Neural/Cloud Interface to Extend Human-Computer Interaction for WebXR Applications

Daniel Burger

Department of Web Development
Middlesex University London

This thesis is submitted for the degree of
Bachelor of Science, Web Development

SAE Institute Zürich

June 2022

Abstract

This is a rough draft of the abstract (not intended for reader as of now): There are various types of neural interfaces. There are various types of software for neural interfaces. There are various types of users for neural interfaces. The advantages and disadvantages of using local software versus software running in the cloud. A neural/cloud-based interface is defined as a production-ready and mainstream-ready BCI application in this thesis. Connecting web-based BCIs to the future of software, moving towards 3D and spatial computing, and how the web can play an essential role alongside BCI unobtrusive BCI technologies. Paradigm-shift for BCI software and 3D software running in browsers.

The goal is to provide a comprehensive overview of a neural/cloud interface and the components that comprise it. To lay the groundwork for future developers based on empirical technical experience in developing a real-world neural/cloud interface for IDUN Technologies' in-ear EEG sensor product. As part of this project, a public example code is provided.

We also discuss 3D on the web and the implications for human-computer interaction with a BCI based on a neural/cloud interface. Demonstrating the potential for additional use cases and the future of BCI software, web applications, and 3D software.

This work is dedicated to the team at IDUN Technologies, who have been so helpful on my journey entering the neurotechnology industry. They taught me a lot about working in a scientific setting and gave me the opportunity to investigate various aspects of non-invasive brain-computer interfaces in combination with cloud computing and virtual reality.
I'd also like to thank the open-source collective Poimandres for the support of their WebGL libraries, which has greatly aided me in comprehending some of the most complex challenges in 3D graphics programming.

Table of contents

List of figures

List of tables

Chapter 1

Introduction

This chapter introduces the reader to this thesis's primary focus and key topics and their explanations. It also displays the research question, aims, objectives, and distinctions of the thesis's primary contents and structure.

1.1 Background

There has been a long-standing interest in developing neural interfaces, systems that sense electrical impulses from the nervous system and use them to intercommunicate with the human brain. Successful research into the development of technologies that enable neural interfaces has been going on for decades, with the first experiments being conducted by Jacques J. Vidal in the late 1970s (Vidal, 1977). Progress has accelerated significantly in the past few years, especially since the advent of modern processing capabilities such as in deep learning with convolutional neural networks (CNN) or generative adversarial networks (GAN) (Gonfalonieri, 2019). In particular, a related discipline called brain-computer interfacing (BCI), a field focused on the direct interaction between brains and computers, has accumulated much momentum since the popularity of companies like Neuralink and Kernel.

One aspect of neural interfaces is hardware tailored to the human body. Whether it is an invasive sensor, such as in electrocorticography (ECoG), a method which uses electrodes placed on the surface of the brain, or a non-invasively placed sensor on the body, such as in electroencephalography (EEG). Both methods measure electrical activities produced by neurons; however, with decreasing spatial precision, the farther the electrode is placed from the brain, the more body structures (e.g. bones) are between firing neurons and the measuring sensor. The other aspect is software that reads and interprets data of these hardware sensors. Both aspects present their own set of challenges and complexities. Nonetheless, complete and applicable neural interfaces work in practice and have been used for many years in patients with neurological disorders (BrainGate, n.d.). There are also consumer and non-clinical neural interfaces available, such as the Neurosity and OpenBCI products, which aim to democratise the use of EEG sensors by offering low-cost hardware and simple-to-use software.

Fig. 1.1: Les Baugh, an amputee, is using a neural interface to control two robotic arms with his thoughts (Campbell, 2014).

1.2 Relevance

The possibilities of connecting the human brain with computers are almost limitless because one has to think that we are the brain, that our own perception of reality, all our feelings, memories and actions are supposed to be contained in the electrical impulses of our brain. The ability to communicate directly with our thoughts and the outside world — whether through digital or physical objects — is a fantastic prospect. There are several use cases: Controlling prosthetic limbs for amputees (Murphy et al., 2017), communication for people with locked-in syndrome (Chaudhary et al., 2022), diagnosing neurological problems and improving the mental capacities of elderly patients (Belkacem et al., 2020) are promising examples, to name a few.

