편집 디자이너가 목표라면?

정말 탄탄한 편집 디자인 포트폴리오 클래스

리메인

the decoded signal (not shown). During stimulation-off period, the decoded signal was computed, but no stimulation was delivered to the spinal cord. Figure 1C compares the functional performance during stimulation-on and stimulation-off periods. When the stimulation was on, the animal produced robust and natural movements. With stimulation off, the LFP decoder output still predicted the forelimb movements, but the animal produced significantly less force on the level ($p<0.001$). Discussion: This experiment demonstrates that LFP-controlled epidural spinal stimulation can reanimate volitional forelimb movement in rats with spinal cord injury. Contrary to functional muscle stimulation or peripheral nerve stimulation, epidural stimulation produced graded movement and fatigue resistant contractions in targeted muscles. Our multi-channel LFP based decoder reliably detected movement intention before the animals attempted to push the lever. The electrical stimulation artifact did not affect the decoding performance after removal of 2ms post-artifact signal using a sample-and-hold approach. This allowed the brain-controlled stimulation system to restore robust forelimb control after spinal cord injury. Significance: To our knowledge, this is the first study that demonstrates the effectiveness of closed-loop continuous control of epidural spinal cord stimulation based on LFP signals recorded from brain activity. LFP decoding required reduced user input compared to spike-sorting, and provided remarkably stable decoding performance across days without re-fitting the model. These are substantial benefits as we move toward implantable systems for clinical use.

1-A-4 Using a convolutional neural network for improved click detection in an implanted BCI setup

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Introduction A lot of current work in neuroscience is focused on providing a robust high-performance Brain-Computer interface (BCI) system to allow locked-in patients to communicate. Our lab has recently shown that one of the effective BCI strategies is detecting an attempted hand movement from motor cortex and translating it to a "click" for selecting options on the screen [1]. A late-stage ALS patient was implanted with a "click"-based BCI system for permanent use at home. The patient makes an attempted hand movement to generate a "click" and select letters of the screen to spell words. The system detects the "click" based on a combination of increase in brain activity in high frequency and its decrease in beta frequency band. Until now, this has been our default "click" detection strategy which overall provides reliable performance of 80-90% [1]. The present work aims at improving our default "click" detection strategy. Here we show that combining advanced machine learning techniques with effective preprocessing of the brain data can provide a 10% gain in performance. Materials, methods and results A locked-in patient was permanently implanted with a BCI system as described in [1]. We collected data from a channel implanted on the hand motor cortex (M1) while the patient was playing a whack-a-mole game. The brain signal was amplified with the Activa PC+S implant and transmitted with Nexus-1 (both Medtronic; investigational devices) to a tablet with custom software. In the game an 4 by 5 grid of holes is presented with a mole in one. Each position is highlighted sequentially at a rate of 2.5 s, first rows and then columns ('Scanning'). The patient was to generate a 'click' by attempting a hand movement only when the mole was highlighted. Overall, we collected 1386 trials (886 train and 502 test trials). Data for each trial (recorded at 200 Hz) consisted of 2 s preceding the moment a click (correct or incorrect) was detected. The time-frequency representation of the brain signal was obtained by convolving it with Gabor wavelets at different frequencies (1 to 100 Hz, 1 Hz bin spacing) with decreasing window length (4 wavelength full width at half max). A shallow 2D convolutional neural network (CNN) was trained on 2D brain input (time × frequency) to predict "click" (1) or "no-click" (0) class labels per trial. Ground truth labels were obtained based on the actual location of the mole and the selection box. The details of the CNN architecture are shown in Figure 1B. The CNN was trained using Adam optimizer in combination with early stopping. The network weights were regularized using a weight decay of 50. The CNN performance was cross-validated using a 20-fold cross-validation. Compared to the results using a default "click" detection strategy from [1] (85% correct), the CNN-based "click" strategy provided a considerable increase in performance, reaching 95% correct on average. Cross-validation ROC-curves are shown in Figure 1C. Confusion matrices in Figure 1D show that the improvement is due to decrease of both misses (false negatives) and false positives. Figure 1E shows examples of trials incorrectly classified by the CNN model. Figure 1F shows that when making a prediction the CNN model relies on combinations of spectro-temporal patterns across multiple frequency bands (see [2] for visualization details). Discussion The results show that using a combination of an advanced machine learning approach and efficient brain data processing leads to a considerable improvement in offline "click" detection accuracy by reducing the number of both false positive and false negative predictions. To make accurate predictions, the CNN model extracts complex combinations of spectro-temporal patterns. Future work tests feasibility of using this approach in real-time decoding. Significance The present work offers possible improvement to the default "click"-detection strategy of our BCI system. The present results can be useful for a future generation of BCI systems. References [1] M. J. Vansteensel et al., "Fully Implanted Brain-Computer Interface in a Locked-In Patient with ALS," N. Engl. J. Med., vol. 375, no. 21, pp. 2060-2066, Nov. 2016. [2] D. Erhan, Y. Bengio, A. Courville, and P. Vincent, "Visualizing higher-layer features of a deep network," Univ. Montr., vol. 1341, p. 3, 2009.

