A Riemannian Geometry Framework With Applications to Brain–Computer Interfaces *IEEE Trans. Biomed. Eng.* **65** 1107–16

[33] Kumar S, Yger F and Lotte F 2019 Towards Adaptive Classification using Riemannian Geometry approaches in Brain-Computer Interfaces *2019 7th International Winter Conference on Brain-Computer Interface (BCI)* 2019 7th International Winter Conference on Brain-Computer Interface (BCI) pp 1–6

[34] Leeb R, Perdikis S, Tonin L, Biasiucci A, Tavella M, Creatura M, Molina A, Al-Khodairy A, Carlson T and Millán J D R 2013 Transferring brain-computer interfaces beyond the laboratory: successful application control for motor-disabled users *Artif. Intell. Med.* **59** 121–32

[35] Anon Brain-Computer Interface Race

[36] Lotte F and Jeunet C 2018 Defining and quantifying users' mental imagery-based BCI skills: a first step *J. Neural Eng.* **15** 046030

[37] Lawhern V J, Solon A J, Waytowich N R, Gordon S M, Hung C P and Lance B J 2016 EEGNet: A Compact Convolutional Network for EEG-based Brain-Computer Interfaces *arXiv.org*

[38] Kobler R J, Hirayama J, Zhao Q and Kawanabe M 2022 SPD domain-specific batch normalization to crack interpretable unsupervised domain adaptation in EEG *arXiv.org*

[39] Rossiter H E, Boudrias M-H and Ward N S 2014 Do movement-related beta oscillations change after stroke? *J. Neurophysiol.* **112** 2053–8

[40] Orlandi S, House S C, Karlsson P, Saab R and Chau T 2021 Brain-Computer Interfaces for Children With Complex Communication Needs and Limited Mobility: A Systematic Review *Front. Hum. Neurosci.* **15** 643294

[41] Fadhli M, Brick B, Setyosari P, Ulfa S and Kuswandi D 2020 A Meta-Analysis of Selected Studies on the Effectiveness of Gamification Method for Children *Int. J. Instr.* **13** 845–54

[42] Mikołajewska E and Mikołajewski D 2014 The prospects of brain — computer interface applications in children *Open Med.* **9** 74–9

[43] Keough J R, Irvine B, Kelly D, Wrightson J, Comaduran Marquez D, Kinney-Lang E and Kirton A 2024 Fatigue in children using motor imagery and P300 brain-computer interfaces *J. Neuroengineering Rehabil.* **21** 61

[44] Edlow B L, Claassen J, Schiff N D and Greer D M 2021 Recovery from disorders of consciousness: mechanisms, prognosis and emerging therapies *Nat. Rev. Neurol.* **17** 135–56

[45] Jadavji Z, Zewdie E, Kelly D, Kinney-Lang E, Robu I and Kirton A Establishing a Clinical Brain-Computer Interface Program for Children With Severe Neurological Disabilities *Cureus* **14** e26215

[46] Natalie Mrachacz-Kersting, Jennifer Collinger, Donatella Mattia, Davide Valeriani, Mariska Vansteensel, and Gernot Müller-Putz 10th International BCI Meeting 2023 Abstract Book; Balancing Innovation and Translation; June 6 - 9, 2023, Sonian Forest, Brussels, Belgium (Verlag der Technischen Universität Graz)

[47] Oehrn C R, Cernera S, Hammer L H, Shcherbakova M, Yao J, Hahn A, Wang S, Ostrem J L, Little S and Starr P A 2023 Personalized chronic adaptive deep brain stimulation outperforms conventional stimulation in Parkinson's disease 2023.08.03.23293450

[48] Opri E, Cernera S, Molina R, Eisinger R S, Cagle J N, Almeida L, Denison T, Okun M S, Foote K D and Gunduz A 2020 Chronic embedded cortico-thalamic closed-loop deep brain stimulation for the treatment of essential tremor *Sci. Transl. Med.* **12** eaay7680

[49] Wang W, Collinger J L, Degenhart A D, Tyler-Kabara E C, Schwartz A B, Moran D W, Weber D J, Wodlinger B, Vinjamuri R K, Ashmore R C, Kelly J W and Boninger M L 2013 An electrocorticographic brain interface in an individual with tetraplegia *PloS One* **8** e55344

[50] Dold M, Pereira J, Sajonz B, Coenen V A, Janssen M L F and Tangermann M 2024 A modular open-source software platform for BCI research with application in closed-loop deep brain stimulation