It may appear evident that neural interfaces can significantly impact the field of therapeutics and accessibility for a small subset of the human population. However, one can envision not only alleviating deplorable living conditions but also improving the lives of healthy people through more natural or efficient ways of interacting with things or by directly altering human brains for certain benefits. Because most current neural interface applications concentrate on the first aspect of therapeutics and accessibility, other use cases, such as stimulating the brain to improve concentration, modifying cognitive load, or even uploading new knowledge directly into the brain, may appear to be science fiction ideas.

Regardless, many capable people — research labs and even entire companies — are developing neural interface hardware and software aimed at the general population without conditions that envision a future for such use cases in the long term. The applicability of a neural interface system to the mainstream will depend on several factors, presumably an important factor of which is the hardware's form factor. Nonetheless, the totality of the ecosystem in which the software resides is a valuable aspect that should not be overlooked.

1.3 Research question

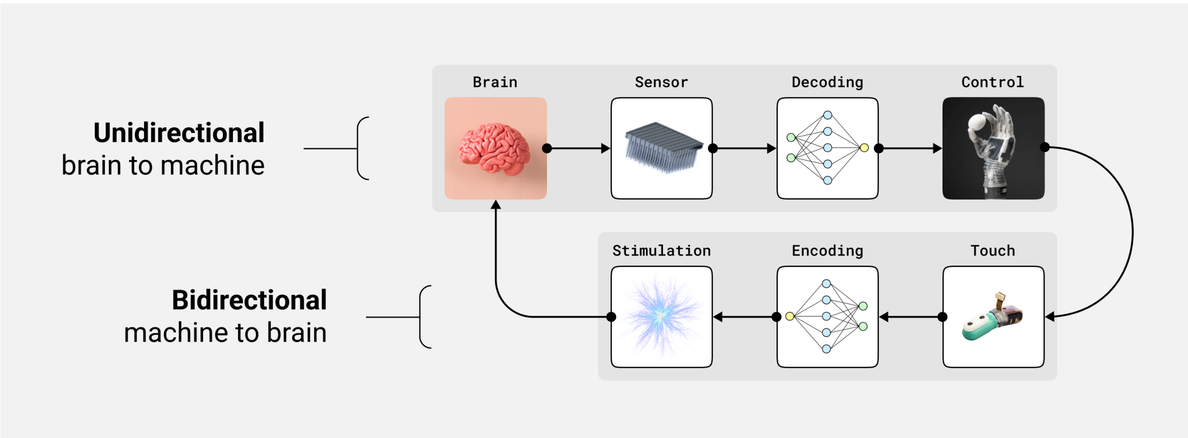

Fig. 1.2: Difference between an unidirectional and bidirectional neural interface and its components (own representation, 2022).

Whether it is a bidirectional and invasive neural interface with the potential to be implanted on a large scale, as, e.g. Neuralink is aiming to do, or a unidirectional and non-invasive interface in various form factors that are also aimed at the mass market, such as in a pair of glasses or a pair of headphones, the data collected from the brain would always need to be processed, contextualised, and classified to produce an intelligible output. The research question of the present thesis is on determining what technological components such a software system would require to be production-ready and suitable for a mass-market product. The emphasis is on a holistic view of such a system, which means that the entire technology stack is taken into account in answering the research question.

Furthermore, most current neural interface software systems in production, for example, for an interface implanted in a living patient, are typically run in a local environment, i.e. the software system and its components are typically located on a physically nearby computer, usually connected by a cable, to reduce latency and avoid complexities introduced by a wireless protocol. There is already promising research on wireless mobile brain-computer interfaces (mBCI) by Minguillon et al. (2017) or possible implications of human brain/cloud interfaces (B/CI) by Martins et al. (2019) or by Angelica et al. (2021), which analyse bringing hypothetical future large-scale brain-computer interface software systems into the cloud.

1.4 Hypothesis

Previous research on brain/cloud interfaces has tended to focus on speculations based on hypothetical scenarios in the future, usually based on the premise of other developed technologies such as neural nanorobotics, vital advances in 5G, or the presence of super-computers in the cloud, e.g. for the augmentation of the human brain, or a communication network for brain-to-brain interfacing (BTBI), and are thus somewhat distant from today's pertinence. To distinguish the research presented in this thesis, the author coins the term neural/cloud interface (N/CI), which refers to a holistic software interface that connects a neural interface device to the cloud and then to other neural interfaces, software applications, cloud systems, or physical devices.