1-A-5 Simple vs. complex brain computer interfaces for restoring upper limb function via neuromuscular stimulation

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Introduction: Desired movement commands can now be reliably decoded from paralyzed individuals using many types of brain computer interface (BCI) systems. By combining a BCI with stimulators that reanimate paralyzed muscles, we have the potential to restore a paralyzed person's own arm movements by thought. However, unlike using a BCI to control cursors or robots, restoring arm movement also requires solving the difficult problem of determining what muscle stimulation values need to be applied at each timestep in order to produce the desired limb motion. Instead of trying to design a complex non-linear algorithm to solve this very difficult problem ourselves, our lab took an alternative approach--we simply imposed a linear mapping directly between the recorded brain signals and the muscle stimulators with the hope that the brain would learn over time how to generate the neural signals that would produce accurate movements via this unnatural brain-to-muscle mapping. Material, Methods and Results: To test this theory, we trained macaques implanted with intracortical microelectrode arrays to control a realistic computational model of a human paralyzed arm that ran in real time. We used easy-to-collect empirical data about the arm's response to stimulation to generate an Nx6 linear matrix that we used to convert N firing rates into six muscle stimulation adjustment terms at each time step. During real-time brain control, these muscle adjustment terms were used to update the activation levels of the six muscles spanning shoulder and elbow joints in the model arm. The animals were rewarded with juice if they successfully moved the fingertip of the model arm to targets presented throughout the workspace. In spite of the simplicity of the brain-to-muscle mapping matrix, the animals were able to move the model arm to most targets immediately albeit using curved inefficient trajectories. However, with regular practice, the animals learned to produce new neural patterns that moved the arm to the desired targets using straighter, more efficient paths. Post hoc analysis of the neural data suggested the animals' neurons were actually still encoding just a low dimensional directional vector, which the animals learned to scale and rotate in a manner that would correct for the movement errors produced by mapping the neural firing rates directly to the muscle stimulators. The implications of this unexpected result is that even simple BCIs that produce low dimensional movement direction or velocity vectors, such as those driven by EEGs and ECoGs, should also be effective at controlling a paralyzed arm via our simple linear mapping process. Further simulation work has confirmed this to be true. Discussion: This study demonstrated that one can easily relearn to generate brain-controlled arm movements after paralysis by employing a simple linear mapping matrix to convert neural signals into muscle stimulation values in real time. Significance: Our simple, clinically feasible, empirical method of identifying an effective brain-to-muscle mapping matrix should make it easy to customize linear mapping functions for each unique user's paralyzed arm properties. Additionally, our results suggest useful arm movements can be achieved with both low-dimensional movement commands, such as those decoded from simple BCIs, as well as from mapping large numbers of firing rates directly to the muscle stimulators.