[51] Herz D M, Little S, Pedrosa D J, Tinkhauser G, Cheeran B, Foltynie T, Bogacz R and Brown P 2018 Mechanisms Underlying Decision-Making as Revealed by Deep-Brain Stimulation in Patients with Parkinson's Disease *Curr. Biol. CB* **28** 1169-1178.e6

[52] Gao Q, Schmidt S L, Chowdhury A, Feng G, Peters J J, Genty K, Grill W M, Turner D A and Pajic M 2023 Offline Learning of Closed-Loop Deep Brain Stimulation Controllers for Parkinson Disease Treatment *Proceedings of the ACM/IEEE 14th International Conference on Cyber-Physical Systems (with CPS-IoT Week 2023)* ICCPS '23 (New York, NY, USA: Association for Computing Machinery) pp 44–55

[53] Castaño-Candamil S, Piroth T, Reinacher P, Sajonz B, Coenen V A and Tangermann M 2020 Identifying controllable cortical neural markers with machine learning for adaptive deep brain stimulation in Parkinson's disease *NeuroImage Clin.* **28** 102376

[54] Swann N C, de Hemptinne C, Thompson M C, Miocinovic S, Miller A M, Gilron R, Ostrem J L, Chizeck H J and Starr P A 2018 Adaptive deep brain stimulation for Parkinson's disease using motor cortex sensing *J. Neural Eng.* **15** 046006

[55] Bocci T, Prenassi M, Arlotti M, Cogiamanian F M, Borellini L, Moro E, Lozano A M, Volkmann J, Barbieri S, Priori A and Marceglia S 2021 Eight-hours conventional versus adaptive deep brain stimulation of the subthalamic nucleus in Parkinson's disease *NPJ Park. Dis.* **7** 88

[56] Oehrn C R, Cernera S, Hammer L H, Shcherbakova M, Yao J, Hahn A, Wang S, Ostrem J L, Little S and Starr P A 2024 Chronic adaptive deep brain stimulation versus conventional stimulation in Parkinson's disease: a blinded randomized feasibility trial *Nat. Med.* 1–12

[57] Kothe C 2024 sccn/labstreaminglayer

[58] Castano-Candamil S, Piroth T, Reinacher P, Sajonz B, Coenen V A and Tangermann M 2019 An Easy-to-Use and Fast Assessment of Patient-Specific DBS-Induced Changes in Hand Motor Control in Parkinson's Disease *IEEE Trans. Neural Syst. Rehabil. Eng. Publ. IEEE Eng. Med. Biol. Soc.* **27** 2155–63

[59] Hossain K M, Islam M A, Hossain S, Nijholt A and Ahad M A R 2023 Status of deep learning for EEG-based brain–computer interface applications *Front. Comput. Neurosci.* **16**

[60] Han Y, Valentini E and Halder S 2022 Classification of Tonic Pain Experience based on Phase Connectivity in the Alpha Frequency Band of the Electroencephalogram using Convolutional Neural Networks *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) pp 3542–5

[61] Horing B, Sprenger C and Büchel C 2019 The parietal operculum preferentially encodes heat pain and not salience *PLOS Biol.* **17** e3000205

[62] Mari T, Henderson J, Maden M, Nevitt S, Duarte R and Fallon N 2022 Systematic Review of the Effectiveness of Machine Learning Algorithms for Classifying Pain Intensity, Phenotype or Treatment Outcomes Using Electroencephalogram Data *J. Pain* **23** 349–69

[63] Furman A J, Meeker T J, Rietschel J C, Yoo S, Muthulingam J, Prokhorenko M, Keaser M L, Goodman R N, Mazaheri A and Seminowicz D A 2018 Cerebral peak alpha frequency predicts individual differences in pain sensitivity *NeuroImage* **167** 203–10

[64] Salomons T V, Johnstone T, Backonja M-M, Shackman A J and Davidson R J 2007 Individual differences in the effects of perceived controllability on pain perception: critical role of the prefrontal cortex *J. Cogn. Neurosci.* **19** 993–1003

[65] Han Y, Valentini E and Halder S 2023 Validation of Cross-Individual Pain Assessment with Individual Recognition Model from Electroencephalogram *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) pp 1–4

[66] Glaser J I, Benjamin A S, Farhoodi R and Kording K P 2019 The roles of supervised machine learning in systems neuroscience *Prog. Neurobiol.* **175** 126–37

[67] Tseng P-H, Urpi N A, Lebedev M and Nicolelis M 2019 Decoding Movements from Cortical Ensemble Activity Using a Long Short-Term Memory Recurrent Network *Neural Comput.* **31** 1085–113