The primary hypothesis is that a neural/cloud interface is feasible with modern software technologies, requiring only theoretical groundwork based on empirical engineering in a deployable and producible system. To shed more light on this, this thesis looks at the process and lessons learned from the author's perspective in developing a N/CI in the industry for an actual mainstream-capable neural interface device for a BCI end-user application.

1.5 Goals and aims

The overall goal of this thesis is to give the reader an overview of the definition of a N/CI, its components, and the lessons learned in building a reproducible production-grade and end-user-facing N/CI application with a non-invasive, unidirectional neural interface hardware. In addition to the overall goal, the thesis aims to illustrate a powerful demonstration of the possibilities of neural interfaces on the World Wide Web for virtual reality (VR) or augmented reality (AR) applications running in a browser environment in order to exemplify how to extend the human-computer interaction (HCI) for future 3D applications when combined with a BCI.

1.6 Objectives

The hypothesis of the present thesis states that a N/CI is realisable with contemporary technologies and thus distinguishes itself from previous work with the term brain/cloud interface from Martins et al. and Angelica et al., which, as already mentioned, rather aims at speculative future scenarios. Based on the research question of which components make up a N/CI, the goal is to establish a holistic N/CI and thus identify and evaluate suitable methods for creating such a N/CI. In order to achieve this goal, the author must achieve the following objectives:

1. Identify and illustrate the most relevant software components required to realise a production-grade N/CI.
2. Identify and deploy the most effective software components in a given and appropriate context to build a production-grade N/CI.
3. Develop and publicly release an example N/CI application codebase that is easy to understand and extend.
4. Demonstrate the applicability and impact for HCI of a N/CI with web-based VR/AR applications.

Chapter 2

Research Context

This chapter describes the research question's context and the current literature findings. The reader is educated on the limitations of current non-invasive and unidirectional BCIs, the paradigm shift in developing cloud-based and production-ready software versus running software in a research environment, and the implications and hypotheses of web-based approaches to BCIs and 3D applications for VR and AR that relate to the future of software in general in the field of spatial computing.

2.1 Limitations of BCIs

The possibilities of BCIs are not without limitations. In addition to the hardware limitations, the author attempts to address a broader issue related to neuropsychology that directly correlates with the software aspects, in addition to the challenges of computability.

2.1.1 Decoding brain data

As outlined in the previous chapter, a holistic view of BCI must take into account the aspect of decoding measured neural data and making it intelligible to computer software. It is important to emphasise that the task of decoding neural data is different from decoding thoughts, which is a critical factor for software. Moreover, decoding neural data and extracting the thoughts behind it so that the software can understand them are disciplines on their own. For example, getting computers to recognise letters written on a photograph is a very different problem from reading the written words in the sentences (i.e. computer vision and natural language processing).

Another part is understanding the sentences and their meaning, as in natural language understanding (NLU). NLU is considered an AI-hard problem, which means that the difficulty of these computational problems is equivalent to solving the central problem of artificial general intelligence (AGI) (Demasi et al., 2010), assuming that general human-level intelligence is computational. Understanding less structured data, such as EEG data, is more complicated than understanding structured and human-generated syntax such as written language because it contains more hidden features than a paragraph of text. As a result, the author assumes that understanding brain data might be considered an AI-hard problem.

