Enabling Cloud-Based Brain-Computer Interface Software for the Mass Market

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

SAE Institute Zürich July 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 **IDUN Technologies team,** who have been extremely helpful in my journey into the neurotechnology industry. They taught me a lot about working in a scientific setting and allowed me to investigate various aspects of non-invasive brain-computer interfaces in combination with cloud computing and web development.*

*Additionally, I would like to express my sincere gratitude to **Dr. Cao Tri Do,** who advised me and patiently taught me a great deal about the aspects of theoretical neuroscience, which was essential for completing this thesis.*

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Chapter 1

Introduction

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

1.1 Background

There has been a long-standing interest in developing neural interfaces, systems that sense and interact with the electrical activity from the nervous system. Successful research into the development of technologies that enable neural interfacing has been going on for decades, with the first experiments being conducted by Jacques J. Vidal in the late 1970s (Vidal, 1977). In particular, a related discipline focusing on the direct interaction between brains and computers via a brain-computer interface (BCI), has accumulated much momentum since the popularity of companies like Neuralink.

One aspect of BCIs is the development of imaging technologies that enable the measurement of brain activity. A distinction is made between different methods of measuring of brain activity signals at different locations, such as invasive and non-invasive sensors. 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 the electrical field elicited by the firing of neuronal populations; however, with decreasing spatial precision, the farther the electrode is placed from the brain, the more tissues (e.g., bones) are between firing neurons and the measuring sensor.

The other aspect is the development of software that aims at reading and interpreting data from e.g. hardware sensors. Both aspects present their own set of challenges and complexities. Nonetheless, complete and applicable BCIs 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 BCIs available, such as the OpenBCI and Neurosity products, which aim to normalise the use of EEG sensors by offering low-cost hardware and open-source software.

1.2 Relevance

The possibilities for directly connecting the human brain to the outside world via or with computers are seemingly endless, given the (purely physical) assertion that all of our feelings, memories, dreams, and thoughts are most likely the sum of electrical activities taking place in our brain. There are several use cases for utilising insights from our brain to interface with computers such as controlling prosthetic limbs for amputees as shown on Figure 1.1, enabling communication for people with locked-in syndrome[1] (Chaudhary et al., 2022), or diagnosing neurological problems and improving the mental capacities of elderly patients (Belkacem et al., 2020) are promising examples, to name a few.

Fig. 1.1: Les Baugh, an amputee, is using his mind to control two robotic arms to perform several tasks that require fine motor control of his fingers and arms (Campbell, 2014)

[1]Lock-in syndrome describes the paralysis of all voluntary muscles in its entirety, therefore making it impossible for people to communicate with the outside world.

It may appear evident that BCIs 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 such as the possibility to enhance or delete bad memories (Spiers & Bendor, 2014) or record and guide dreams (Haar Horowitz et al., 2020).

Many use-cases still seem a long way from being applicable today, yet many capable people, and even entire companies are developing BCI hardware and software aimed at the general population such as e.g. Neuralink (Urban, 2017). The applicability of a BCI system to the mass-market will depend on several factors, of which the form factor and invasiveness of the hardware is likely to be an important aspect. Nevertheless, the totality of the ecosystem in which the software resides is a valuable aspect that should not be overlooked.

1.3 Research question

Whether it is a bidirectional and invasive BCI or a unidirectional and non-invasive BCI, the data collected from the brain would always need to be processed, contextualised, and classified to produce an intelligible output to interface with things as shown on Figure 1.2.

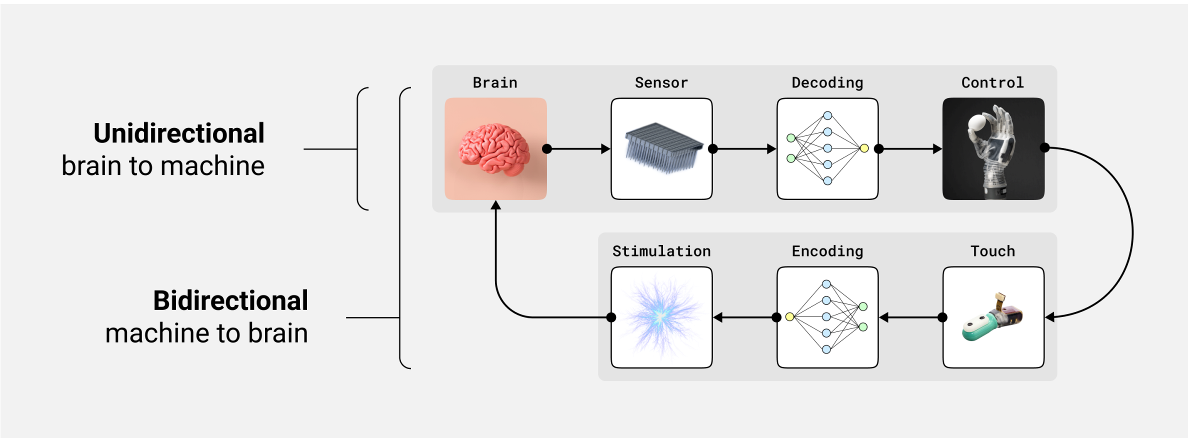

Fig. 1.2: Conceptual difference between a unidirectional and a bidirectional BCI and a simplified overview

Most current BCI software systems being developed, e.g. for a BCI implanted in a living patient, are typically deployed in a local environment, i.e. the software system and its components are located on a physically nearby computer. The author sees a need to move BCI software away from local environments and into the cloud in order to enable mass-market ready BCIs.

The research question of the present thesis is on determining what components such a cloud-based and mass-market-ready software system would require. The emphasis is on a holistic view of such a system, which means that the entire technology stack and context is taken into account in answering the research question.

1.4 Hypothesis

There is already promising research on implications of brain/cloud interfaces (B/CI) by Martins et al. (2019) or by Angelica et al. (2021), which analyse bringing hypothetical large-scale BCI software systems into the cloud. Nonetheless, their research is focusing 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 supercomputers in the cloud, e.g. for the augmentation of the human brain, 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 system that connects a neural interface device such as a BCI to the cloud and then to other neural interfaces, software systems, or physical devices.

The primary hypothesis is that a N/CI is feasible with contemporary software technologies, requiring only theoretical groundwork based on empirical software engineering. To shed more light on this, this thesis looks at the process and lessons learned from the author's perspective in developing a real-life N/CI in the industry.

1.5 Goal and objectives

The overall goal of this thesis is to give the reader an overview of the definition of a N/CI, and the software components that make it up. In order to achieve the goal the author must achieve the following objectives:

1. Describe the motivation for this new and interdisciplinary field between BCI and cloud computing.
2. Establish a clear definition of an N/CI, its distinction and advantages compared to existing BCI software systems.
3. Identify and define the most relevant software components and aspects required to realise a N/CI.

Chapter 2

Research Context

This chapter describes the research question's context and the current literature findings. The reader is educated on neuroscientific limitations, the state of current non-invasive BCIs, the motivation for developing cloud-based and mass-market-ready BCI software and the general definition of a N/CI.