[68] Livezey J A, Bouchard K E and Chang E F 2019 Deep learning as a tool for neural data analysis: Speech classification and cross-frequency coupling in human sensorimotor cortex *PLoS Comput. Biol.* **15** e1007091

[69] Neumann W-J, Gilron R, Little S and Tinkhauser G 2023 Adaptive Deep Brain Stimulation: From Experimental Evidence Toward Practical Implementation *Mov. Disord. Off. J. Mov. Disord. Soc.* **38** 937–48

[70] Merk T, Peterson V, Köhler R, Haufe S, Richardson R M and Neumann W-J 2022 Machine learning based brain signal decoding for intelligent adaptive deep brain stimulation *Exp. Neurol.* **351** 113993

[71] Colucci A, Vermehren M, Cavallo A, Angerhöfer C, Peekhaus N, Zollo L, Kim W-S, Paik N-J and Soekadar S R 2022 Brain-Computer Interface-Controlled Exoskeletons in Clinical Neurorehabilitation: Ready or Not? *Neurorehabil. Neural Repair* **36** 747–56

[72] Al-Quraishi M S, Elamvazuthi I, Daud S A, Parasuraman S and Borboni A 2018 EEG-Based Control for Upper and Lower Limb Exoskeletons and Prostheses: A Systematic Review *Sensors* **18** 3342

[73] Buccelli S, Tessari F, Fanin F, De Guglielmo L, Capitta G, Piezzo C, Bruschi A, Van Son F, Scarpetta S, Succi A, Rossi P, Maludrottu S, Barresi G, Creatini I, Taglione E, Laffranchi M and De Michieli L 2022 A Gravity-Compensated Upper-Limb Exoskeleton for Functional Rehabilitation of the Shoulder Complex *Appl. Sci.* **12** 3364

[74] Garro F, Fenoglio E, Forsiuk I, Canepa M, Mozzon M, De Michieli L, Buccelli S, Chiappalone M and Semprini M 2023 NeBULA: A Standardized Protocol for the Benchmarking of Robotic-based Upper Limb Neurorehabilitation *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) pp 1–4

[75] Choi S W, Chi S E, Chung S Y, Kim J W, Ahn C Y and Kim H T 2011 Is alpha wave neurofeedback effective with randomized clinical trials in depression? A pilot study *Neuropsychobiology* **63** 43–51

[76] Trambaiolli L R, Kohl S H, Linden D E J and Mehler D M A 2021 Neurofeedback training in major depressive disorder: A systematic review of clinical efficacy, study quality and reporting practices *Neurosci. Biobehav. Rev.* **125** 33–56

[77] Vujic A, Nisal S and Maes P 2023 Joie: a Joy-based Brain-Computer Interface (BCI) *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology* UIST ’23 (New York, NY, USA: Association for Computing Machinery) pp 1–14

[78] Vujic A, Martin A, Nisal S, Mohammed M and Maes P 2023 Demonstration of Joie: A Joy-based Brain-Computer Interface (BCI) with Wearable Skin Conformal Polymer Electrodes *Adjunct Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology* UIST ’23 Adjunct (New York, NY, USA: Association for Computing Machinery) pp 1–3

[79] Oxley T J, Yoo P E, Rind G S, Ronayne S M, Lee C M S, Bird C, Hampshire V, Sharma R P, Morokoff A, Williams D L, MacIsaac C, Howard M E, Irving L, Vrljic I, Williams C, John S E, Weissenborn F, Dazenko M, Balabanski A H, Friedenberg D, Burkitt A N, Wong Y T, Drummond K J, Desmond P, Weber D, Denison T, Hochberg L R, Mathers S, O’Brien T J, May C N, Mocco J, Grayden D B, Campbell B C V, Mitchell P and Opie N L 2021 Motor neuroprosthesis implanted with neurointerventional surgery improves capacity for activities of daily living tasks in severe paralysis: first in-human experience *J. NeuroInterventional Surg.* **13** 102–8

[80] Jasper H H 1958 The Ten-Twenty Electrode System of the International Federation *Electroencephalography and Clinical Neurophysiology* **10** 371–5

[81] Chatrian G E, Lettich E and Nelson P L 1985 Ten Percent Electrode System for Topographic Studies of Spontaneous and Evoked EEG Activities *Am. J. EEG Technol.* **25** 83–92

[82] Oostenveld R and Praamstra P 2001 The five percent electrode system for high-resolution EEG and ERP measurements *Clin. Neurophysiol. Off. J. Int. Fed. Clin. Neurophysiol.* **112** 713–9

