Classification of 3D Shape Imagery Using a Brain-Computer Interface

A Thesis

Presented to

The Interdivisional Committee for

Computer Science and Psychology

Reed College

In Partial Fulfillment

of the Requirements for the Degree

Bachelor of Arts

Ian L. Jackson

December 2020

Approved for the Committee

(Computer Science and Psychology)

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Acknowledgments

The path that has led to writing this thesis has been one of intense growth, both academically and personally. I am thankful to have had people by my side who have been a part of and helped to facilitate this development.

To begin, my gratitude goes to my mother. Thank you, mom, for your endless support at all hours, and for having me write your thesis citations as a teen. It really prepared me for writing my own.

To my sisters, who have provided nothing but support all my life, and are my constant reminders that I am truly loved. Thank you.

I would like to thank my friend Jessie Willson, who has been a constant example of pursuing one's passions. Every day I have known you has been an inspiration to reach higher, learn more, and try something new. Thank you.

I am incredibly grateful for my aunts, Tía Henry and Olivia, for being my family and guides at Reed during my first couple of years. I have never met anyone as sweet and badass as you two, and I miss you both dearly.

To my brothers, Arthur, Hunter, Jeremiah, Renard, Eric. Your constant love and unwavering friendship have kept me afloat these years. Thank you.

For their comforting virtual presence and laughs throughout our online interactions during the quarantine, I would like to thank a few online groups, namely Otaku Chat, No Weebs AllUwUd, and Hololive.

To my academic advisor, Kris Anderson. Four years ago, I approached you after your lecture, and asked you to be my advisor although I was nearly failing the class. Thank you for continuing to push and believe in me.

I want to thank my thesis advisors, Michael Pitts and Eitan Frachtenberg, who agreed to be a part of a project that was outside of their usual research areas. Your trust in me has built my independence as a researcher over the past year.

To Maria Panopoulos. You have been such an amazing and close friend, a patient and understanding listener, and the most fun partner in crime I could ever ask for. From classroom antics to post-Qual fast food runs, you have brightened my time here, and surprised me repeatedly with the depth of your innate wisdom. I only wish we could have classes together for four more years.

And to my dad, who taught me to love science, to value inquiry, and to appreciate the sublimity of the natural world. Thank you.

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Abstract

This thesis unfolds in two main parts: the first is an exploration of brain-computer interfaces and mental imagery, the second is a follow-up study from a 2012 paper by Ehsan Esfahani and V. Sundararajan. In the first section, I review history, definitions, and applications in the deeply interdisciplinary realm of brain-computer interfaces. Afterward, the brief chapter on mental imagery discusses some history, as well as the neuroscience behind mental imagery. Connecting the two is the present study, which is a brain-computer interface for classifying shape mental imagery, a subject on which there is little existing research. The goal of the study is to replicate the classification accuracy results of Esfahani & Sundararajan, particularly Experiment 1.2, in which researchers were able to classify the five shapes with a **44.6% average accuracy** across all participants (n = 10). We performed an extension to this study that employs similar preprocessing, feature extraction, and classification methods, but using a standard wet EEG system with 64 electrodes, as compared to the dry 14-electrode wireless system used in the original study. We hypothesized that the addition of both more electrodes as well as the use of the conductive gel that gives "wet" EEG systems their names will significantly increase classification accuracy of the five shapes. Results showed that, in fact, overall classification accuracy was comparable (43.3%) to the 14-electrode system, even in a second experiment that increased the number of trials. These findings support the growing evidence that portable, dry EEG systems are equally as reliable as traditional systems for brain-computer interface use. All code is available in a Github repository: https://www.github.com/orbitalhybridization/bci-shape.

Brain-Computer Interfaces

The ability to interface directly with the enigmatic electro-chemical wiring of the human body is an idea that has long existed in the collective imagination of scientific endeavor and fiction alike. With the introduction of computers into the realm of scientific research decades ago, this technology supplemented brain recording tools to create brain-computer interfaces (BCIs), making possible a new modality of interaction between humans, machines, and their shared environment. Since their introduction, BCIs have increasingly garnered attention for their use as prostheses and communication devices in primarily laboratory settings, with even more excitement toward their futuristic implications. However, in order to understand how these systems work, we must first begin with a little history.

A Brief Overview of Neurotechnology

We will define neurotechnology as technology that interacts with any of the biological circuitry of the central or peripheral nervous systems. This definition sets a wide scope, but we will focus our history on those technologies most pivotal to the development of BCIs (summarized in Figure 1), which are defined in the subsequent section.