2.1.2 Abstract thoughts

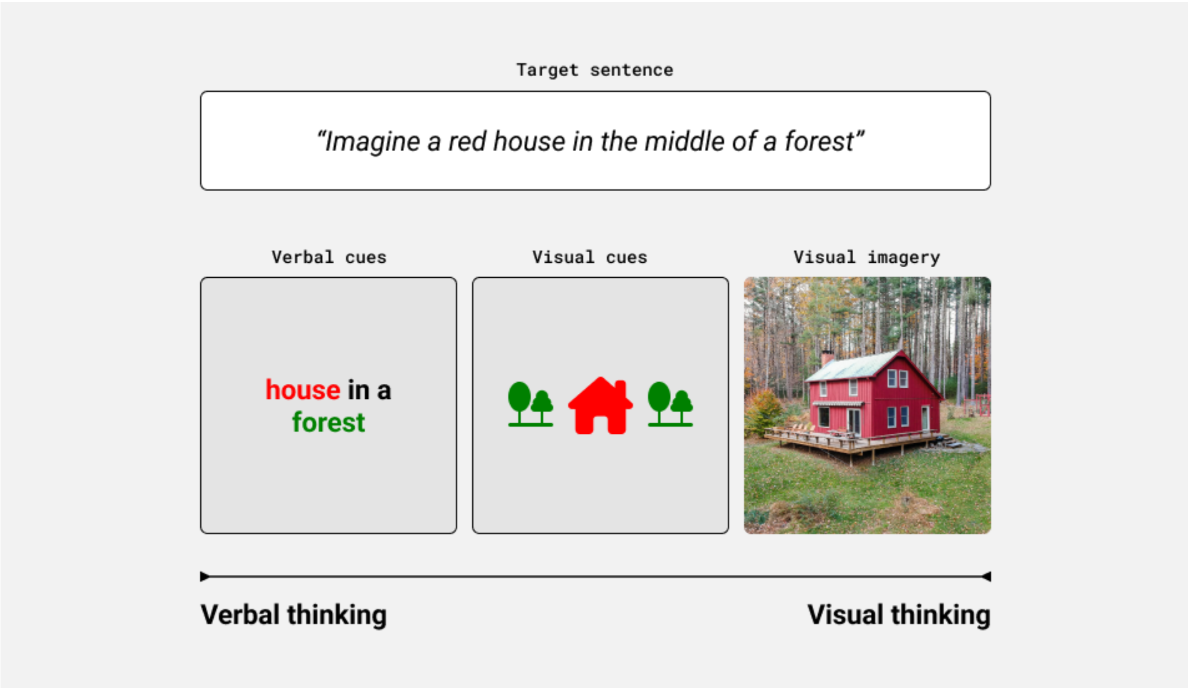

Fig. 2.1: Difference between verbal and visual thinking using the target sentence of a red house in the middle of a forest (own representation, 2022).

Imagine a red house in the middle of a forest. Depending on the individual thought process, one can imagine the house with temporary visual imagery in mind, as in visual thinking, or one can imagine it more verbally, such as conceptually comprehending each word sequentially of what a red house is and that it is located in a forest (Amit et al., 2017). Additionally, it should also be addressed that different types of thoughts exist at different levels of abstraction and complexity. One can assume that the visual image of a red house in the forest is more abstract and far-fetched than, say, the movement of one's own thumbs, which has a clear physical counterpart. It gets even more complicated when one imagines concepts that are inconceivable to visualise, such as the idea of a company. A company is only an abstract, collectively agreed upon concept without a physical counterpart and is, therefore, even less straightforward and more complex to decode the meaning of measured brain activity than the other mentioned examples of the red house.

