very cumbersome and inconvenient. Recently, several researchers propose to measure the SSVEPs from the non-hair-bearing areas, such as frontal area, neck area, behind-the-ear area, and etc, but the resulting classification performance may be significantly degraded [2,3]. For this reason, we aim to propose an area-to-area transfer method that learns from SSVEPs at parietal-occipital area to enhance the classification performance of SSVEPs from non-hair-bearing areas as there is common knowledge between SSVEPs from these two areas. Material, Methods and Results: By utilizing the relation between the subject's SSVEPs from different areas, we apply the knowledge between the SSVEPs from source area and target area for the single-channel SSVEPs classification (see Fig. 1). The hypothesis is that there exists an invariant transformation between the SSVEPs from source area (e.g., parietal-occipital area) and target area (e.g., frontal area) since the frontal SSVEPs come from the occipital SSVEPs theoretically. In this preliminary study, such a transformation can be considered as a linear combination, which can be found by performing the canonical correlation analysis (CCA) [4] between the SSVEPs from two areas. To validate our idea, the CCA methods without learning, with learning from single-channel SSVEPs and with learning from multi-channel SSVEPs are compared using a benchmark SSVEP dataset [5]. Results show that there is significant performance difference between using the single-channel SSVEPs at FPz and Oz, which is consistent with [2,3], and importantly the CCA method with learning from multi-channel SSVEPs can boost the performance significantly in both cases. Discussion: Although the classification performance of the SSVEPs at FPz is not satisfactory, this is only a proof-of-concept study to verify that some knowledge of the SSVEPs from different areas can be transferred such that the classification performance of the single-channel SSVEPs can be enhanced. As a matter of fact, there are large intersubject variations in their performance. For example, some subjects can achieve around 80% accuracy. The following study should focus on this issue. In addition, we can also apply the other advanced transfer learning technologies to improve the performance. Significance: Area-to-area transfer should be helpful to classify the SSVEPs from the non-hair-bearing area. Acknowledgement Supported in part by Macau Science and Technology Development Fund (036/2009/A, 142/2014/SB and 055/2015/A2) and Univ. of Macau Research Committee (MYRG: 139-FST11-WF, 079-FST12-VMI, 069-FST13-WF, 201400174-FST, 2016-00240-FST and 2017-00207-FST). Reference: [1] X. Chen, Y. Wang, M. Nakanishi, X.
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3-F-54 Artifact propagation in electrocorticography stimulation

Jeffrey Lim[1], Po Wang[1], Susan Shaw[1], Michelle Armacost[1], Hui Gong[1], Charles Liu[1], Payam Heydari[1], An Do[1], Zoran Nenadic[1]

[1]University of California, Irvine

Introduction:Current brain-computer interfaces (BCIs) primarily rely on visual feedback. However, visual feedback may not be sufficient for applications such as movement restoration, where somatosensory feedback plays a crucial role. For electrocorticography (ECoG)-based BCIs, somatosensory feedback can be elicited by cortical surface electro-stimulation [1]. However, simultaneous cortical stimulation and recording is challenging due to stimulation artifacts. Depending on the orientation of stimulating electrodes, their distance to the recording site, and the stimulation intensity, these artifacts may overwhelm the neural signals of interest and saturate the recording bioamplifiers, making it impossible to recover the underlying information [2]. To understand how these factors affect artifact propagation, we performed a preliminary characterization of ECoG signals during cortical stimulation.Materials/Methods/ResultsECoG electrodes were implanted in a 39-year old epilepsy patient as shown in Fig. 1. Pairs of adjacent electrodes were stimulated as a part of language cortical mapping. For each stimulating pair, a charge-balanced biphasic square pulse train of current at 50 Hz was delivered for five seconds at 2, 4, 6, 8 and 10 mA. ECoG signals were recorded at 512 Hz. The signals were then high-pass filtered (≥1.5 Hz, zero phase), and the 5-second stimulation epochs were segmented. Within each epoch, artifact-induced peaks were detected for each electrode, except the stimulating pair, where signals were clipped due to amplifier saturation. These peaks were phase-locked across electrodes and were 20 ms apart, thus matching the pulse train frequency. The response was characterized by calculating the median peak within the 5-second epochs. Fig. 1 shows a representative response of the right temporal grid (RTG), with the stimulation channel at RTG electrodes 14 and 15. It also shows a hypothetical amplifier saturation contour of an implantable, bi-directional, ECoG-based BCI prototype [2], assuming the supply voltage of 2.2 V and a gain of 66 dB. Finally, we quantify the worstcase scenario by calculating the largest distance between the saturation contour and the midpoint of each stimulating channel.Discussion:Our results indicate that artifact propagation follows a dipole potential distribution with the extent of the saturation region (the interior of the white contour) proportional to the stimulation amplitude. In general, the artifacts propagated farthest when a 10 mA current was applied with the saturation regions extending from 17 to 32 mm away from the midpoint of the dipole. Consistent with the electric dipole model, this maximum spread happened along the direction of the dipole moment. An exception occurred at stimulation channel RTG11-16, for which an additional saturation contour emerged away from the dipole contour (not shown), extending the saturation region to 41 mm. Also, the worst-case scenario was observed at 6 mA stimulation amplitude. This departure could be a sign of a nonlinear, switch-like behavior, wherein additional conduction pathways could become engaged in response to sufficiently high stimulation.Significance:While ECoG stimulation is routinely performed in the clinical setting, quantitative studies of the resulting signals are lacking. Our preliminary study demonstrates that stimulation artifacts largely obey dipole distributions, suggesting that the dipole model could be used to predict artifact propagation. Further studies are necessary to ascertain whether these results hold across other subjects and combinations of stimulation/recording grids. Once completed, these studies will reveal practical design constraints for future implantable bi-directional ECoG-based BCIs. These include parameters such as the distances between and relative orientations of the stimulating and recording electrodes, the choice of the stimulating electrodes, the optimal placement of the reference electrode, and the maximum stimulation amplitude. These findings would also have important implications for the design of custom, low-power bioamplifiers for implantable bi-directional ECoG-based BCIs.References:[1] Hiremath, S. V., et al. "Human perception of electrical stimulation on the surface of somatosensory cortex." PloS one 12.5 (2017): e0176020.[2] Rouse, A. G., et al. "A chronic generalized bi-directional brain-machine interface." Journal of Neural Engineering 8.3 (2011): 036018