Perhaps the most prominent and widely used of these is electroencephalography (EEG), meaning scalp-measured electricity (electro= "electricity," head/scalp= "cephalus," measure= "graph"). The first to discover that there was live, measurable brain activity in the form of tiny voltages from the scalp was Hans Berger in a series of experiments that occurred between 1924 and 1929, and it marked a cornerstone discovery in both neuroscience and electrical engineering alike (Wolpaw & Wolpaw 2012). In its purest form, an EEG system requires two electrodes, one for recording and one to act as a baseline for reference, and ideally some method to output the information, which in Berger's time was a simple pen writer on paper. Though taken at first with some skepticism, EEG's introduction led to a spike in related research in laboratories around the world. Of this research, one of the most notable findings was the discovery that EEG could measure a difference in brain activity between epileptic and healthy patients (Walter, 1940). This allowed clinicians to more easily diagnose epilepsy in patients, though the approach lacked some reliability in its early stages, which led some to over-interpret abnormal EEG readings (Kennett, 2012). However, with the passing decades, gradual improvements to EEG systems ever-improved their diagnostic capabilities, which are still widely used for epilepsy cases today.

Invented nearly a century ago, EEG was an early modality that bridged two previously unrelated fields: neuroscience and electrical engineering. This marriage of fields turned the problem of understanding the brain into one of engineering. Rather than relying on lesion studies (cutting out parts of the brain for medical purposes and observing changes in subjective experience and/or behavior) and other anatomy-related techniques that were popular in 19th century neurology, solving the inner workings of the brain suddenly became a matter of recording tools and computation. A closing note from Grey Walter's 1940 paper on EEG and epilepsy diagnosis stated that "the method is still too complicated to be used by anyone but an electrical expert." (Walter, 1940). Thus, with the establishment of EEG, the problems of neuroscience gained solutions that lay in electrical engineering, and Hans Berger's revolutionary technology leapt both fields forward. With the digitization of signals via the laboratory-accessible computers in the 70s, which allowed for further processing of the data to more easily observe features in a signal, EEG became even more useful.

Related to EEG is magnetoencephalography (MEG), which came along soon after following the discovery of the ability to detect magnetic fields generated from within the body by physicist David Cohen in the 1960s (Stefan & Trinka, 2017). MEG measures the magnetic fields associated with neuronal activity; the sum of excitatory and inhibitory potentials flowing through a given neuron. Related by their electromagnetic approaches to brain interfacing, both EEG and MEG have high temporal resolution. In other words, they are both able to measure activity at the millisecond-level, a time-scale that matches common neural firing rates. At the same time, however, they have poor spatial resolution, meaning they are less equipped to elucidate the exact location of a given signal from the brain. This limitation is due in part to the location of the EEG/MEG sensors on the scalp, and in part to the ability of electrical potentials to spread across wide swaths of neural tissue. EEG and MEG signals related to specific sensory or motor processing also can suffer from a low signal-to-noise ratio due to the distance between the source signal and the sensors, the obstructing material of the meninges, skull, skin, and the spatio-temporal overlap of background neural activity.

The next neurotechnology for review, electrocorticography (ECoG), bypasses many of these limitations due to its invasiveness; it is a modality that interfaces directly with brain tissue. One of the main benefits of non-invasive technologies is that it is unethical to recruit participants for open-brain surgery for purely experimental purposes (due to the high level of medical risk involved in penetrating the skull). For this reason, invasive technologies are typically used either when an individual is already undergoing brain surgery, or in animal subjects. ECoG's history stretches back to 1929, when a pioneering electrophysiologist, Edgar Adrian, used glass electrodes paired with platinum wiring to record from nerve activity (peripheral nervous system), which was later extended to recordings from the central nervous system (Patil & Thakor, 2016). From this point, developments in materials science improved the quality of invasive recordings, allowing for a plethora of ECoG-based discoveries to be made. A most notable of these subsequent findings comes from the Nobel Prize-winning studies of Hubel and Wiesel, who used electrodes to map with unprecedented spatial precision the sensory cortex processing of visual stimuli in cats and monkeys (Hubel & Wiesel, 1962).

Upon the introduction of electrode arrays in the late 1960s and the fabrication techniques that gave rise to integrated circuitry about a decade later, ECoG technology enjoyed a massive upgrade. This improvement came in three main forms: 1) smaller electrodes, allowing for higher density recording over a given area, 2) more flexible electrodes 3) multiplexing, which granted the ability for the number of output lines to be fewer than the number of electrodes (Patil & Thakor, 2016). Nowadays, even further developments of fabrication technology have allowed for a wider array of biocompatible materials to be used for ECoG on the scale of nanometers, compared to the micrometer-level of their beginnings.