2.1 Limitations of BCIs

The possibilities of BCIs are not without limitations. In addition to the hardware limitations, the author addresses 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

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 assumed to be equivalent to solving the central problem of artificial general intelligence[1] (Demasi et al., 2010). Understanding less structured data, such as neural data, is more complicated than understanding structured and human-generated syntax such as written language because it contains more hidden features and semantics than a paragraph of text. As a result, the author strongly assumes that understanding neural data can be considered an AI-hard problem too.

[1] Based on the assumption that general human-level intelligence could be computable.

2.1.2 Abstract thoughts

To further emphasise the complexity of interpreting neural data, a practical example will be presented: Imagine a red house in the middle of a forest. Depending on the individual thought process, one might imagine the house with temporary visual imagery in mind, as in visual thinking, or one might 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) as shown on Figure 2.1.

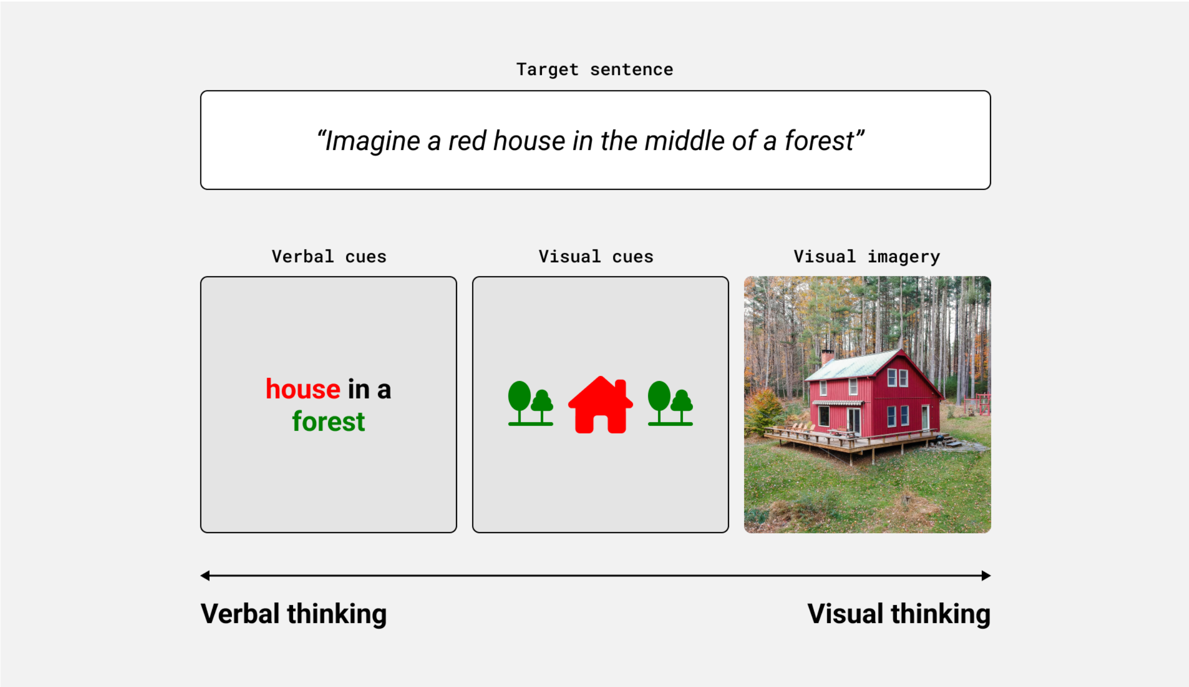

Fig. 2.1: Difference between verbal and visual thinking using the target sentence of a red house in the middle of a forest

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 abstract concepts that are inconceivable to visualise, such as the idea of a company. A company is an abstract, collectively agreed upon concept without a clear physical counterpart[2] 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.

[2]Some people might think of a company building when imaging a company, others might imagine their website, their logo or physical products.

2.1.3 Technological limitations

Most 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.

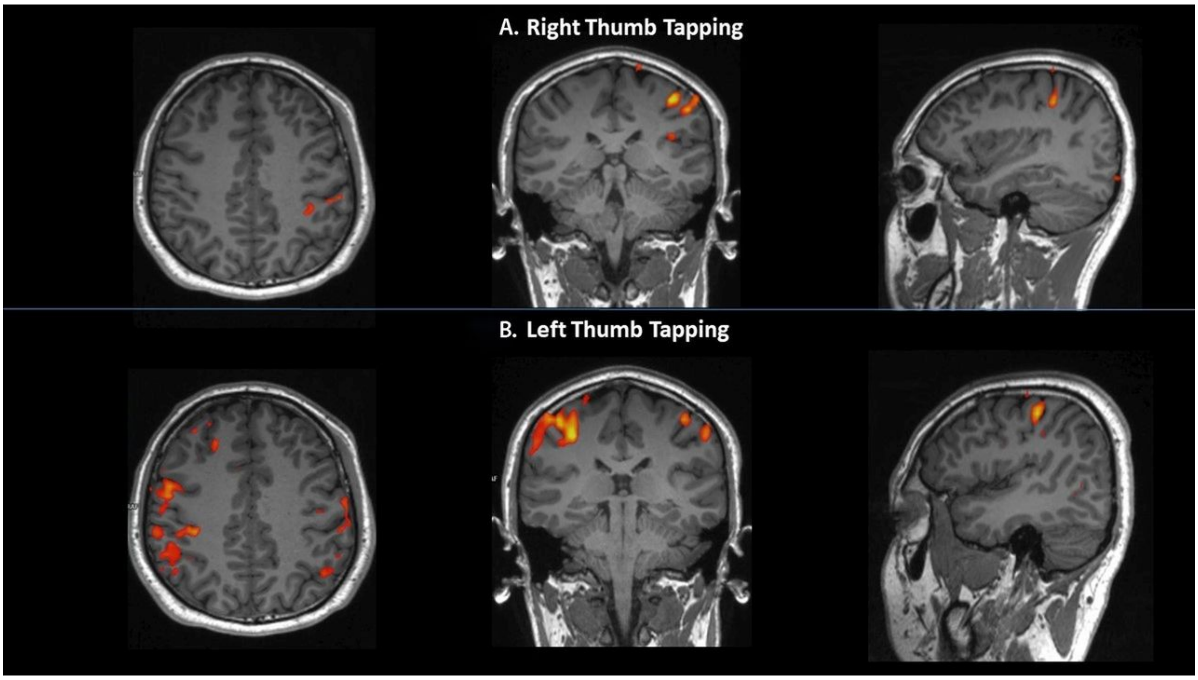

Fig. 2.2: Localised neurons during right and left thumb movement using functional magnetic resonance imaging (fMRI) (Rashid et al., 2018)

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 input for BCI software to e.g. move a prosthesis. However, the more specific, more behavioural and abstract the thoughts are, the less the brain areas are spatially visible. With the intention of identifying, e.g. the thought of a red house in a forest, the author has identified three technological limitations:

- To understand single thoughts, it is essential to have sufficiently clear data with a certain level of detail (e.g., at the level of detail of eliciting action potentials of individual neurons[3]) and temporal precision (an action potential has a short duration of about 1 millisecond (Byrne, 2021)) to perform studies to extract possible localisation of individual thoughts. Current neuroimaging technologies cannot capture every process in

[3]Action potentials are the fundamental neurobiological and neurochecmical processes through which neurons transfer information to each other.

sufficient detail of the entire brain at once to extract the activity of 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[4] per neuron that represents the rate of change in voltage with respect to time with a frequency of 1 ms 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 commercially available storage and processing resources.
- Even if we have the technology, it is a challenge because reproducibility of experiments is very difficult for neuroscientific studies (usually referenced as the replication crisis (Maxwell et al., 2015)). It is probably impossible to generate clean-slate brain data that is comparable to previously recorded data since our neurophysiological brain tissue changes over time due to neuroplasticity (Puderbaugh & Emmady, 2022), and since 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, the last two points depend on advances in data storage systems or the possibility that we do not actually need such precise brain data to understand single thoughts. However, to address the first point, 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 the company Kernel employs in its Flow device (Ban et al., 2021). The TD-fNIRS system detects changes in 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 neuroimaging spectrum of brain activity when compared to, e.g. EEG. According to Kernel, 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.).

[4] As a reference for the calculation the author took the size of a float on a Windows 64-bit application which has the size of 4 bytes.

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; as a result, most published neuroscience studies with dozens or even hundreds of people could all be incorrect (Marek et al., 2022). In such research, brain tissue and activity variations have been linked to variances in cognitive capacity, mental health, and other behavioural features. In addition it has been show in numerous studies that understanding the brain in more depth may help to distinguish people with depression. Neuromarkers[5] of behavioural features are frequently sought in studies. The recent publication from Marek et al. claims that most of these so-called neuromarkers would not work when the collected data set is more extensive, which would prose a general problem for the field of neuroscience. 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 since e.g. Marek himself claims that we might even need millions of data sets to start understanding the brain (Callaway, 2022). This is both fascinating and a possible significant constraint for BCIs, because understanding the brain is essential to making sense of the measured data to interface with it.

However, there is the other side of this argument from people like Andrew Ng, artificial intelligence pioneer and founder of the Google Brain research lab, who believes that machine learning, who underpins all of BCI software, should be developed in a data-centric manner, which means that the quality of the data on which models are trained should be as high as possible in order to answer very specific research questions (Brown, 2022). However, this brings us back to the replication crisis, which is the difficulty in generating clean brain data that is comparable to previously collected data due to the nature of our ever-changing consciousness.

Ultimately, there will almost certainly always be a mix of both approaches. As a result, for production- and mass-market-ready BCIs, a relatively large amount of qualitative brain data collected in specific and reproducible experiments or environments is required. This is where high-end, customer-focused BCIs could come into play, because the adoption rate of a device suitable for everyday use is higher than the amount of subjects in research labs, resulting in larger and more longitudinal datasets. This, combined with more targeted experiments and improved neuroimaging technologies, as well as advances in machine learning, could unlock enormous potential in brain research.

[5] A neuromarker is a biomarker that is based on neuroscientific data to detected biologically properties such as e.g. a disease or illness (Jollans & Whelan, 2018).

2.2 BCI landscape

In this section, we will discuss the current state of non-clinical and non-invasive BCIs, their applications and the distinctions that lie within their software offerings.

2.2.1 Real-world BCI applications

As mentioned in section 1.1, consumer-oriented BCI products are already commercially available. OpenBCI, which is one of the non-medical BCI companies, does not provide a specific use case but rather hardware, as depicted on Figure 2.3, and software which are universally applicable. It can be used in research where EEG is to be used or in developing BCI applications. Several neurofeedback or research apps have been created using OpenBCI's products (OpenBCI, n.d.-b). Taking this information into consideration, we can see that the OpenBCI customer is responsible for developing their own BCI application or incorporating it into their research, rather than having a sophisticated end-user application from OpenBCI.

Fig. 2.3: OpenBCI's EEG device (Be Superhvman, 2017)

Fig. 2.4: NextMind's BCI device (Louise, 2019)

Fig. 2.5: Muse's meditation headband (Muse, n.d.)

Another example is NextMind's product as shown on Figure 2.4. They do not focus on having an end-user application for their BCI, but they focus on offering an SDK for the Unity real-time engine to use their technology for brain-controlled actions in video games. One significant difference between NextMind and OpenBCI is that NextMind includes a built-in classification of brain waves captured by hardware, in this case, classification of active visual focus on virtual objects based on steady-state visual evoked potentials (SSVEP). Because their business model is presumably based on the unique selling point of their active visual focus classifier, NextMind does not provide access to the raw EEG data collected by the sensors. Nonetheless, NextMind's product is less focused on a specific use case, as its applicability is limited to games inside the Unity game engine.

A relatively closed and specific BCI is, for example, the EEG headband by Muse as shown on Figure 2.5. Its purpose is to measure meditation and sleep. They also offer an end-user app to help people better understand their meditation and sleep and how to improve them. The Muse headband is not unidirectional BCI per se, as there is also biofeedback based on neural signals, but the vital difference between Muse and, e.g. OpenBCI is that they abstract away the neurotechnology. Users do not need to know anything about neuroscience, neurotechnology or the interpretation and classification of neural data to get useful functionality for their use case. They also do not need to understand the software system's underlying architecture. They only need to know how to pair the device with their smartphone via Bluetooth.

Aside from full-stack BCI solutions, where a company provides a complete BCI solution including hardware and software, some companies focus solely on the software aspect. Neuromore, a company that provides a neural signal processing software platform, is one example. The company is hardware agnostic, which means one can plug any hardware or sensor into their computer and connect it to the Neuromore Studio software.

Fig. 2.6: Screenshot of the Neuromore Studio software (Neuromore, n.d.).

Neuromore Studio, as shown on Figure 2.6 , is free and open-source software that runs locally on various platforms. It provides a variety of drag-and-drop interfaces for creating and managing signal processing pipelines. For example, one can transform EEG data to extract band power, create triggers based on band power selection, and generate conditional outputs for a game to, e.g. move a character.

The author attempts to differentiate the offerings of the consumer-oriented BCIs mentioned: They either provide the hardware (with software that at least connects to the device) but are then more broadly applicable to use cases not defined by the company behind the BCI, such as OpenBCI, or they are application-specific in terms of both the software and the hardware, such as the Muse headband.

Although this thesis focuses on consumer-oriented BCIs, the applications of various BCI offerings can still be distinguished based on whether they are more consumer-oriented or research-oriented, such as the distinction between, e.g. NeuroSky, creating EEG-based BCIs for hobbyists and Emotiv's professional and expensive EEG systems, which are more research-oriented. However, NeuroSky and Emotiv provide a research version and a consumer or enterprise version of their software and hardware, aiming for general-purpose applicability across customer segments and use cases.