B- BCI Implant- Other

1-B-6 Primary motor cortex encodes a value function consistent with reinforcement learning that can be used for an autonomously updating BMI

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Introduction: Our aim is to produce an autonomously updating BMI through the use of Reinforcement learning (RL). Specifically, Actor-Critic RL methods allow for designing a generalizable autonomous BMI. The Actor, in such a BMI, would compute intended actions by using the neural data from the primary motor cortex (M1) whereas the Critic would provide a qualitative feedback of the Actor's performance. The goal is to autonomously learn the optimal policy that dictates the BMI's actions such that it maximizes the expected reward/return of the user. The expected, temporally discounted reward, from a given state, is captured by the value function, synonymous with Critic. Necessary for this goal is our ability to decode the Critic signal from the user's neural activity itself. Here, we show that M1 encodes a value function in line with Temporal Difference (TD) RL. Material, Methods, and Results: We used two separate experimental paradigms with four non-human primates (NHP) as our subjects. Utah arrays were implanted in M1, S1, PMd, and PMv. In task 1 (a) NHPs either made movements to a single color-cued target manually or passively observed cursor motion to the target. The color indicated the reward value of the trial, which was awarded upon successful trial completion. Shown in (d) is the average activity from a single unit over time. Note the initial significant difference between the rewarding (R) (red) and non-rewarding (NR) (blue) trials as indicated by an asterisk (d.1-2). The separability moves forward in a trail with learning (d.4-9). In (e) we show a subpopulation of units that demonstrate the same learning-related activity pattern across sessions, reminiscent of the TD-RL value function as seen in (g). In (e.2-7, first column) we plotted the top 10% of units sorted with respect to their correlation to reward. To the right of these average plots are the full ensemble PSTHs in false color with a solid black line indicating the population average. In (e.1) we plotted the % units that show significant separability between R and NR trials for this purely predictable sequence version of the observation task. The sequence was R followed by NR repeated. Notice how the % units jump from session 1 to 2 and that the separability is pre-cue as the NHPs are predicting the next trial type after learning the sequence. M1 lost and regained its ability to encode the expected reward accurately during reversal learning. In our second set of experiments, NHPs controlled the grip force of an anthropomorphic robotic arm as seen in (b). In this work, the value of the trial could be between multiple levels depending on the session, up to 5 levels. (c) shows example units with linear representations of value, where the x-axis is reward value if successful and the y-axis is mean firing rate. In general, we found many more units that had a positive relation between value and rate, but there were units that had negative relations as seen in the figure. Plotted in (c) are the % of units with either positive or negative linear relationships with value. Finally, we plotted results from an RL simulation using the Microstimulus (MS) temporal encoding basis (f-g). These simulations used the same timing and structure as the real experiments performed by the NHPs. We did not explicitly optimize the model to reproduce the NHPs results but did run a small set of parameters to determin¬¬e what would¬ look similar. Note how the model also learns to predict the trial type as indicated by a peak in the value function pre-cue (f). The value function also peaks around the time of reward (f). Note the similarities between the neural data and model predictions, compare (d) and (f); (e.2-4) and (g). Discussion: Contra/ipsilateral M1 responds to the delivery of unpredictable reward, and shifts its value related response earlier in a trial, becoming predictive of expected reward, when the reward is predictable. This is observed in tasks performed manually or observed passively. The MSTD model, known to accurately capture RL related dopaminergic activity, extends to account for M1 reward-related neural activity. Significance: M1 encodes a value function consistent with RL. Therefore, M1 carries information not only useful for decoding the intended movement but also carries the evaluative information.

1-B-7 Injecting instructions into premotor cortex using intracortical microstimulation - implications for cortico-cortical BCI systems