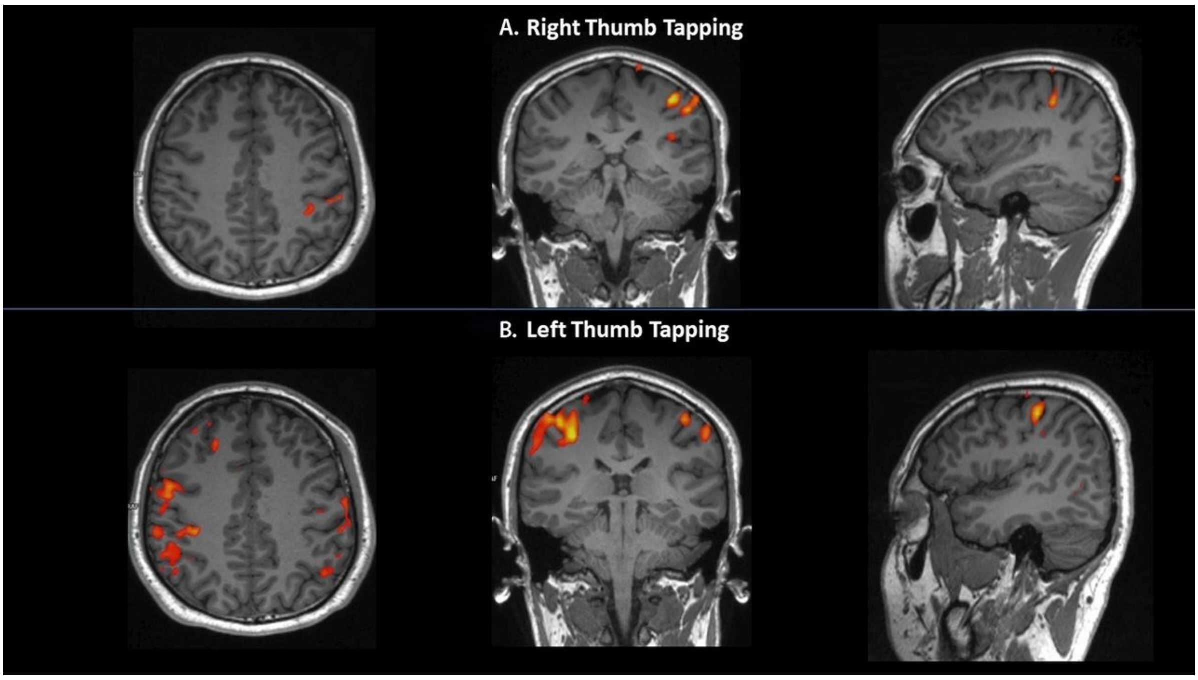

Fig. 2.2: Image of localised activation of neurons during right and left thumb movement using functional magnetic resonance imaging (fMRI) (Rashid et al., 2018).

2.1.3 Technological limitations

Functional tasks of the brain are localised, which means that these signals are generated by local brain areas that can be identified, such as the motor cortex, which has been shown to be responsible for muscle movement as shown in Figure 2.2. Examining the areas of the brain responsible for activating individual muscle strands can yield a comparable response of muscle stimulation in the brain and thus be measured as output for software to move a prosthesis, for example. However, the more specific, less functional, more behavioural and abstract the thoughts are, the less the brain areas are spatially visible. The intent of identifying, for example, the thought of a red house in a forest in verbal thought, the author identified three technological problem statements:

- To understand single thoughts, it is essential to have sufficiently clear data from experiments with a certain level of detail (e.g., at the level of detail related to the firing of action potential of individual neurons) as well as temporal precision (an action potential takes about 1 ms to arise) to perform studies to extract possible localisations of individual thoughts. Current neuroimaging technologies cannot capture every process in sufficient detail of the entire brain at once to extract the activity of, e.g. individual neurons while also having high temporal precision.

- Even if we could measure every single neuron in the brain with high temporal precision, we would have an extreme amount of data generated concisely. Let us say we would collect a float per neuron that represents the rate of change in voltage with respect to time in milliseconds and then record each neuron in the brain a million times a second, taking into account that the average human brain has around 86 billion neurons; we would generate 305.53337637684 petabytes of data per second. This is currently not feasible for most of the commercially available storage and processing resources available.

- Even if we have the technology, it is a challenge because reproducibility of experiments is very difficult for neuroscientific studies. It is probably impossible to generate clean-slate neural data that is comparable to previously recorded data. Our neurophysiological brain structure changes over time due to neuroplasticity (Puderbaugh & Emmady, 2022), and we are in different states of mind every millisecond of our existence, which can have different influences, such as insufficient sleep, something disturbing someone, mental distraction due to an important event that may have occurred since the last measurement, or a salient thought that occurs during a measurement.

2.1.4 Lack of data

As pointed out in the previous section, points 2 and 3 depend on advances in data storage systems or the possibility that we do not actually need 3such precise brain data to understand single thoughts. However, to address point 1, some promising solutions already exist for measuring large parts of the brain with high temporal and spatial precision, such as time-domain functional near-infrared spectroscopy (TD-fNIRS), which Kernel employs in its Kernel Flow device. The TD-fNIRS system detects changes concentrations of oxygenated (oxyHb) and deoxygenated brain cell activity by using near-infrared light in response to neuronal activity. This is a newer and more promising technology for measuring the full spectrum of neuroimaging of brain activity when compared to EEG. According to Kernel's, the precision of TD-fNIRS is sufficient for better understanding the brain and using it for BCI applications. They, however, claim that collecting and organising longitudinal brain data from a variety of subjects is the key to solving the most difficult challenges in neuroscience (Kernel, n.d.).

