Brain-Computer Interface

see also Implantable brain-computer interface.

Brain-computer interfaces (BCI) and brain machine interfaces (BMI), sometimes collectively called neural interface systems (NIS), are being developed to provide a more powerful control signal by decoding movement intentions in real-time directly from neural activity.

Applications such as brain computer interfaces require recordings of relevant neuronal population activity with high precision, for example, with electrocorticography (ECoG) grids. In order to achieve this, both the placement of the electrode grid on the cortex and the electrode properties, such as the electrode size and material, need to be optimized. For this purpose, it is essential to have a reliable tool that is able to simulate the extracellular potential, i.e., to solve the so-called ECoG forward problem, and to incorporate the properties of the electrodes explicitly in the model. In this study, this need is addressed by introducing the first open-source pipeline, FEMfuns (finite element method for useful neuroscience simulations), that allows neuroscientists to solve the forward problem in a variety of different geometrical domains, including different types of source models and electrode properties, such as resistive and capacitive materials. FEMfuns is based on the finite element method (FEM) implemented in FEniCS and includes the geometry tessellation, several electrode-electrolyte implementations and adaptive refinement options. The Python code of the pipeline is available under the GNU General Public License version 3 at https://github.com/meronvermaas/FEMfuns. We tested our pipeline with several geometries and source configurations such as a dipolar source in a multi-layer sphere model and a five-compartment realistically-shaped head model. Furthermore, we describe the main scripts in the pipeline, illustrating its flexible and versatile use. Provided with a sufficiently fine tessellation, the numerical solution of the forward problem approximates the analytical solution. Furthermore, we show dispersive material and interface effects in line with previous literature. Our results indicate substantial capacitive and dispersive effects due to the electrode-electrolyte interface when using stimulating electrodes. The results demonstrate that the pipeline presented in this paper is an accurate and flexible tool to simulate signals generated on electrode grids by the spatiotemporal electrical activity patterns produced by sources and thereby allows the user to optimize grids for brain computer interfaces including exploration of alternative electrode materials/properties [1)].

Most brain machine interface (BMI) studies have focused only on the active state of which a BMI user performs specific movement tasks. Therefore, models developed for predicting movements were optimized only for the active state. The models may not be suitable in the idle state during resting. This potential maladaptation could lead to a sudden accident or unintended movement resulting from prediction error. Prediction of movement intention is important to develop a more efficient and reasonable BMI system which could be selectively operated depending on the user's intention. Physical movement is performed through the serial change of brain states: idle, planning, execution, and recovery. The motor networks in the primary motor cortex and the dorsolateral prefrontal cortex are involved in these movement states. Neuronal communication differs between the states. Therefore, connectivity may change depending on the states. In this study, we investigated the temporal dynamics of connectivity in dorsolateral prefrontal cortex and primary motor cortex to predict movement intention. Movement intention was successfully predicted by connectivity dynamics which may reflect changes in movement states. Furthermore, dorsolateral prefrontal cortex is crucial in predicting movement intention to which primary motor cortex contributes. These results suggest that brain connectivity is an excellent approach in predicting movement intention [2].

Electrocorticography (ECoG) based Brain-Computer Interfaces (BCIs) have been proposed as a way to restore and replace motor function or communication in severely paralyzed people. To date, most motor-based BCIs have either focused on the sensorimotor cortex as a whole or on the primary motor cortex (M1) as a source of signals for this purpose. Still, target areas for BCI are not confined to M1, and more brain regions may provide suitable BCI control signals. A logical candidate is the primary somatosensory cortex (S1), which not only shares similar somatotopic organization to M1, but also has been suggested to have a role beyond sensory feedback during movement execution.

Case reports

Ajiboye et al. report the findings of an individual with traumatic high-cervical spinal cord injury who coordinated reaching and grasping movements using his own paralysed arm and hand, reanimated through implanted FES, and commanded using his own cortical signals through an intracortical brain-computer interface (iBCI).

They recruited a participant into the BrainGate2 clinical trial, an ongoing study that obtains safety information regarding an intracortical neural interface device, and investigates the feasibility of people with tetraplegia controlling assistive devices using their cortical signals. Surgical procedures were performed at University Hospitals Cleveland Medical Center (Cleveland, OH, USA). Study procedures and data analyses were performed at Case Western Reserve University (Cleveland, OH, USA) and the US Department of Veterans Affairs, Louis Stokes Cleveland Veterans Affairs Medical Center (Cleveland, OH, USA). The study participant was a 53-year-old man with a spinal cord injury (cervical level 4, American Spinal Injury Association Impairment Scale category A). He received two intracortical microelectrode arrays in the hand area of his motor cortex, and 4 months and 9 months later received a total of 36 implanted percutaneous electrodes in his right upper and lower arm to electrically stimulate his hand, elbow, and shoulder muscles. The participant used a motorised mobile arm support for gravitational assistance and to provide humeral abduction and adduction under cortical control. We assessed the participant's ability to cortically command his paralysed arm to perform simple single-joint arm and hand movements and functionally meaningful multi-joint movements. We compared iBCI control of his paralysed arm with that of a virtual three-dimensional arm. This study is registered with ClinicalTrials.gov, number NCT00912041.

FINDINGS: The intracortical implant occurred on Dec 1, 2014, and we are continuing to study the participant. The last session included in this report was Nov 7, 2016. The point-to-point target acquisition sessions began on Oct 8, 2015 (311 days after implant). The participant successfully cortically commanded single-joint and coordinated multi-joint arm movements for point-to-point target acquisitions (80-100% accuracy), using first a virtual arm and second his own arm animated by FES. Using his paralysed arm, the participant volitionally performed self-paced reaches to drink a mug of coffee (successfully completing 11 of 12 attempts within a single session 463 days after implant) and feed himself (717 days after implant).