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Introduction: Intracortical microstimulation (ICMS) is currently being used to deliver sensory information for users of brain-computer interfaces (BCIs). Given the somatotopically organized neural responses and percepts evoked by electrical stimulation in the primary somatosensory cortex (S1), for example, this cortical area frequently has been targeted for delivering bio-mimetic feedback using ICMS. Association areas of the cerebral cortex, however, may also be viable targets for delivering information with ICMS. The premotor cortex (PM) traditionally has been related to the preparation of motor plans for producing specific movements. PM receives inputs from parietal cortical areas representing processed visuospatial information, translates that information into plans for particular movements, and communicates those plans to the primary motor cortex (M1) for execution. Consistent with this general function, ICMS in PM of sufficient frequency, amplitude, and duration has been shown to evoke complex movements of the arm and hand that vary systematically depending on the locus of stimulation. Using ICMS at amplitudes and frequencies too low to evoke muscle activity, however, we found that through learned, conditional associations, ICMS in PM can provide instructions to perform specific actions. Material, Methods and Results: Two monkeys previously had been trained to perform a task using visual cues that instructed which of four objects to reach toward, grasp, and manipulate (RGM). We trained these monkeys to use low-amplitude ICMS at arbitrary PM locations as instructions for performing the same movements. Initially, low-amplitude ICMS was delivered at a different, arbitrarily-selected PM location concurrently with each of the four visual cues. As the visual cues then were gradually dimmed, the monkeys learned to associate even brief, low-frequency, PM-ICMS instructions with specific RGM movements. Eventually, using only the ICMS instructions, both monkeys performed the task with success rates, reaction times, and movement times equivalent to or better than when using visual cues. Performance was unimpaired when ICMS was delivered through a different single electrode to instruct each object, and remained unimpaired after frequency information was eliminated by delivering ICMS pulses at stochastically jittered inter-pulse intervals. Furthermore, after the assignments of ICMS at different PM loci to instruct particular RGM movements had been shuffled, the monkeys re-learned the shuffled assignments, confirming that the arbitrary associations were learned, not fixed. At the low current amplitudes used to deliver ICMS instructions, stimulus-triggered averaging of EMG activity showed a small output effect from only one PM electrode in one monkey, indicating that the monkeys could not have used twitches in different muscles as instructions for the four different movements. Discussion: Our findings demonstrate that low-amplitude, low-frequency, short-duration ICMS at different PM loci produces distinguishable experiences that the subject can report by performing arbitrarily-associated movements. Such ICMS in PM provides a novel means of injecting information into the nervous system. Both subjects were able to learn to associate ICMS at different electrodes with performing particular movements. The ability to deliver interpretable information using ICMS in cortical association areas will be valuable for future BCI systems, expanding the available "neural real-estate" through which information potentially can be delivered to the brain. Future work may identify additional association areas in which interpretable information can be delivered with non-biomimetic ICMS. Significance: Injection of interpretable information in cortical association areas has the potential to serve as the output limb of a cortico-cortical BCI. Focal neurologic diseases such as stroke or multiple sclerosis produce functional deficits in part by disrupting communication between cortical areas. Cortico-cortical BCIs could decode information from neural activity recorded upstream and inject appropriate information downstream to bridge over focal injuries in neural pathways, thereby restoring lost function to such patients.

1-B-8 Augmenting intracortical brain-computer interfaces in monkeys and humans with neurally driven error detectors