Other considerations include whether the applications are rather steady-state evoked, such as based on a frequency of noise laid on top of virtual objects to detect which object the person is looking at (e.g. as NextMind is doing), or whether they track the totality of mental states without evoking neural signals with external stimuli, such as in tracking sleep or concentration levels, both of which arise primarily evoked from inside the mind. This distinction can be made as passive, active or reactive BCI, as Alimardani and Hiraki coined in their work on passive BCIs (Alimardani & Hiraki, 2020). However, we do not want to include this dimension because it would introduce unnecessary and additional complexities related to the BCI software application layer.

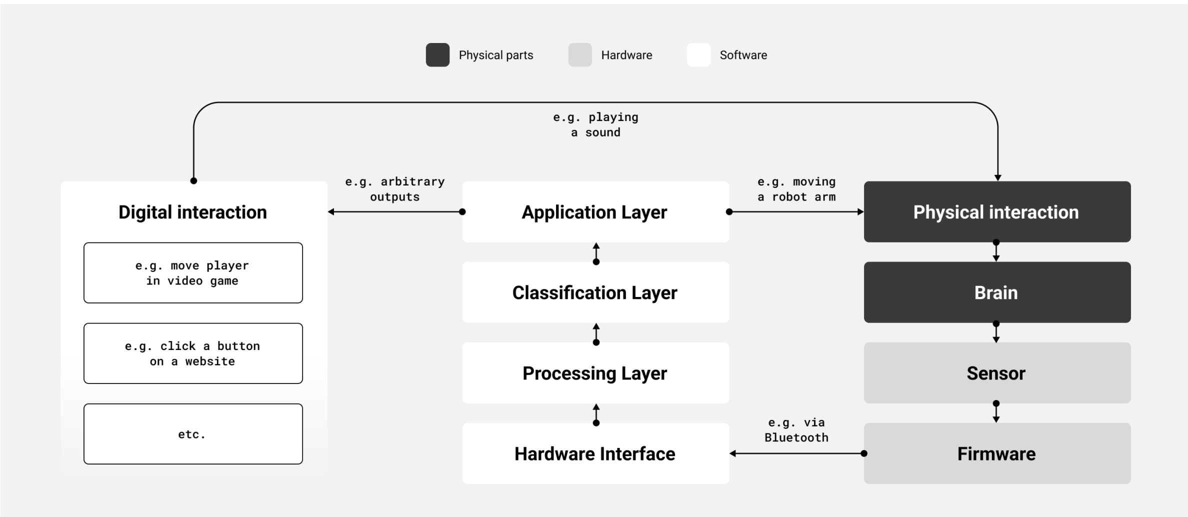

Fig. 2.7: Architectural overview of BCI components including a bidirectionality due to neurofeedback in form of e.g. playing a sound in a certain frequency to enable SSVEP

The application layer, as shown on Figure 2.7 is the part of a BCI that gets the interpreted data from e.g. a classification model and turns it into applicable functionality to interface with a physical or digital counterpart to, e.g. move a player in a game or start playing sound on the computer via its speakers. There is also the physical part, e.g. the brain and a physical interaction counterpart in the form of, e.g. a robot arm. The totality of the software stack is responsible for the processing of the data, e.g. extracting the relevant information from the raw data and turning it into a any desired and meaningful output for the application layer.

2.2.2 Unobtrusive hardware and software

The unobtrusiveness of hardware and software is another aspect to consider when discussing BCIs. Unobtrusiveness in hardware means that it is either not visible at all[6], such when sensors are implanted beneath the skull, or that it is in a form factor that is already socially established.

Fig. 2.8: IDUN Guardian hardware, unobtrusive BCI

Fig. 2.9: Neurosity Notion hardware, obtrusive BCI

The prototype of e.g. IDUN Technologies' hardware as shown in Figure 2.8 measures brain activity in the ear canal that aims to resemble the form factor of established in-earbuds. Figure 2.9 shows the Notion device from Neurosity, which measures EEG on the head and is not comparable to a socially established form factor such as earbuds.

[6]There are other things related to the overall user experience (UX) that are sometimes included in the notion of unobtrusiveness, such as comfort, reusability and convenience, where the author only implies physical characteristics such as shape and size

What is considered socially established and accepted truly depends on the society and context, as one could argue that wearing a Neurosity device under a hat while talking to a friend is more acceptable than wearing in-earbuds. Still, the implications of different form factors must also be considered, such as the possibility of moving the device and thus creating motion artefacts in the signals or the position of the sensors. The ear canal, for example, is ideally closely located to the brain's auditory cortex but not so much for the visual cortex, which is located at the back of the head. However, further hardware implications for BCIs are not a topic covered in this thesis.

Furthermore, it is perhaps not as simple to discuss the unobtrusiveness of software as it is with hardware. Unobtrusive[7] software, as defined by the author, is the abstraction of the underlying software or system that executes the logic to fulfil a task without the user knowing what the technical requirements are. As an example: To use an HP ENVY Photo 6200 printer with one's Android phone, one must first download the HP Smart app and the HP Print Service Plugin app that acts as a driver for the printer in order to get it set up and running (HP, n.d.). In the case of the HP printer, the user must understand some of the underlying technical requirements in order for it to work, rather than simply concentrating on the task of printing something. For example, unobtrusive software is when one gets a new computer mouse that they simply plug in and it works[8].

Unobtrusive software in BCI refers to the ability to connect one's hardware to the computer or smartphone and use it without the need for additional software such as drivers or command-line interface (CLI) software. As an example: To use an OpenBCI device, one needs to open the GUI app, connect the hardware, presumibly test its quality, begin a data stream session, output the stream via a network protocol such as a Lab Streaming Layer (LSL), connect to the signal from, e.g. Neuromore Studio (OpenBCI, n.d.-a), run the data through a classification pipeline, and then connect the output from Neuromore to a video game via the engine itself to have controls for the video game. It should go without saying that this is not unobtrusive software. There are examples of software that is included as an executable file and thus is relatively unobtrusive, but the software is closely linked with the hardware and the brand behind the hardware, or it is in the proof of concept (PoC) stage rather than a production-ready application. Buying a new pair of headphones and plugging them into one's computer to enjoy neuro-enhanced[9] experiences that interact with the brain's outputs or measure brain data across all apps and the operating system would be an example of proper unobtrusive BCI software.

[7] Other words for unobtrusive could be discreet, fully-integrated, invisible or simply "in the background".

[8] Unobtrusiveness usually correlates with usability, but it is not always the case, e.g. more advanced users would not consider locked-in abstraction as more usable.

[9] Neuro-enhanced software can be described as adding additional features to input methods via the brain.