There are, on the other hand, other brain interfacing techniques that utilize the metabolic and molecular properties of the brain rather than endogenous electromagnetic processes for measuring activity. One of these is functional magnetic resonance imaging (fMRI), widely used since the 1990s, which extends a structural imaging technique (MRI) that utilizes an exogenously-produced magnetic field to change the spin axes of hydrogen atoms in the area of effect (typically the entire brain). This way, one can image the brain at different time periods, contrasting the blood oxygenation-level dependent (BOLD) signals. Because more active nervous tissues require more oxygen carried by the blood for metabolic processes, these BOLD signals give information about what areas of the brain are more active at a given time. This technique has the improved spatial precision that EEG and MEG lack, but is limited in temporal precision, which comes from the fact that the movement of blood is slow (on the order of seconds) compared to the actual firing activity of neurons (on the order of milliseconds). Regardless, fMRI has been invaluable to the mapping of brain regions and related activity using 2- and 3-dimensional imaging.

Our final two neurotechnologies for review, positron emission tomography (PET) and functional near-infrared spectroscopy (fNIRS) are less common than EEG/MEG but are more accessible for BCI applications than fMRI and ECoG. PET is an imaging technique that utilizes the radioactive properties of unstable isotopes, known as tracers, that are injected in very small amounts (in the sub-picomolar concentration range) into a patient's bloodstream. The biological principle used for imaging is that more active brain regions recruit more of the blood-borne isotopes, and so more radioactivity will be detected from these regions. PET has somewhat poor temporal resolution, as it requires at least 40 seconds to construct a single image (Wolpaw & Wolpaw, 2012). fNIRS, on the other hand, exposes the brain non-invasively to near-infrared light, using spectroscopy at this frequency to measure the difference of oxygenation levels in the blood (the BOLD signals that fMRI uses). Though faster than PET, fNIRS is only able to measure activity only a few millimeters beyond the surface of the cortex, and has poorer spatial resolution (Wolpaw & Wolpaw, 2012).

Neuroimaging method	Activity measured	Direct/Indirect Measurement	Temporal resolution	Spatial resolution	Risk	Portability
EEG	Electrical	Direct	~0.05 s	~10 mm	Non-invasive	Portable
MEG	Magnetic	Direct	~0.05 s	~5 mm	Non-invasive	Non-portable
ECoG	Electrical	Direct	~0.003 s	~1 mm	Invasive	Portable
Intracortical neuron recording	Electrical	Direct	~0.003 s	~0.5 mm (LFP) ~0.1 mm (MUA) ~0.05 mm (SUA)	Invasive	Portable
fMRI	Metabolic	Indirect	~1 s	~1 mm	Non-invasive	Non-portable
NIRS	Metabolic	Indirect	~1 s	~5 mm	Non-invasive	Portable

Figure 1: A summary of some neuroimaging methods (from Nicolas-Alonso & Gomez-Gil, 2012)

There are other forms of neurotechnology such as cell therapy, electrostimulation, and pharmacological approaches, but the goal of this section is to provide an overview of the foundational technology that has driven forward the development of BCIs. In all of its century of development, the history of neurotechnology is not a particularly ancient one. Nevertheless, it is a rich history with a variety of approaches that offer implications reaching far into the possibilities of engineering and human biology.

What's In A BCI?

A comprehensive textbook definition of a BCI can be found in *Brain-Computer Interfaces: Principles and Practice*, edited by Johnathan and Elizabeth Wolpaw:

> "...a system that measures [central nervous system] activity and converts it into artificial output that replaces, restores,

enhances, supplements, or improves natural [central nervous system] output and thereby changes the ongoing interactions between the [central nervous system] and its external or internal environment." (Wolpaw & Wolpaw, 2012)