Based on Kernel's claim, a recent publication from 2022 also claims that even data sets with several hundred people are too tiny to consistently offer insights about the brain (Marek et al., 2022). As a result, most published brain-wide association studies with dozens or even hundreds of people could all be incorrect. In such research, variations in brain structure and activity have been linked to variances in cognitive capacity, mental health, and other behavioural features. Numerous studies, for example, have revealed brain structure or activity patterns that may help distinguish persons with depression from those who are not. Neuromarkers of behavioural features is frequently sought in studies. The recent publication from Marek et al. claims that most of these so-called neuro markers would not work when the collected data set is more extensive, which prose a general problem for the field of neuroscience.

This is both fascinating and a significant constraint for BCIs, because understanding the brain is essential to making sense of the measured and classified data for interfacing with it. Therefore a large amount of brain data collected in reproducible experiments is a must for production-ready and mainstream-ready BCIs. UK Biobank's collection of brain scans is one of the first efforts to solve this problem ("Imaging study", n.d.), but it is still far from what we might need. Marek himself claims that we might even need millions of data sets to start understanding the brain (Callaway, 2022).

2.2 BCI landscape

2.2.1 Real-world BCI applications

2.2.2 Unobtrusive hardware and software

2.2.3 Active and passive BCIs

2.3 Production-grade software

2.3.1 Cloud paradigm-shift

2.3.2 Web-first BCI architecture

2.3.3 3D applications in the browser

2.3.4 Web-based AR and VR

2.4 N/CI challenges

Chapter 3

Methodologies

3.1 Participants

3.2 Design

3.3 Materials

3.4 Procedure

3.5 Data Analysis

3.6 Goals

Chapter 4

Implementation

4.1 Lorem ipsum

Chapter 5

Results

5.1 Steps Before The Analysis

5.2 Main Results

5.3 Figures And Tables

5.4 Goals

5.5 Conclusion

Chapter 6

Discussion

6.1 Summary

6.2 Interpretation

6.3 Integration

6.4 Implications

6.5 Limitations

Bibliography

Amit, E., Hoeflin, C., Hamzah, N., & Fedorenko, E. (2017). An asymmetrical relationship between verbal and visual thinking: Converging evidence from behavior and fMRI. *NeuroImage*, *152*, 619–627. https://doi.org/10.1016/j.neuroimage.2017.03.029

Angelica, A., Opris, I., Lebedev, M. A., & Boehm, F. J. (2021). Cognitive Augmentation Via a Brain/Cloud Interface. In I. Opris, M. A. Lebedev, & M. F. Casanova (Eds.), *Modern Approaches to Augmentation of Brain Function* (pp. 357–386). Springer International Publishing. https://doi.org/10.1007/978-3-030-54564-2_17

Belkacem, A. N., Jamil, N., Palmer, J. A., Ouhbi, S., & Chen, C. (2020). Brain Computer Interfaces for Improving the Quality of Life of Older Adults and Elderly Patients. *Frontiers in Neuroscience*, *14*. Retrieved May 8, 2022, from https://www.frontiersin.org/article/10.3389/fnins.2020.00692

BrainGate. (n.d.). Publications Timeline. Retrieved May 8, 2022, from https://www.braingate.org/publications-timeline

Callaway, E. (2022). Can brain scans reveal behaviour? Bombshell study says not yet [Bandiera_abtest: a Cg_type: News Number: 7903 Publisher: Nature Publishing Group Subject_term: Neuroscience, Brain]. *Nature*, *603*(7903), 777–778. https://doi.org/10.1038/d41586-022-00767-3

Campbell, P. (2014). Amputee becomes first to simultaneously use two APL Modular Prosthetic Limbs. Retrieved May 8, 2022, from https://hub.jhu.edu/2014/12/17/amputee-makes-history/

