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Continuously Decoding Grasping Movements using Stereotactic Depth Electrodes

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***Abstract*— Brain-Computer Interfaces (BCIs) that decode a patient's movement intention to control a prosthetic device could restore some independence to paralyzed patients. An important step on the road towards naturalistic prosthetic control is to decode movement continuously with low-latency. BCIs based on intracortical micro-arrays provide continuous control of robotic arms, but require a minor craniotomy. Surface recordings of neural activity using EEG have made great advances over the last years, but suffer from high noise levels and large intra-session variance. Here, we investigate the use of minimally invasive recordings using stereotactically implanted EEG (sEEG). These electrodes provide a sparse sampling across many brain regions. So far, promising decoding results have been presented using data measured from the subthalamic nucleus or trial-to-trial based methods using depth electrodes. In this work, we demonstrate that grasping movements can continuously be decoded using sEEG electrodes, as well. Beta and high-gamma activity was extracted from eight participants performing a grasping task. We demonstrate above chance level decoding of *movement vs rest* and *left vs right*, from both frequency bands with accuracies up to 0.94 AUC. The vastly different electrode locations between participants lead to large variability. In the future, we hope that sEEG recordings will provide additional information for the decoding process in neuroprostheses.**

I. INTRODUCTION

Continuously decoding movement from neural signals is an important step towards naturalistic prosthetic control. Promising advances have been made using non-invasive electro-encephalographic (EEG) [1] or invasive cortical methods, e.g. microelectrode arrays [2]. However, brain-computer interfaces (BCIs) using stereotactic or sEEG electrodes, capturing neural activity from subcortical structures, are relatively unexplored, while holding potential to contribute to higher performing decoding algorithms [3]. These electrodes cover a wide variety of areas across the brain and provide access to harder to reach structures, such as the basal ganglia, insula or hippocampus. Additionally, the electrodes provide simultaneous access to local high frequency oscillations in multiple areas, which could be used as control signal for BCIs. Exploiting these high frequency signals can decrease the decoder's response latency to the users' intended action, contributing to naturalistic prosthetic control. Additionally, activity from subcortical structures might uncover additional control signals for adaptive deep brain stimulation [4].

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II. BACKGROUND — RELATED WORK

So far, several studies have presented decoding results using local field potentials (LFPs) measured with depth electrodes. All depth electrode implantations are based solely on clinical needs, which results in two main patient populations: Parkinson's disease (PD) patients with deep brain stimulation electrodes and medication-resistant epilepsy patients implanted for presurgical focus localization. The electrodes in PD patients cover the globus pallidus interna (GPi) and the subthalamic nucleus (STN), and thus decoding efforts utilize activity from these areas. Loukas and Brown [5] were able to predict the onset of voluntary hand movement with 95% sensitivity and 77% specificity on a trial-to-trial basis. Mamun et al. [6] improved on these results by showing $91.5\pm2.3\%$ accuracy on movement detection and $74.0\pm6.4\%$ accuracy on laterality detection, also on trial-to-trial basis and averaged over patients with STN and GPi electrodes. Further efforts on decoding movements using DBS electrodes aimed to decode gripping force from the STN [7], [8]. Recently, Shah et al. [9] decoded gripping force with a correlation up to 0.76 between decoded and actual gripping force, and were able to do so continuously.

Opposed to the specific and consistently targeted regions in PD patients, areas covered in epilepsy patients are spread throughout the brain, which makes comparisons between patients and studies significantly more complicated. Above chance gesture decoding has been demonstrated in several studies [10], [11]. Breault et al. [12] decoded movement speed with a correlation of 0.38 ± 0.03, and $70\%\pm3\%$ when decoding three speed levels.

The studies discussed so far mostly utilize the beta frequency band (12-30 Hz) and (high-)gamma band (30-55 and 55-90 Hz). Beta activity, especially in the STN, but also (sensori-)motor cortex, is decreased during movement. An increase in beta power is consequently associated with the inhibition of (imagined) movement [13][14]. Gamma or high-gamma activity is considered to hold localized information of movement [15] and is known to increase during movement. Khawaldeh et al. [14] showed that high-gamma activity was predictive of intended contralateral and ipsilateral limb movements, supported by a decoding performance of 0.79 to 0.80 area under the receiver operator curve (AUC).