2.2.3 Production-grade software

There is no clear definition of what production-grade software is, but in most cases, software developers agree on the following points:

- The software works at any time when access is required. It is therefore capable of frequent and intensive use in e.g. commercial or industrial environments.
- Software whose behaviour is deterministic and predictable and is, therefore, well-tested, well-documented and optimised in terms of speed, efficiency and security for the given context (e.g. the size of the user base). Usually, developers agree on a Definition of Done (DoD) inside their team to what is considered production-ready, e.g., test coverage of 80+%, peer-reviewed and commented code, and a common code style guide, to name a few.
- Software that runs in a production environment, i.e. on a cloud computing cluster for actual users rather than in a test environment for test users or, for example, on hardware delivered to real customers, and that can adapt itself to the context, e.g. to a higher access rate or insecure user-generated input. In most cases, especially in cloud computing, production-grade also means larger data sets, such as in databases, the possibility of a more significant number of edge cases due to a larger user base, and, most importantly, more available computing power on production instances.

As stated in previous sections, most BCIs, such as the OpenBCI, are not intended for production. They are intended for PoCs used in examples, such as controlling objects in games or conducting simple research. End-to-end and full-stack BCIs for production are rare, as most are very specific and not intended for general purposes, such as the Muse headband, or the software aspect is intended for PoCs or research, such as with e.g. Emotiv, another BCI company from the USA. Pure software products, such as Neuromore, lack the hardware component and miss, for example, an SDK that can be integrated into existing software for different platforms. Neurosity, for example, aims to provide a universally usable and unobtrusive software stack that is even open-source. However, because the hardware is not unobtrusive enough, it does not qualify the author's definition as production-grade (apart from the fact that it is not known whether their software stack is aimed to be used in production (Neurosity, 2022) due to e.g. third-party developers providing disclaimers of being a work in progress (Turney, 2022)). Companies such as e.g. Neuralink are presumably working on a general-purpose, unobtrusive and production-ready software system which enables developers to build production apps and even platforms on top of it for a variety of use cases without being limited (Musk, 2019), in their case, since it is a bidirectional BCI, developers are also able to write data back to the brain. Since their aimed hardware is also as unobtrusive in the form factor (since it is implanted), they have a high potential to become one of the first mass-market-ready BCIs if we ignore the fact that we need surgery to get the device itself (Neuralink, n.d.) and other considerations as a harder opt-out of the device compared to, e.g. plugging out earphones.

2.3 Neural/cloud interface definition

This section discusses the definition, need and differentiation of a N/CI and the paradigm shifts associated with it when discussing BCI software.

2.3.1 BCI software on the cloud

Looking at Figure 2.10, we can see that the three software layers of a BCI-component illustration, as pictured on Figure 2.7 are highlighted. This is because these components can run on the cloud, i.e. on a public cloud provider such as Amazon Web Services (AWS).

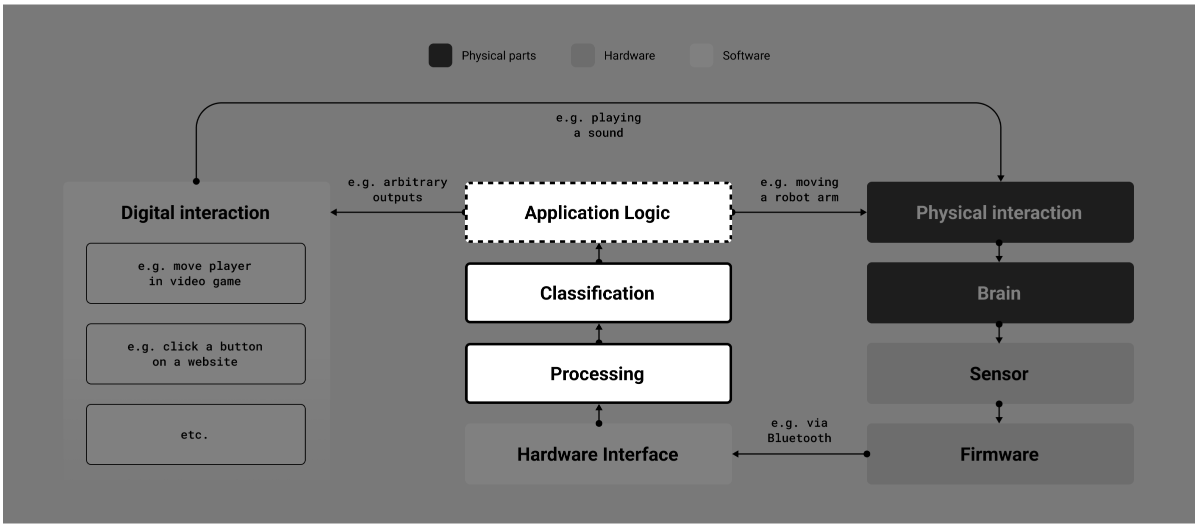

Fig. 2.10: Highlight of the software components as shown on Figure 2.7 of a BCI that could be moved to the cloud.

Running software on the cloud means that developers or companies can access provisioned information technology (IT) infrastructure through the internet, usually with a pay-as-you-go pricing model (Amazon Web Services, n.d.). The development speed of software applications can drastically improve since software developers can only focus on software rather than incorporating the hardware and network aspect of setting up their server farms, therefore abstracting the hardware part away. What started with simple computers that can be rented on a server such as it was with, e.g. AWS Elastic Compute Cloud (EC2) (Barr, 2006) ended up being a diverse offering from cloud providers with various abstraction levels as shown on Table 2.1.

Type	Description
Infrastructure as a Service (IaaS)	IaaS gives access to data storage space, virtual or dedicated computers, and network services. The greatest degree of flexibility and administrative control over your IT resources are provided by utilising IaaS.
Platform as a Service (PaaS)	PaaS lets developers concentrate on developing and managing their code rather than worrying about the underlying infrastructure (often hardware and operating systems). An example is Kubernetes.
Software as a Service (SaaS)	SaaS provides a whole product that is run and controlled by the service provider. The phrase SaaS often refers to end-user apps (e.g. web-based email). Developers don't have to be concerned about how the service is handled or whether the underlying infrastructure is maintained.

Table 2.1: The three abstraction levels and types of cloud computing (Amazon Web Services, n.d.).

The majority of businesses are anticipated to embrace a cloud-first strategy by 2025, according to Milind Govekar, vice president of IT research and consultancy company Gartner, and will not be able to fully implement their digital plans without the usage of cloud-native architectures and technologies (Gartner, n.d.-b). The impact and importance of cloud computing cannot be underestimated, and its success is also reflected in the annual spending on cloud computing resources, estimated at €474 billion in 2022 (Gartner, n.d.-b). Cloud computing is such an extensive and complex topic that it could quickly fill entire books. In the following list, the author categorises three essential points from a bird's eye view that certainly plays a vital role in BCI software: 1. Dedicated and deterministic environments, which explains that an environment of a software programme always stays the same independent of the end-users hardware, 2. elastic and high-performance availability, which explains cloud computers that have an on-demand and adjustable high-performance and 3. provided services for speed, which explains the concept of pre-made and dedicated software written primarily for the cloud and specific use cases. The following list goes more into detail of the mentioned topics in the context of BCI software:

- **Dedicated and deterministic environments:** Running code for BCIs on different end-user platforms, such as Windows or Android, can have drawbacks because each device has its processor, graphics card, operating system version and drivers, which can make developing software that requires stable and good performance, such as a neural data processing pipelines, time-consuming and difficult to maintain, as developers must keep track of every factor of the end-user devices. This is fine for BCIs that are not intended for the general public, such as specially designed BCIs for people with, say, locked-in syndrome, but for the general public, a variety of different end-user devices come into play. When code is run on a dedicated machine, such as a cloud computer with clearly defined hardware and operating system specifications, it becomes less error-prone and more deterministic.