Chaudhary, U., Vlachos, I., Zimmermann, J. B., Espinosa, A., Tonin, A., Jaramillo-Gonzalez, A., Khalili-Ardali, M., Topka, H., Lehmberg, J., Friehs, G. M., Woodtli, A., Donoghue, J. P., & Birbaumer, N. (2022). Spelling interface using intracortical signals in a completely locked-in patient enabled via auditory neurofeedback training [Number: 1 Publisher: Nature Publishing Group]. *Nature Communications*, *13*(1), 1236. https://doi.org/10.1038/s41467-022-28859-8

Demasi, P., Szwarcfiter, J. L., & Cruz, A. J. O. (2010). A Theoretical Framework to Formalize AGI-Hard Problems [ISSN: 1951-6851], 64–65. https://doi.org/10.2991/agi.2010.14

Gonfalonieri, A. (2019). Deep Learning Algorithms and Brain-Computer Interfaces. Retrieved May 8, 2022, from https://towardsdatascience.com/deep-learning-algorithms-and-brain-computer-interfaces-7608d0a6f01

Imaging study. (n.d.). Retrieved June 12, 2022, from https://www.ukbiobank.ac.uk/explore-your-participation/contribute-further/imaging-study

Kernel. (n.d.). Hello-humanity.pdf. Retrieved June 12, 2022, from https://www.kernel.com/hello-humanity.pdf

Marek, S., Tervo-Clemmens, B., Calabro, F. J., Montez, D. F., Kay, B. P., Hatoum, A. S., Donohue, M. R., Foran, W., Miller, R. L., Hendrickson, T. J., Malone, S. M., Kandala, S., Feczko, E., Miranda-Dominguez, O., Graham, A. M., Earl, E. A., Perrone, A. J., Cordova, M., Doyle, O., ... Dosenbach, N. U. F. (2022). Reproducible brain-wide association studies require thousands of individuals [Number: 7902 Publisher: Nature Publishing Group]. *Nature*, *603*(7902), 654–660. https://doi.org/10.1038/s41586-022-04492-9

Martins, N. R. B., Angelica, A., Chakravarthy, K., Svidinenko, Y., Boehm, F. J., Opris, I., Lebedev, M. A., Swan, M., Garan, S. A., Rosenfeld, J. V., Hogg, T., & Freitas, R. A. (2019). Human Brain/Cloud Interface. *Frontiers in Neuroscience*, *13*, 112. https://doi.org/10.3389/fnins.2019.00112

Minguillon, J., Lopez-Gordo, M. A., Morillas, C., & Pelayo, F. (2017). A Mobile Brain-Computer Interface for Clinical Applications: From the Lab to the Ubiquity. In J. M. Ferrández Vicente, J. R. Álvarez-Sánchez, F. de la Paz López, J. Toledo Moreo, & H. Adeli (Eds.), *Biomedical Applications Based on Natural and Artificial Computing* (pp. 68–76). Springer International Publishing. https://doi.org/10.1007/978-3-319-59773-7_8

Murphy, D. P., Bai, O., Gorgey, A. S., Fox, J., Lovegreen, W. T., Burkhardt, B. W., Atri, R., Marquez, J. S., Li, Q., & Fei, D.-Y. (2017). Electroencephalogram-Based Brain-Computer Interface and Lower-Limb Prosthesis Control: A Case Study. *Frontiers in Neurology*, *8*, 696. https://doi.org/10.3389/fneur.2017.00696

Puderbaugh, M., & Emmady, P. D. (2022). Neuroplasticity. *StatPearls*. StatPearls Publishing. Retrieved June 12, 2022, from http://www.ncbi.nlm.nih.gov/books/NBK557811/

Rashid, A., Suppiah, S., Hoo, F. K., & Masiran, R. (2018). Bilateral Motor Cortex Control for Left Thumb Movement: An Incidental Finding Through Functional MRI (fMRI) [Publisher: BMJ Publishing Group Section: Unexpected outcome (positive or negative) including adverse drug reactions]. *Case Reports*, *2018*, bcr. https://doi.org/10.1136/bcr-2017-221129

Vidal, J. J. (1977). Real-time detection of brain events in EEG. *Proceedings of the IEEE*. https://doi.org/10.1109/PROC.1977.10542

Appendix A

This is an Appendix

Lorem ipsum

Appendix B

This is another Appendix

Lorem ipsum