Up to now, most movement decoding efforts are targeting a trial-to-trial prediction. However, an important step towards naturally controlled closed-loop BCIs is to decode intention continuously. The work by Shah et al. [9] already showed promising results on continuous force decoding using STN activity, but it has not yet been demonstrated in other brain areas using depth electrodes. In this work, we demonstrate that it is possible to decode grasping movements continuously and detect laterality using sEEG electrodes. Due to the large variability in covered cortical and white matter regions in each patient, results varied drastically and highlight the importance of target selection.

III. METHODS

A. Participants

Eight patients (mean age 39.5 ± 15.8, 4 male, 4 female) with medication-resistant epilepsy participated in our study, while being under presurgical assessment to identify epileptogenic zones. Written informed consent was provided by all participants, and all agreed to participate voluntarily during the monitoring period. The experiments were conducted under the supervision of experienced healthcare staff in a clinical environment, and were approved by the IRB of Maastricht University and Epilepsy Center Kempenhaeghe (METC 2018-0451).

B. Experimental paradigm

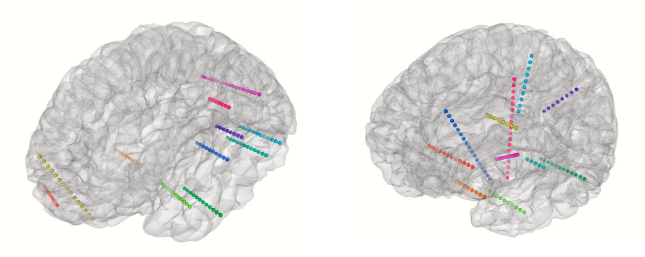
Participants were asked to execute opening and closing their left or right hand continuously when a 3-second instruction was shown on a screen. There was a 3-second rest period in between trials. The task was repeated 30 times per hand in random order, resulting in a total of 60 trials.

C. Electrode Locations

Electrode locations were solely based on clinical needs. Co-registration of a pre-operative T1-weighted MRI and a post-operative CT scan were used to determine the electrode locations. FREESURFER [16] and `img_pipe` [17] were used for both co-registration and anatomical labeling of the electrodes. A 3D view of the electrode placement of two of the participants is shown in Figure 1a and 1b. The sparse coverage of many different brain regions, including temporal gyri, frontal gyri, hippocampus and amygdala (figure 1a), provides a variety of cortical and white matter signals.

D. Data Acquisition

The implanted sEEG-electrodes (Microdeep intracerebral electrodes; Dixi Medical, Beçanson, France) had a diameter of 0.8mm and contained 5 to 18 contacts. Electrode contacts were 2mm long and the inter-contact distance was 1.5mm. The recordings were common ground referenced. Neural data were acquired at 1024 Hz using a 128-channel Micromed SD LTM amplifier (Micromed S.p.A, Treviso, Italy). Incoming data were synchronized to the experimental timings using LabStreamingLayer [18].



(a) P2 (b) P5

Fig. 1: Electrode placements of two participants. Electrodes cover a wide variety of (sub-)cortical areas across both hemispheres.

E. Signal Processing

Data were first detrended and high-pass filtered using a finite impulse response filter with a cutoff frequency of 0.5 Hz. Then, beta or high-gamma activity were extracted by applying two band pass infinite impulse response filters (12 - 30 Hz for beta and 55 - 90 Hz for high-gamma) and a notch filter of 48 - 52 Hz to attenuate line noise of 50 Hz. Next, the envelop of the frequency bands was calculated by applying a Hilbert transform. The resulting signal was windowed using 1s windows with 100ms frame shift and the average was calculated for each window. These windowing settings were considered to include enough data to capture the neural dynamics reliably, while also facilitating a low-latency prediction. The same windowing algorithm was applied to the trial labels, but the mode was used as aggregation method. The resulting matrix was of form $[NWindows \times Nchannels]$. All analyses are implemented using Python 3.7.5, filters were applied using the MNE package (v0.21.0) [19]. The learning algorithms described in the next section were implemented using Sci-kit learn (v0.22) [20]. Source code is available at [github.com/mottenhoff/continuous-grasp-decoding].

F. Model Development & Validation

A linear discriminant analysis (LDA) classifier using singular value decomposition as solver was trained and validated on either beta or high-gamma band activity from all channels. The LDA was fitted on a 3-class problem (rest, left hand movement and right hand movement) using 10-fold non-shuffled cross-validation. Performance was evaluated by calculating the average area under the receiver operator curve (AUC) over all folds. The label distribution in the data was 900 left hand, 900 right hand and 1800 rest labels.