3-F-55 Does previous experience with a steady-state visual evoked potential-based BCI for text-entry affect user performance?

James Norton[1], Nisha Patel[2], Timothy Bretl[2]

[1]*Wadsworth Center, New York State Department of Health,* [2]*University of Illinois at Urbana-Champaign*

Introduction: We investigated whether previous experience with a steady-state visual evoked potential (SSVEP)-based brain-computer interface (BCI) text-entry system affected user performance. Most studies investigating SSVEP-based BCIs study BCI naïve populations for a single session of BCI use. If SSVEP-based BCIs are to be used as an alternative augmentative communication device for those with severe motor disabilities, they will be used for many sessions over weeks or months. Thus, it is important to understand if user input performance with an SSVEP-based BCI changes over time. To help answer this, we conducted a pilot study where we asked three participants to use an SSVEP-based BCI (Fig. 1a; previously described in Akce [2015]) twice a week for four weeks. Material, Method, and Results: Electroencephalographic (EEG) activity was recorded from six occipital electrodes. Each of the eight sessions had three phases: a calibration phase; a training phase; and a spelling phase. During the calibration phase, participants were asked to attend to a sequence of targets. Each target flashed for four seconds at one of five frequencies (6, 6.67, 7.5, 8.57, or 10 Hz). The first participant attended to 40 targets, the second and third to 50 targets. Data from the calibration phase was used to set two parameters (window-length and threshold) for a classifier based on canonical correlation analysis that were then used in the training and spelling phases (Lin 2007). During the training phase, participants used an online SSVEP-based BCI to select target letters (10 targets for each frequency, 50 targets total). Finally, during the spelling phase, participants were asked to spell five texts. Two of these texts were repeated during every session and three were unique to the specific session. Analysis of the calibration data showed that SSVEPs (indicated by an increase in the canonical correlation coefficients) appeared sooner after the onset of the target stimulus in later sessions than in earlier sessions in two of the three participants (Fig. 1b). In the third participant, the time between stimulus onset and the appearance of an SSVEP varied from session to session. Because data from the calibration phase were used to set the window-length for the classifier, a change in window-length might indicate a change in the signal-tonoise ratios of the SSVEPs. The window-lengths did not change significantly across the eight sessions. Together, these two results indicate that the participants learned to respond to the targets faster. Data from the spelling phase show that the three participants increased their average character entry rates from 11.62 characters/min (CPM) to 16.07 CPM over the first seven sessions (Fig. 1c; spelling data from session 8 for Participant 2 were lost due to a technical error). Participant 3 even achieved a text-entry rate of 34.60 CPM spelling "brain-computer interface" in session 6. Most of the change in text-entry rate was for the repeated texts (169% increase from session 1 to session 7 [averaged across participants]). Increased text-entry rates could be the result of an increase in selection accuracy, a decrease in the time