[83] Lee H S, Schreiner L, Jo S-H, Sieghartsleitner S, Jordan M, Pretl H, Guger C and Park H-S 2022 Individual finger movement decoding using a novel ultra-high-density electroencephalography-based brain-computer interface system *Front. Neurosci.* **16** 1009878

[84] Bera S, Roy R, Sikdar D and Mahadevappa M 2019 An Ensemble Learning Based Classification of Individual Finger Movement from EEG

[85] Liao K, Xiao R, Gonzalez J and Ding L 2014 Decoding Individual Finger Movements from One Hand Using Human EEG Signals *PLoS ONE* **9** e85192

[86] Schreiner L, Sieghartsleitner S, Mayr K, Pretl H and Guger C 2023 Hand gesture decoding using ultra-high-density EEG *2023 11th International IEEE/EMBS Conference on Neural Engineering (NER)* 2023 11th International IEEE/EMBS Conference on Neural Engineering (NER) pp 01–4

[87] Branco M P, Geukes S H, Aarnoutse E J, Ramsey N F and Vansteensel M J 2023 Nine decades of electrocorticography: A comparison between epidural and subdural recordings *Eur. J. Neurosci.* **57** 1260–88

[88] Flinker A, Chang E F, Barbaro N M, Berger M S and Knight R T 2011 Sub-centimeter language organization in the human temporal lobe *Brain Lang.* **117** 103–9

[89] Menon V, Freeman W J, Cutillo B A, Desmond J E, Ward M F, Bressler S L, Laxer K D, Barbaro N and Gevins A S 1996 Spatio-temporal correlations in human gamma band electrocorticograms *Electroencephalogr. Clin. Neurophysiol.* **98** 89–102

[90] Geukes S H, Branco M P, Aarnoutse E J, Bekius A, Berezutskaya J and Ramsey N F 2024 Effect of Electrode Distance and Size on Electrocorticographic Recordings in Human Sensorimotor Cortex *Neuroinformatics* **22** 707–17

[91] Flesher S N, Collinger J L, Foldes S T, Weiss J M, Downey J E, Tyler-Kabara E C, Bensmaia S J, Schwartz A B, Boninger M L and Gaunt R A 2016 Intracortical microstimulation of human somatosensory cortex *Sci. Transl. Med.* **8** 361ra141-361ra141

[92] Flesher S N, Downey J E, Weiss J M, Hughes C L, Herrera A J, Tyler-Kabara E C, Boninger M L, Collinger J L and Gaunt R A 2021 A brain-computer interface that evokes tactile sensations improves robotic arm control *Science* **372** 831–6

[93] Chavarriaga R, Sobolewski A and Millán J del R 2014 Errare machinale est: the use of error-related potentials in brain-machine interfaces *Front. Neurosci.* **8**

[94] Wimmer M, Weidinger N, Veas E and Muller-Putz G R 2023 Neural and Pupillometric Correlates of Error Perception in an Immersive VR Flight Simulation *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Int. Conf.* **2023** 1–4

[95] Wimmer M, Weidinger N, Veas E and Müller-Putz G R 2024 Multimodal decoding of error processing in a virtual reality flight simulation *Sci. Rep.* **14** 9221

[96] Wimmer M, Weidinger N, ElSayed N, Müller-Putz G R and Veas E 2023 EEG-Based Error Detection Can Challenge Human Reaction Time in a VR Navigation Task 2023 IEEE International Symposium on Mixed and Augmented Reality (ISMAR) (IEEE Computer Society) pp 970–9

[97] Keeser D, Meindl T, Bor J, Palm U, Pogarell O, Mulert C, Brunelin J, Möller H-J, Reiser M and Padberg F 2011 Prefrontal Transcranial Direct Current Stimulation Changes Connectivity of Resting-State Networks during fMRI *J. Neurosci.* **31** 15284–93

[98] Beeli G, Koeneke S, Gasser K and Jancke L 2008 Brain stimulation modulates driving behavior *Behav. Brain Funct.* **4** 34

[99] Schreuder M, Höhne J, Blankertz B, Haufe S, Dickhaus T and Tangermann M 2013 Optimizing event-related potential based brain–computer interfaces: a systematic evaluation of dynamic stopping methods *J. Neural Eng.* **10** 036025

[100] Trees H L V 2004 *Detection, Estimation, and Modulation Theory, Part I: Detection, Estimation, and Linear Modulation Theory* (John Wiley & Sons)

[101] Thielen J, van den Broek P, Farquhar J and Desain P 2015 Broad-Band Visually Evoked Potentials: Re(con)volution in Brain-Computer Interfacing *PloS One* **10** e0133797