IV. RESULTS

Both beta and high-gamma-based models performed well above chance in most participants. Figure 2 shows the results per participant and frequency band. Chance level is 0.5. In move vs rest predictions, the trained models reached a performance of up to 0.80 AUC (0.77 to 0.83; 95% confidence interval) when trained on beta activity and 0.81 (0.79 to 0.84) using high-gamma activity. When considering laterality

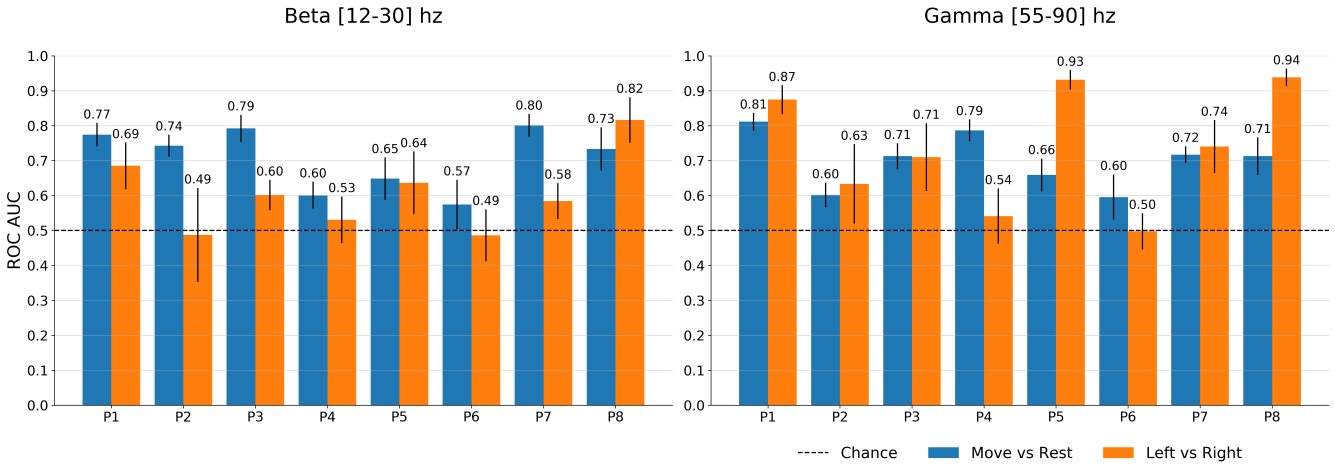


Fig. 2: Overall results of LDA models trained on beta and high-gamma. High performance is seen in both models, notably in laterality detection using high-gamma activity. However, there is large variability between and within participants. *ROC AUC: Area under the receiver operator curve*

detection, the maximum performance was comparable to grasping movement detection with an AUC of 0.82 (0.75 to 0.88) using beta activity. The maximum performance of the high-gamma models predicting laterality was excellent with 0.94 (0.91 to 0.96) AUC. However, the results show high variation in performance between and within participants. For example, models trained on $P2_{gamma}$, $P4_{beta}$ and P6 only reached an AUC at chance level or slightly above for all comparisons, whereas $P5_{gamma}$ shows excellent performance on laterality discrimination (0.93, 0.90 to 0.96) but performance just above chance level on detecting movement vs rest (0.66, 0.62 to 0.70).

V. DISCUSSION

We showed that LFP measured with sEEG electrodes contain enough information to accurately decode grasping movements and movement laterality in a continuous way. We improved on previous work that decoded on a trial-to-trial basis using sEEG electrodes [10], [11], and put a step forward towards closed-loop movement decoding systems from depth electrodes. Additionally, we expand on the results of Shah et al. [9], by showing that accurate movement predictions can also be made from a sparse brain-wide coverage of the brain using depth electrodes.

However, our results show high variability in performance within and between participants, which we attribute to the wide variety of covered brain areas. It is plausible that the low performing models simply did not have access to the areas encoding movement related activity. Moreover, if one only considers the high performing models, it remains challenging to identify informative areas. Based on fMRI studies in (non-)human primates and humans, reach and grasp related neural activity is seen in dorso-medial and dorso-lateral pathways between the parietal cortex and fronto-medial areas [21]. However, within the many covered areas, only few overlap and there is too few data to identify systematically involved areas; electrodes of the eight included participants cover > 50 areas with > 600 contacts. Note that bilateral locations are aggregated as single unique area and that the labels are based on the definitions by the FREESURFER software. Additionally, a significant proportion of these contacts are located in white matter ($n = 270$) or unknown areas ($n = 69$). Unknown areas were labeled as such because they could not be defined during anatomical labeling. Both white matter and unknown areas are included in the models, as they could hold important information. However, interpretation of white matter signals is an unsolved challenge and requires an in-depth multi-site analysis[22]. Initial investigations into the identification of important areas showed highly variable results and indicated that a more in-depth analysis was required, which was outside the scope of this work.