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Introduction: Intracortical brain-computer interfaces (iBCI) recording from motor cortex have shown promising results in pilot clinical trials. While much work continues to be done to reduce iBCI errors by improving the accuracy and reliability of movement intention decoders, here we explore a complementary and less explored approach: attempting to automatically identify, using neural activity, when an error occurs so that the BCI system can automatically undo the error. This 'automatic error detect-and-undo' strategy takes advantage of the closed-loop nature of a BCI; the user has constant visual feedback and is aware of when the BCI performs an unintended action (i.e., an error). Somewhere in the brain, the user's neural activity will reflect this detection and recognition of an error. Here, we asked two primary questions: (1) does an outcome error signal exist in the motor cortex used for iBCI?, and (2) can decoding this signal benefit BCI performance?. To answer those questions we first investigated them in preclinical monkey experiments and then extended our results to the case of human participants in the BrainGate2 clinical trial. Material, Methods and Results: In both monkey and human experiments, the user controlled a 2D cursor through an iBCI system and performed a random grid task, in which they needed to select a cued target among a grid (e.g., 6 x 6) of selectable targets. During the task, the neural activity was recorded using 96-channel intracortical silicon microelectrode arrays (Blackrock Microsystems) implanted in the hand area of the motor cortex, and was decoded into a velocity control signal using previously described methods [Gilja et al 2012, Pandarinath et al 2017]. First, we investigated our questions with two monkeys. Surprisingly, we found task outcome neural correlates, and we were able to decode trial outcomes shortly after and even before a trial ended with 96% and 84% accuracy, respectively. This led us to develop and implement in real-time a first-of-its-kind intracortical iBCI error 'detect-and-act' system that attempts to automatically 'undo' or 'prevent' mistakes. The detect-and-act system works independently and in parallel to a kinematic iBCI decoder. In a challenging task that resulted in substantial errors, this approach improved the iBCI performance by up to 18%. After the encouraging results with monkeys, we investigated whether this task outcome-related neural signal was present in two human participants (T5 and T6). T5 was a 63 years old at the time of these experiments and was diagnosed with a C2-3 ASIA C spinal cord injury prior to study enrollment. T6 was a 51 years old at the time of these experiments and was diagnosed with ALS and had a resultant motor impairment (functional rating scale (ALSFRS-R) measurement of 16). We found that human motor cortex was also modulated by task outcome, and in offline analysis of previously collected data, we were able to decode errors with high accuracy (70-85%) with minimal (0-3%) misclassifications of successful trials. We also found that decoders trained on a random grid task could be generalized to a virtual typing task in which the targets are not cued for the participants. This suggests that these task outcome neural correlates were at least to some degree task-independent. Discussion: After showing the benefit of an automatic error detect-and-undo strategy in real-time in monkeys and subsequently showing similar error-related neural modulation in humans, our next step will be to augment a human clinical trial iBCI with real-time detect-and-undo capability . A detect-and-undo system could be used for various BCI applications. During typing this could be used for immediate character auto-deletion or for error tracking to improve upon word prediction algorithms. Detect-and-undo systems can also be utilized for returning to the previous menu during application use, and returning to a previous position when using a robotic arm. Though encouraging, whether or not similar task outcome error signals exist in more complex tasks such as prosthetic limb control remains an open question for future research. Significance: Detecting and undoing errors in real-time should make hard tasks feel easier, increase iBCI performance, and improve the user experience.

1-B-9 Retrospective analysis of the effects of nonstationarities on decoding performance in people using an intracortical brain computer interface

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Background: Intracortical brain computer interfaces (iBCIs) use information recorded from the cortex to provide people with paralysis the ability to control devices in their environment, such as computer cursors for communication. An ongoing area of research in iBCI systems is to ensure long-term robust and reliable control for the user. Degradation in neural control is often attributed to short-term nonstationarities in the recorded signals (Perge et al., 2013). The most common approach to addressing these nonstationarities involves recalibrating the decoder coefficients by incorporating recent neural data (Orsborn et al., 2014, Jarosiewicz et al., 2015). While recalibration has been shown to provide users with long-term control, the underlying nonstationarities have not been fully characterized. Gains in decoding performance could be made by understanding the frequency of nonstationarities and quantifying their effects on modern decoding algorithms. Material, Methods and Results: Participants T9 (52 year-old man right-handed man with ALS, ALSRFS-R=7) and T10 (35 year-old man with C4-AIS Grade A spinal cord injury) were enrolled in the ongoing BrainGate2 clinical trial. We retrospectively analyzed all closed-loop cursor control research sessions spanning 731 and 365 days, respectively. Channel spike counts and broad-band signal power were used as neural features (Brandman et al., 2017), recorded in non-overlapping 20ms bins. For each research session, a Kalman decoder was trained using a random subsample of data (without replacement), and then used to predict the decoded velocity vector of each time-step in the testing dataset. We quantified decoder performance for each session by computing the angular error between the kinematic cursor's decoded velocity and the assumed intended vector to target (Willet et al., 2017). We retrospectively analyzed 137 and 96 sessions for T9 and T10, respectively, where the participant performed closed-loop neural control of a computer cursor. Across all research sessions, we did not observe a linear trend in overall decoder performance for either participant (T9 R2 = 0.001, T10 R2 = 0.071). For individual research sessions, we found a linear relationship between decoding performance and z-score offsets in the observed neural features. To mitigate the effect of nonstationarities, we swept a variety of z-score threshold values and found that saturation above 2-zscores did not impact decoding performance (saturation below this level degraded decoding performance). We found that features with z-scores greater than 2 accounted for 5% of all observed values (once per second), including those features that were highly informative with high signal-to-noise ratios (Malik et al., 2015). Discussion: Intra-day nonstarionarities in closed-loop neural signals are detrimental to closed-loop control. We did not observe depredations in decoding performance over days. The linear relationship found between shifts in feature magnitude and closed-loop performance indicate that large z-score deviations are detrimental to decoding, and can be mitigated by principled feature saturation. Significance: These results suggest that additional and substantial gains can be made in decoding performance by addressing anomalous feature values, and mitigating their effects.