- **Elastic and high-performance availability:** Because the cloud model usually runs as an as-needed model, the initial purchase cost of computer hardware is split and shared across usage. Developers have access to tremendous computing power that would not be easily afforded if purchased independently. As a result, when developing a computationally intensive algorithm, developers can use high-performance central processing units (CPUs) and graphics processing units (GPUs) to complete tasks much faster than consumer hardware on end-user devices. Performance can also be increased as needed, for example, to handle heavier tasks that are not used as frequently or to handle more requests when, for example, the demand for the software increases due to an increase in the number of users, which is a process known as elasticity (Gartner, n.d.-a). Furthermore, the cloud provides far more storage capacity than end-user devices.

- **Provided services for speed:** The vast majority of cloud providers are providing more specialised services as we move closer to PaaS. Provisioned database servers, for example, exist solely to serve as a database, so the underlying hardware is optimised for the database software running on it, such as, e.g. PostgreSQL. Hundreds of cloud computing services are available, including 200 from AWS alone (Amazon Web Services, n.d.), all of which address specific use cases. This is extremely useful when it comes to cloud-based BCI software. One example is the aspect of live streaming of brain data, which we will go over in greater detail in the implementation chapter of this thesis. The services provided accelerate development by eliminating the need for teams to reinvent the wheel repeatedly, and they also provide out-of-the scalability, such as in the serverless model (RedHat, 2022).

A N/CI utilises cloud computing by running certain software components of a BCI system in the cloud as, e.g. shown on Figure 2.10. Multiple BCIs can communicate with each other or with other software or hardware over the internet, enabling remote HCI. Figure 2.11 depicts how two or more BCIs can interface with one another using cloud software. The red arrows represent the typical local BCI. The blue arrow depicts how the person on the left can execute business logic via the cloud over the internet, enabling digital and physical interactions with, e.g. high performance. The green arrow depicts how the person on the right can communicate with their BCI via a N/CI with the person on the left even if they are not in the same geographical location.

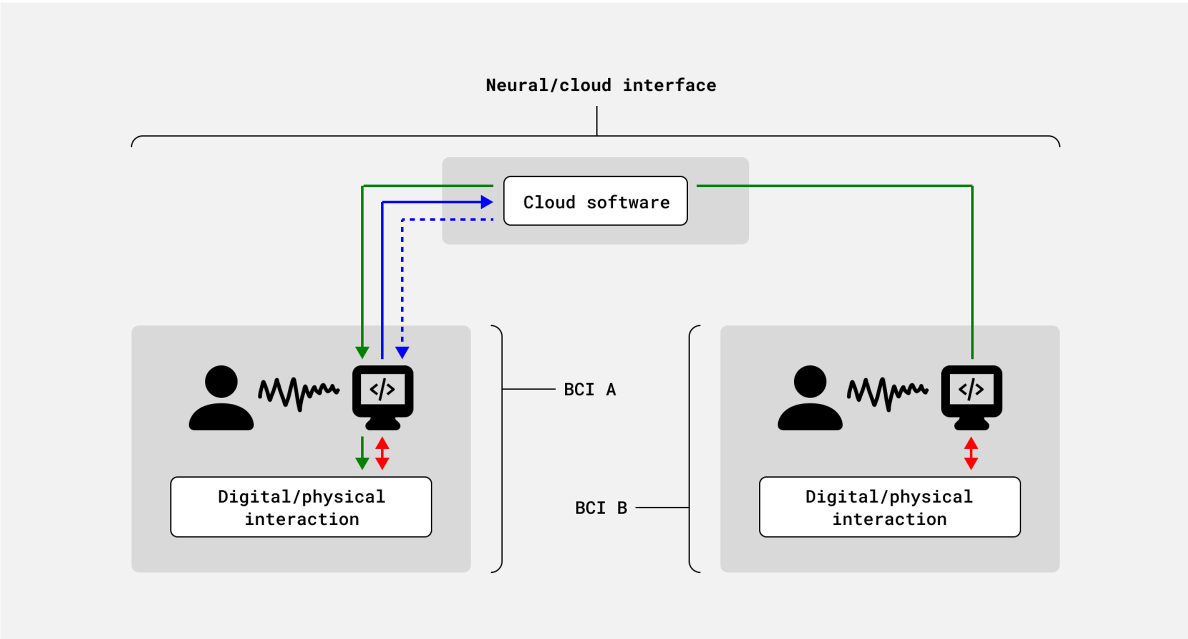

Fig. 2.11: A N/CI is the connection between multiple BCIs

2.3.2 Distinction between existing research

The concept of running BCI software components remotely and on servers is not new and novel, as research into the concept known as asynchronous BCI (An et al., 2016) or internet-based BCI (Lampe et al., 2014), has been ongoing for some time. When we look at the research from e.g. Zhang et al. from 2018 on their deep learning framework to enable as they describe Human-Thing Cognitive Interactivity, we see a strong emphasis on algorithms and machine learning but less on aspects such as cloud architecture and production-readiness (Zhang et al., 2018). They address the latency and the size of EEG samples sent in real-time to a server, as well as the corresponding calculation, but there are no more details in regards to the proposed and very simplified architecture chart's protocols, and effective cloud architecture, all of which factor in to the author's task to develop a N/CI system. Another paper by Ahamad looks at the system architecture of a BCI for the Internet of Things (IoT), but this time from the perspective of algorithms optimised for time series data such as EEG, with no mention of the effective cloud architecture of such a system (Ahamad, 2022).

The author of this thesis introduces the concept of three-dimensionality for the definition of a N/CI based on the previously mentioned topics and research that touch on the issues of this thesis, which are essential to achieve mass-adoption for BCIs from the perspective of the software system for the actual implementation of such a system.

2.3.3 Requirements of a N/CI

The term N/CI positions itself as a software system in the intersection that can undoubtedly be defined as production-grade rather than being in the PoC stage, unobtrusive implementation rather than obtrusive software and general-purpose applicability rather than being made just for a specific use case. Figure 2.12 illustrates the position of a N/CI within the mentioned properties. Subsequently, Table 2.2 summarises the definitions as described in this thesis.