Both the beta and high-gamma envelopes were extracted, as both frequencies are identified to modulate movement [13], [15] and successfully implemented in decoding models [9]. Our results strengthen these findings as both the beta and high-gamma model perform well above chance, where the highest performance was seen using high-gamma activity. However, the high-gamma models also show larger variability in performance, which might be caused by the higher spatial localization of high-gamma. High-gamma spreads less far in a volume than the lower beta frequency, thus making it less likely that the relevant signal is captured from a specific area. Despite this, our results indicate that in the current implementation, the high-gamma local field potential holds enough information to achieve excellent performance. Many other frequencies, such as alpha or theta, might also be important, especially in areas within the broad coverage of sEEG electrodes. We did not include more frequency bands, as it would increase the complexity of the models and potentially decrease the reliability of the models. Even within the included frequency bands, the information that the oscillation encodes may differ per area. One example is that

beta activity in STN is suggested to suppress the basal ganglia to encode relevant information of intended actions [14], while beta activity in the sensorimotor cortex is associated with movement planning and response errors [23]. In this work, we chose the same frequencies as used in Shah et al. [9] to increase comparability. With carefully implemented machine learning approaches to avoid overfitting, it is not necessarily required to know what information the signal encodes. However, to improve BCI reliability, especially in the varying coverage of sEEG electrodes, it is important to be able to identify which specific areas are used in the decoding models. In short-term, this can guide experimental paradigms based on the implanted locations, and in the long-term, it can increase performance and reliability between participants and experiments.

VI. LIMITATIONS

Participants suffering from epilepsy performed the experiments. It is unknown if and how the signal is modulated by epilepsy. Furthermore, the used experimental design did not allow for investigation of additional promising factors such as speed.

VII. CONCLUSION

In conclusion, we show that movement related activity can be decoded continuously using sEEG electrodes in various brain areas with excellent performance in some participants. However, the sparse covering of the brain also results in large variability in performance within and between participants. The current work is a next step towards naturally controlled BCIs, but future research should focus on identification of important areas covered by sEEG electrodes.

REFERENCES

[1] B. J. Edelman, J. Meng, D. Suma, C. Zurn, E. Nagarajan, B. S. Baxter, C. C. Cline, and B. He, "Noninvasive neuroimaging enhances continuous neural tracking for robotic device control," *Science Robotics*, vol. 4, no. 31, 2019.

[2] L. R. Hochberg, D. Bacher, B. Jarosiewicz, N. Y. Masse, J. D. Simeral, J. Vogel, S. Haddadin, J. Liu, S. S. Cash, P. Van Der Smagt, and J. P. Donoghue, "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature*, vol. 485, no. 7398, pp. 372–375, 2012. Publisher: Nature Publishing Group.

[3] C. Herff, D. J. Krusienski, and P. Kubben, "The Potential of Stereotactic-EEG for Brain-Computer Interfaces: Current Progress and Future Directions," *Frontiers in Neuroscience*, vol. 14, 2020. Publisher: Frontiers.

[4] J. G. Habets, M. Heijmans, M. L. Kuijf, M. L. Janssen, Y. Temel, and P. L. Kubben, "An update on adaptive deep brain stimulation in Parkinson's disease," *Movement Disorders*, vol. 33, no. 12, pp. 1834–1843, 2018.

[5] C. Loukas and P. Brown, "Online prediction of self-paced hand-movements from subthalamic activity using neural networks in Parkinson's disease," *Journal of Neuroscience Methods*, vol. 137, pp. 193–205, Aug. 2004.

[6] K. A. Mamun, M. Mace, M. E. Lutman, J. Stein, X. Liu, T. Aziz, R. Vaidyanathan, and S. Wang, "Movement decoding using neural synchronization and inter-hemispheric connectivity from deep brain local field potentials," *Journal of Neural Engineering*, vol. 12, no. 5, 2015. Publisher: IOP Publishing.

[7] H. Tan, A. Pogosyan, K. Ashkan, A. L. Green, T. Aziz, T. Foltynie, P. Limousin, L. Zrinzo, M. Hariz, and P. Brown, "Decoding gripping force based on local field potentials recorded from subthalamic nucleus in humans," *eLife*, vol. 5, no. November, pp. 1–24, 2016.