C- BCI Non-Invasive- Control

1-C-10 Integrating EEG and MEG information to enhance motor imagery classification in brain-computer interface

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Introduction: Brain-computer interface (BCI) is a potential tool for rehabilitation and communication. Most of the BCI experiments relies on the electroencephalography (EEG). Despite its clinical applications, BCI faces to both engineering and user-oriented challenges to improve its spreading. In this work, we assess the possibility of integrating electroencephalographic (EEG) and magnetoencephalographic (MEG) signals to enhance the classification performance in motor imagery-based BCI. Material, Methods and Results: We performed an offline classification from a dataset which gathers simultaneously recorded M/EEG signals from 15 healthy subjects (aged 28.13±4.10 years, 7 women). We used the one-dimensional two-target box-tasks experiment in which the subjects imagined a movement with the right hand or remained at rest, depending on the position of the target. During the first 5 runs, only the target was displayed (training phase) followed by 6 runs with a provided feedback (testing phase). For each modality (EEG, magnetometers -MAG and gradiometers -GRAD), we extracted the relevant features from training recordings. Then, we performed a classification of the testing data by integrating the classifiers' output from each modality via the Bayesian fusion approach, in which contribution of each modality is modulated via an attributed weight computed from the associated posterior probability. To compare classification performances between the fusion and the single-modality approach, the classification accuracy was estimated with the area under the curve (AUC). Significant changes of event-related de/synchronization appeared in alpha and beta band in all modalities. Results show that modality significantly affects the classification performance (ANOVA, $p<0.001$). Averages of 0.58±0.07, 0.58±0.09, 0.61±0.10, and 0.66±0.11 were obtained with EEG, MAG, GRAD and fusion classifiers respectively. In 13 subjects, the fusion led to an improvement of the AUC in comparison with single-modality approach, with relative increments ranging from 1.3% to 50.9%. Discussion: By using a rather simple classifier, we could include a reduced number of specific features involved in the motor-related neural mechanisms such as ERD in alpha and beta bands. More sophisticated approaches using the whole feature space, such as support vector machines and

Riemannian geometry as well as alternative fusion strategies, but also classification in source space to improve spatial resolution, can be further evaluated. Significance: The proposed fusion method led, in a large majority of subjects, to a reduction in the subjects' mental state misclassifications. Our weighting approach enabled to adapt the modality choice according to the subject and the session. Current searches focused on MEG sensors miniaturization will probably enable a larger diffusion of the integration of M/EEG features to further enhance BCIs performances.

1-C-11 A dynamic Chinese character writing based hybrid BCI paradigm for stroke rehabilitation