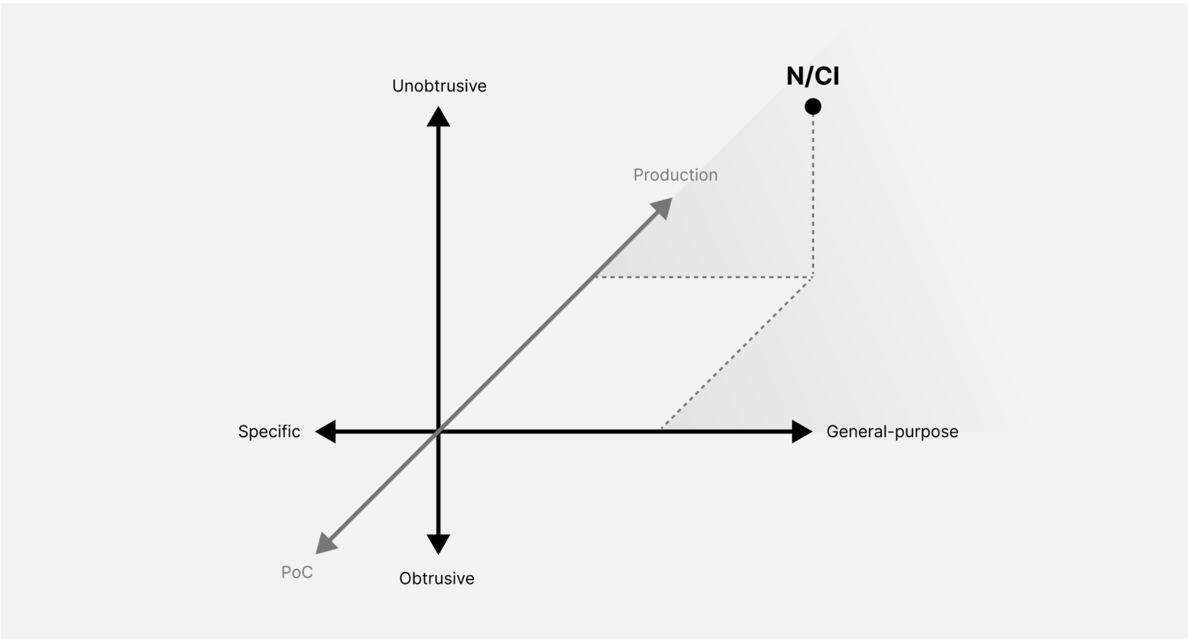

Fig. 2.12: Visualisation of the three-dimensionality of the term neural/cloud interface with its three axes and differentiation of six terms

Axis labelling	Description
Production	As previously stated, this is the range in which a software system is deemed ready for production. Because the definition is vague, it is difficult to identify specific requirements that must be met for a system to be considered production-ready. However, for a N/CI, this means running in a production environment, e.g. in a cloud, on a real-world end-user server rather than, for example, in a proof-of-concept environment such as in a lab.
Unobtrusive	As previously stated, an unobtrusive software system is one in which the end-user does not need to understand the underlying architecture and requirements in order to use the software or even know certain parts of the software system. In the reverse case, users need to install special packages or download additional companion apps. to make a N/CI work on their computer or smartphone is not the aim of the author's definition of a N/CI.
General-purpose	A general-purpose software system is one that can be used for a variety of functions. As an example, consider AWS. It is general-purpose, which means that developers can create cloud software on AWS that can be either a financial application or a backend for a mobile application; there are no specific use cases. This means that a N/CI, unlike the NextMind BCI or the Muse headband, should provide general-purpose functionality rather than specific use cases, i.e. it is not limited to a specific set of functions.
PoC	A BCI software system that serves as a proof of concept cannot be considered N/CI because it is not intended for production and thus all the effort required to create a production system, such as quality assurance with unit or end-to-end testing, is unnecessary. A PoC system does not usually run in a production environment, as the goal is, for example, to test a specific functionality of a use case rather than to deliver the software to end-users.
Obtrusive	An obtrusive BCI system, for example, may still be production-ready if it targets specific use cases while remaining unobtrusive because neuroscientists or developers, for example, expect to have access to the underlying software architecture or technical requirements and thus do not want to abstract from it. If it is obtrusive software, such as OpenBCI, this usually means building the production-ready part on top of it is necessary, which does not fit the author's proposed definition of a N/CI.
Specific	If a BCI system is only used for one use case, such as Muse for sleep and meditation, companies or developers who want to offer a different use case, such as a mind-controlled keyboard with a P300 system will have to reverse engineer Muse's EEG output or use a different BCI hardware that is less specific and closed, and then build their own production-ready and unobtrusive software on top of it.

Table 2.2: Axes label descriptions of the three-dimensionality for the definition of a N/CI as shown on Figure 2.12

With an unobtrusive form factor like the one developed by IDUN Technologies, a significant hardware barrier to become a mass-market BCI has already been overcome. Next to the hardware, IDUN intends to provide a business-to-business (B2B) software platform, allowing third-party developers to create software on top of IDUN's offerings through a universal brain application programming interface (API). Because IDUN allows others to consume this API in end-user-facing apps, it must be production-ready and unobtrusively able to be implemented. IDUN's hardware and software should be general-purpose rather than specific, allowing developers to build any neuro-enhanced application.

All these requirements build one of the first BCI systems aimed at the mass-market, which per definition from the author, form the new concept of a N/CI, which is the key motivation of the author to standardise collaboration and research on this novel interdisciplinary field of BCI software and cloud computing.

Chapter 3

Methodologies

This chapter describes the project-related academic methodologies in the author's given context and the planned approach to achieve the thesis's goals and objectives. The reader is introduced to the rationale for the intended workflows, hardware, and software tools.

3.1 Derivation of the case study

In October 2021, the author began working as a cloud software engineer at IDUN Technologies with the intention of further developing the existing software products. IDUN Technologies had already created a PoC software system that included a web-based single-page application (SPA) hosted on AWS Amplify, an backend-as-a-service that aims at simplifying the deployment of backends for mobile or web apps. IDUN's in-ear headphone sensor sent EEG data to a network bridge via Bluetooth and then to the cloud via the internet. The raw EEG data was saved and made available for download in a variety of file formats.

Fig. 3.1: Difference between raw and filtered EEG data from IDUN's in-ear device.

In addition to raw data, the IDUN app provided transformed data, such as e.g. filtered data, which included low-pass and high-pass filtering of EEG data as shown on Figure 3.1. This transformed EEG data was then saved alongside the raw version on the cloud. The EEG data could also be visualised in near-real time on the web app as a time-series x- and y-axis plot. Additionally, users could control the device by sending start and stop commands to the hardware components. The overview of the architecture is displayed on Figure 3.2.