This is the first report of a combined implanted FES+iBCI neuroprosthesis for restoring both reaching and grasping movements to people with chronic tetraplegia due to spinal cord injury, and represents a major advance, with a clear translational path, for clinically viable neuroprostheses for restoration of reaching and grasping after paralysis [3].

Indications

Assisting people living with disability to acquire relevant skills and knowledge, diagnose and manage depression, communicate, move and interact socially.

Intracortical BCIs have permitted people with tetraplegia to control cursors on computer screens, robotic arms, and other prosthetic devices by simply imagining movements of their own arms [4].

Because it is not possible to map neural activity to actual arm movements in people with tetraplegia, in many previous human intracortical BCI studies the decoder has been calibrated using imagined arm movements [5].

Motor imagery-based brain-computer interfaces (BCIs) use an individual's ability to volitionally modulate localized brain activity as a therapy or to probe relations between brain activity and behavior. However, many individuals cannot learn to successfully modulate their brain activity, greatly limiting the efficacy of BCIs. Experiments designed to probe the nature of BCI learning suggest that activity across functionally diverse cognitive systems is a hallmark of learning. However, little is known about how these networks interact through time to support learning. Here, we address this gap in knowledge by constructing and applying a multimodal network approach to decipher brain-behavior relations in BCI learning using magnetoencephalography. Stiso et al. employed a minimally constrained matrix decomposition method - non-negative matrix factorization - to simultaneously identify regularized, covarying subgraphs of functional connectivity, to assess their similarity to task performance, and to detect their time-varying expression. We find that good learners displayed many subgraphs whose temporal expression tracked performance. Individuals also displayed marked variation in the spatial and temporal properties of subgraphs. From these observations, we posit a conceptual model in which certain subgraphs support learning by modulating brain activity in regions important for sustaining attention. To test this model, we use tools that stipulate regional dynamics on a networked system (network control theory) and find that good learners display a single subgraph whose temporal expression tracked performance and whose architecture supports easy modulation of brain regions important for attention. The nature of our contribution to the neuroscience of BCI learning is both computational and theoretical; we first use a minimally-constrained, individual specific method of identifying mesoscale structure in dynamic brain activity to show how global connectivity supports BCI learning, and then we use a formal network model of control to lend theoretical support to the hypothesis that these identified subgraphs are well suited to modulate attention [6].

Options for people with severe paralysis who have lost the ability to communicate orally are limited. We describe a method for communication in a patient with late-stage amyotrophic lateral sclerosis

(ALS), involving a fully implanted brain-computer interface that consists of subdural electrodes placed over the motor cortex and a transmitter placed subcutaneously in the left side of the thorax. By attempting to move the hand on the side opposite the implanted electrodes, the patient accurately and independently controlled a computer typing program 28 weeks after electrode placement, at the equivalent of two letters per minute. The brain-computer interface offered autonomous communication that supplemented and at times supplanted the patient's eye-tracking device. (Funded by the Government of the Netherlands and the European Union; ClinicalTrials.gov number, NCT02224469 .) [7].

[1]
Vermaas M, Piastra MC, Oostendorp TF, Ramsey NF, Tiesinga PHE. FEMfuns: A Volume Conduction Modeling Pipeline that Includes Resistive, Capacitive or Dispersive Tissue and Electrodes. Neuroinformatics. 2020 Apr 18. doi: 10.1007/s12021-020-09458-8. [Epub ahead of print] PubMed PMID: 32306231.

[2]
Kang BK, Kim JS, Ryun S, Chung CK. Prediction of movement intention using connectivity within motor-related network: An electrocorticography study. PLoS One. 2018 Jan 24;13(1):e0191480. doi: 10.1371/journal.pone.0191480. eCollection 2018. PubMed PMID: 29364932.

[3]
Ajiboye AB, Willett FR, Young DR, Memberg WD, Murphy BA, Miller JP, Walter BL, Sweet JA, Hoyen HA, Keith MW, Peckham PH, Simeral JD, Donoghue JP, Hochberg LR, Kirsch RF. Restoration of reaching and grasping movements through brain-controlled muscle stimulation in a person with tetraplegia: a proof-of-concept demonstration. Lancet. 2017 May 6;389(10081):1821-1830. doi: 10.1016/S0140-6736(17)30601-3. Epub 2017 Mar 28. PubMed PMID: 28363483; PubMed Central PMCID: PMC5516547.

[4] , [5]
Hochberg LR, Serruya MD, Friehs GM, Mukand JA, Saleh M, Caplan AH, Branner A, Chen D, Penn RD, Donoghue JP. Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature. 2006 Jul 13;442(7099):164-71. PubMed PMID: 16838014.

[6]
Stiso J, Corsi MC, Vettel JM, Garcia JO, Pasqualetti F, de Vico-Fallani F, Lucas T, Bassett DS. Learning in brain-computer interface control evidenced by joint decomposition of brain and behavior. J Neural Eng. 2020 May 5. doi: 10.1088/1741-2552/ab9064. [Epub ahead of print] PubMed PMID: 32369802.

[7]
Vansteensel MJ, Pels EG, Bleichner MG, Branco MP, Denison T, Freudenburg ZV, Gosselaar P, Leinders S, Ottens TH, Van Den Boom MA, Van Rijen PC, Aarnoutse EJ, Ramsey NF. Fully Implanted Brain-Computer Interface in a Locked-In Patient with ALS. N Engl J Med. 2016 Nov 24;375(21):2060-2066. PubMed PMID: 27959736.