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Introduction: There were a number of publications have demonstrated the efficacy of Motor imagery (MI) based brain-computer interfaces (BCI) technology in post-stroke rehabilitation[1]. However, the accuracy of MI is often not sufficient to provide reliable control signals in practical applications[2], thus patients must passively accept which upper limbs to be trained. Therefore, a dynamic Chinese character writing based hybrid BCI paradigm was presented for patients to choose which upper limbs to be trained freely that may improve their training initiative. The paradigm was a combination of MI and P300 paradigm. The Chinese characters writing based MI paradigm was used due to its good efficacy in guiding subjects to modulate brain activity effectively for Chinese[3]. The P300 was evoked by the dynamic filling of Chinese characters which could provide reliable control signals. Material, Methods and Results: Three healthy subjects (3 male, aged 22-28 years) participated in the experiment. All subjects' native language was Mandarin Chinese. The experimental protocol consisted of an imagination of a Chinese character write task according to the screen cue. There were two dynamic Chinese characters and a forearm displayed on the screen. Figure 1 (a) illustrated an example of the screen cue shown to subjects where the first column represents left hand imagery, and the second column represents right hand imagery. Figure 1 (b) illustrated the process of a trial of the writing task. The 0-1.9s was preparation phase in which the Chinese character outlines (the first row of Figure 1 (a)) were displayed on the screen, and the subjects were asked to focus on Chinese character on the side of the forearm prompted. The 1.9-7.9s was imaging phase. In this phase, the outlines were filled stroke by stroke according to the writing order in a specific time series (the second row to the last row of Figure 1 (a)), while the subjects were asked to imagine writing the Chinese character follow the fill order. For classification, every stroke in right Chinese character was filled in 200 milliseconds later than the left one. When the subjects focus on the left character and performed the left hand motor imagery, the P300 signal was time lock with left time series. The right writing task was similarly to the left. The 7.9-10s was rest phase. In this paper, four Chinese character combinations ("生-正", "生-末", "仗-正", "仗-末") were used in the experiment. The EEG signals were recorded by 22 scalp electrodes according to the International 10-20 System, with a sampling rate of 256 Hz. The EEG signals were amplified by gHIamp. For P300, a third order Butterworth band pass filter was used to filter the EEG between 0.1 Hz and 12 Hz. The EEG was then down-sampled from 256 Hz to 36.6 Hz from the filtered EEG. In order to increase the distinguishability of the data, the five sub sections of each data segment were averaged. For MI, the EEG data were band-pass filtered from 8 to 30 Hz. Then common special pattern (CSP) was used to further extract features. Finally, both P300 and MI signals were classified by Bayesian linear discriminant analysis (BLDA). Table 1 shows the classification accuracy of MI and P300 using 10-fold cross-validation. Discussion: Preliminary result of three healthy subjects showed that although the classification accuracy of MI (73.02%±7.71%)was relatively low and unstable, but the average classification accuracy of P300 was 93.23%±1.91% which indicate that the hybrid BCI paradigm can meet the requirement of freedom to choose upper limbs for training. We will further proven the efficacy of this paradigm in stroke patients. Significance: The main contribution of this research is that a hybrid BCI paradigm was presented which allows stroke patients choosing which upper limbs to be trained proactive. References [1] Stefano Silvoni et al. Brain-Computer Interface in Stroke: A Review of Progress[J]. Clinical EEG and Neuroscience, 2011, 42(4): 245-252. [2] Blankertz B et al. Neurophysiological predictor of SMR-based BCI performance[J]. NeuroImage, 2010, 51(4): 1303-1309. [3] Qiu Z et al. Optimized motor imagery paradigm based on imagining Chinese characters writing movement[J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2017, 25(7): 1009-1017.

1-C-12 Query exploration for intended task state estimation with BCI

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Introduction: BCI communication systems have two main objectives; evaluating evidence from a user (e.g. EEG) using different queries (e.g. SSVEP, RSVP) and estimating user intent (e.g. intended symbol, string). BCI frameworks can be modeled as recursive state estimators, where the state is unknown user intent. For faster convergence to a correct/accurate estimate, queries can be optimized through objectives such as MMI [1], EPM [2]. BCI systems for language generation can be supported with a language model (LM) that provides prior information for state estimation. LM fusion increases typing speed, since languages are structured. In some cases, the user intent could be to express a phrase that is considered to be unlikely, in which case the user is forced to overcome the adversarial effect of the LM. This leads to slower estimate convergence due to the requirement to gather more evidence from the user (brain). As an edge case, if the user intent is least likely according to the LM prior, the user needs to react negatively to all other queries to be queried for the intended state. In this paper, we propose an exploration based querying mechanism to mitigate the negative effects of an occasionally adversarial LM. Material: We use RSVP Keyboard [3] with EEG data acquired using a g.USBAmp with 16 g.Butterfly electrodes (g.Tec, Graz, Austria), and a simulation framework developed in Python. Method: In this work, we investigated the use of a fixed temporal schedule that alternates between exploitation and exploration after a number of sequences have been spent on each strategy. Initially top letter candidates are shown, but if a confident decision is not possible after several sequences of stimuli, the query method switches to exploration mode and produces queries that maximize the Kullback-Liebler divergence between the expected posterior and prior. After several sequences, the query strategy switches to exploitation. Results: We used Monte Carlo simulations using generative models for EEG features developed based on real calibration data from 12 healthy users with different EEG separability