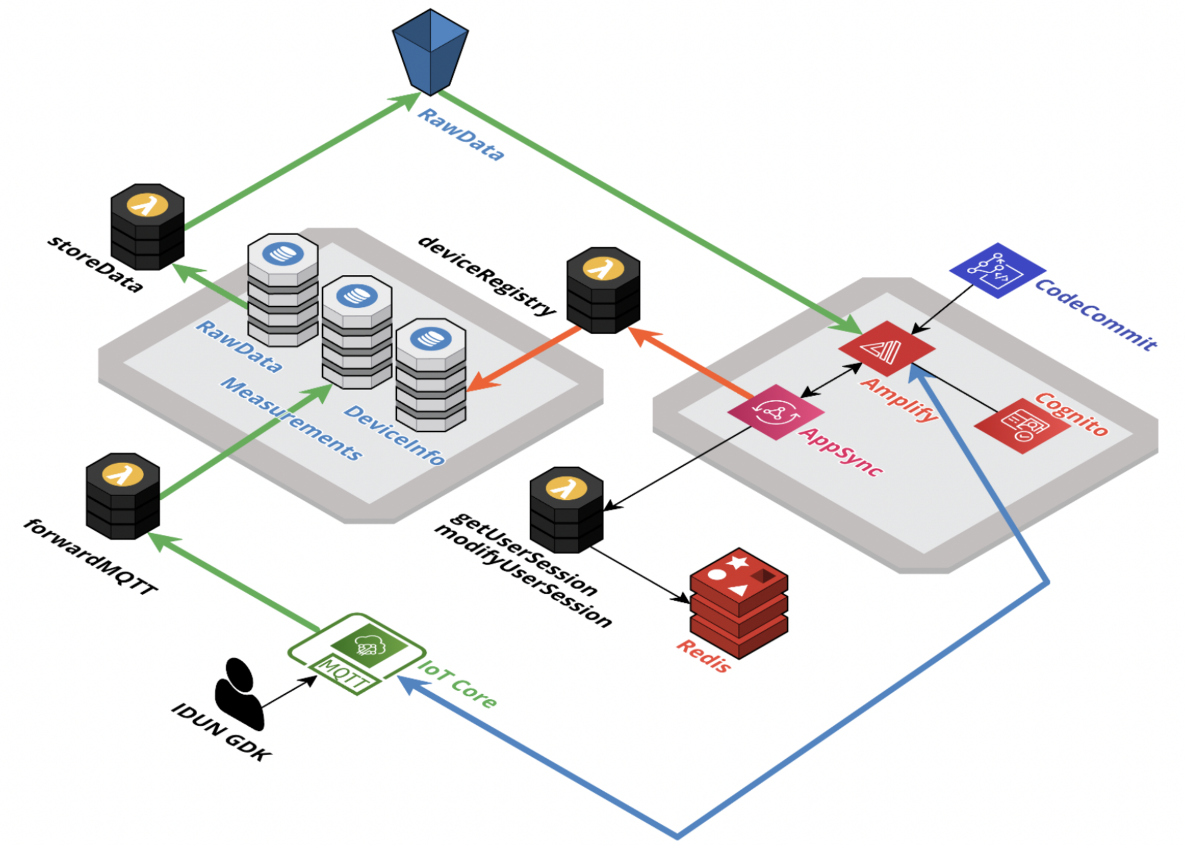

Fig. 3.2: IDUN's software architecture at the end of 2021.

The system itself was in a rather unstable state and had strange error sources that made it impossible to reliably record EEG data for more than a few minutes, making the product unusable for a current customers or in general for a mass-market launch. While working on the system, the author encountered a various amount of technological flaws as listed in the following list:

1. AWS Amplify is great for simple backends with CRUD[1] but not so great for everything custom-made such as the streaming-focused aspect of EEG. Therefore, the need to

[1]CRUD is an acronym describing general operations of a backend system: Create, Read, Update and Delete.

break out of the AWS Amplify system would either way need to happen anytime soon since it would otherwise be building a project with the wrong tools and foundations.

2. The network bridge was a Raspberry Pi running Python code which, after some analysis turned out to be the main source of most bugs. The question was raised if the network bridge was even needed, as IDUN either way would go into being a fully-mobile system rather than network bound and therefore aiming at being connected directly to a mobile phone or computer.

3. The heartbeat functionality of the cloud was missing, which basically meant that the cloud did not know anything about the hardware devices, it just assumed that data would flow in as soon as the start command was sent to the device, therefore having a happy-path-only scenario. There were many happy path scenarios present.

4. The infrastructure of the application was automatically provided by AWS Amplify and used AWS CloudFormation under the hood inside AWS CodePipeline which is AWS's own continuous integration service. The entirety of the software on the cloud was built via the AWS Console (the GUI of AWS) and therefore there was no current state in form of code to reflect the current infrastructure, ergo making reproducibility of the cloud impossible.

5. The streaming of the data happened through MQTT, a publish and subscribe-based protocol usually used for Internet of Things (IoT) devices such as sending periodically health checks. The intent of MQTT was not the real-time sending of EEG data, therefore the need was also there to reconsider this technological decision which was deeply rooted into another AWS service called IoT Core.

6. The end-user of the software product was also still uncertain, therefore making it even harder to define what the system should actually be able to achieve. IDUN needed to figure out if the software system is rather aimed at researchers, developers, end-users etc. The priorisation of the engineering roadmap was therefore uncertain.

7. The web app was a thick client and did not consume one single API endpoint from the AWS backend. Thick client means that the web app did quite a lot of business logic, such as the filtering of the raw data for the near-realime visualisation which was another technological misdecision since the client-side JavaScript ecosystem is way far inferior compared to e.g. the Python ecosystem which could run on the backend.

8. The web app was not connected to a single endpoint on the backend and consumed the MQTT stream and non-real-time aspects of the app (login, list recorded EEG data

and so on) via different sources. E.g. the MQTT stream was directly subscribed from the device itself via AWS IoT Core and did not go through the GraphQL API from AWS Amplify, which made coupling the systems to a cohesive and robust API tedious.

Due to growing problems with the existing software system and an ever-increasing technical debt as a result of the software not being test-driven or developed without code quality standards, resulting in bugs and quirks that are difficult to track down, the author proposed to halt the implementation of new functions and restructure the system from the ground up using a more software engineering oriented approach. The company's management approved the request in for such a redevelopment.

The author was already working on his original Bachelor project, which focused on a mind-controlled multiplayer game, assuming that IDUN's software system would be stable by the time the Bachelor project began. The original bachelor project's focus was officially changed at the end of 2021 to creating this refactored software system.

3.2 Case study

A possibility to conduct research in order to build a N/CI with the assumed requirements as defined with the three-dimensionality was to do a case study at the research and development (R&D) team at IDUN Technologies.

3.3 Procedure

3.3.1 Project stages

3.3.2 Group discussions

3.3.3 Expert interviews

3.4 Outcomes

3.5 Reflection

3.6 Further development

Chapter 4

Implementation

4.1 Web-first approach to software

4.2 Web-based AR and VR

Chapter 5

Results

5.1 Steps Before The Analysis

5.2 Main Results

5.3 Figures And Tables

5.4 Goals

5.5 Discussion

5.6 Conclusion

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Appendix A

User interviews

User interview outline

User interview with Paul Doyle

User interview with Ghena Hammour

User interview with Nicole Zahnd

User interview with Melanie Baumgartner

User interview with Mayank Jain

User interview with Martin Hutchings

User interview with Jacopo de Araujo

Appendix B

Group discussion notes

Notes: First kick-off meeting

Notes: Mid-way collaboration meeting

Notes: Closing meeting

Appendix C

Attached repositories

idn-guardian-cloud

idn-guardian-console

idn-guardian-sdk

idn-internal-sdk

spatial-place

Appendix D

Web-first approach proposal

Appendix E

Project plan

Asana screenshots