[8] P. Fischer, A. Pogosyan, B. Cheeran, A. L. Green, T. Z. Aziz, J. Hyam, S. Little, T. Foltynie, P. Limousin, L. Zrinzo, M. Hariz, M. Samuel, K. Ashkan, P. Brown, and H. Tan, "Subthalamic nucleus beta and gamma activity is modulated depending on the level of imagined grip force," *Experimental Neurology*, vol. 293, pp. 53–61, 2017. Publisher: The Authors.

[9] S. A. Shah, H. Tan, G. Tinkhauser, and P. Brown, "Towards Real-Time, Continuous Decoding of Gripping Force from Deep Brain Local Field Potentials," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 7, pp. 1460–1468, 2018. Publisher: IEEE.

[10] B. A. Murphy, J. P. Miller, K. Gunalan, and A. Bolu Ajiboye, "Contributions of subsurface cortical modulations to discrimination of executed and imagined grasp forces through stereoelectroencephalography," *PLoS ONE*, vol. 11, no. 3, pp. 1–21, 2016.

[11] M. Wang, G. Li, S. Jiang, Z. Wei, J. Hu, L. Chen, and D. Zhang, "Enhancing gesture decoding performance using signals from posterior parietal cortex: a stereo-electroencephalograhy (SEEG) study," *Journal of Neural Engineering*, vol. 17, p. 046043, Sept. 2020. Publisher: IOP Publishing.

[12] M. S. Breault, Z. B. Fitzgerald, P. Sacré, J. T. Gale, S. V. Sarma, and J. A. González-Martínez, "Non-motor Brain Regions in Non-dominant Hemisphere Are Influential in Decoding Movement Speed," *Frontiers in Neuroscience*, vol. 13, pp. 1–13, July 2019.

[13] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 441–446, Dec. 2000. Conference Name: IEEE Transactions on Rehabilitation Engineering.

[14] S. Khawaldeh, G. Tinkhauser, S. A. Shah, K. Peterman, I. Debove, T. A. K. Nguyen, A. Nowacki, M. L. Lachenmayer, M. Schuepbach, C. Pollo, P. Krack, M. Woolrich, and P. Brown, "Subthalamic nucleus activity dynamics and limb movement prediction in Parkinson's disease," *Brain*, vol. 143, pp. 582–596, Feb. 2020.

[15] K. J. Miller, E. C. Leuthardt, G. Schalk, R. P. N. Rao, N. R. Anderson, D. W. Moran, J. W. Miller, and J. G. Ojemann, "Spectral Changes in Cortical Surface Potentials during Motor Movement," *Journal of Neuroscience*, vol. 27, pp. 2424–2432, Feb. 2007. Publisher: Society for Neuroscience Section: Articles.

[16] A. M. Dale, B. Fischl, and M. I. Sereno, "Cortical surface-based analysis. I. Segmentation and surface reconstruction," *NeuroImage*, vol. 9, pp. 179–194, Feb. 1999.

[17] L. S. Hamilton, D. L. Chang, M. B. Lee, and E. F. Chang, "Semi-automated Anatomical Labeling and Inter-subject Warping of High-Density Intracranial Recording Electrodes in Electrocorticography," *Frontiers in Neuroinformatics*, vol. 11, 2017. Publisher: Frontiers.

[18] C. Kothe, "sccn/labstreaminglayer," July 2021. original-date: 2018-02-28T10:50:12Z.

[19] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, D. Strohmeier, C. Brodbeck, L. Parkkonen, and M. S. Hämäläinen, "MNE software for processing MEG and EEG data," *NeuroImage*, vol. 86, pp. 446–460, Feb. 2014.

[20] F. Pedregosa, R. Weiss, and M. Brucher, "Scikit-learn : Machine Learning in Python," *Journal of machine learning research*, vol. 12, pp. 2825–2830, 2011.

[21] L. Turella and A. Lingnau, "Neural correlates of grasping," *Frontiers in Human Neuroscience*, vol. 8, p. 686, 2014.

[22] M. R. Mercier, S. Bickel, P. Megevand, D. M. Groppe, C. E. Schroeder, A. D. Mehta, and F. A. Lado, "Evaluation of cortical local field potential diffusion in stereotactic electro-encephalography recordings: A glimpse on white matter signal," *NeuroImage*, vol. 147, pp. 219–232, 2017. Publisher: Elsevier.

[23] S. Little, J. Bonaiuto, G. Barnes, and S. Bestmann, "Human motor cortical beta bursts relate to movement planning and response errors," *PLOS Biology*, vol. 17, p. e3000479, Oct. 2019. Publisher: Public Library of Science.