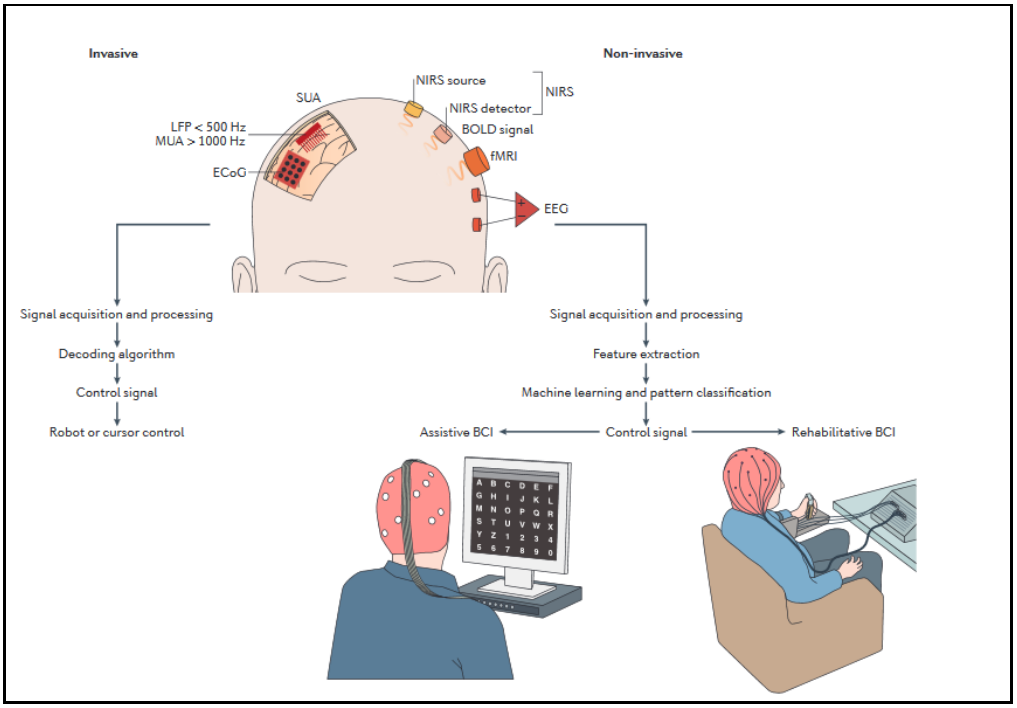


Figure 2: The basic components of a BCI system.
The left side being for invasive systems and the right side for non-invasive. For the purposes of this review, the two will be summarized into a single pipeline, as they are similar in overall design. (from Chaudhary, Birbaumer, & Ramos-Murguialday, 2016).

We now have a definition for a BCI, but what exactly does such a system look like? A basic BCI has the following primary components: data acquisition, feature extraction, feature translation, and output (Wolpaw & Wolpaw, 2012). The first of these, data acquisition is performed using the neurotechnologies that are summarized in the previous section. Of course, depending on the modality of acquisition, the data given to the computer side of a BCI system takes on a different form, which determines how it is processed. In the following section, we will go over the processing steps that lead to output for the most popular forms of BCI data acquisition: EEG and ECoG.

Preprocessing: Filtering & Artifact Rejection

The first step to any signal processing paradigm is to clean the data. In this case, cleaning and transforming the data will help make the input more readable to the computer. As mentioned before, noise is an inherent concern when collecting any kind of signal, so there are special techniques that are employed to reduce and decouple noise. The most basic of these is a filter, which can be implemented at either the hardware or the software level. These take an incoming signal and allow certain frequencies to pass through, while blocking the rest. Common types of filters include: highpass, which cuts off frequencies below a threshold, lowpass, which cuts off frequencies above a threshold, bandpass, which only allows frequencies within a threshold band to pass through (e.g. 4Hz to 8Hz), and notch, which does the opposite of bandpass and blocks frequencies within a band. One standard filter for an EEG signal acquisition device, for example, is a bandpass filter that allows frequencies between .1Hz and 150Hz. These parameters are standard, as the frequencies of interest in the brain tend to be between these thresholds, and because electrode potential offset (the tiny measure of how far off from zero voltage recordings are) tends to occur below .1Hz (Burgess, 2019). Another example of noise comes from power lines, the constant flow of voltage required to power and run the signal acquisition device (60Hz in the USA, 50HZ in Europe). In addition to noise, there are artifacts that occur in brain data. These are aspects of the signal that stand out, but are not of interest, and so tend to confuse rather than help analysis. These include eye blinks (detected by electrodes near the eyes in EEG, but also visible in distant electrodes on the forehead and front of scalp), alpha wave activity (a frequency that occurs when an individual is tired or relaxed), and general physical movement of a participant (especially facial muscle movements). These are usually detected using researcher-arbitrated criteria and removed from the data or corrected using manual or automatic approaches. Though fundamental aspects of processing brain data, filtering and artifact rejection are just the tip of the iceberg.

Feature Extraction: Types of Features & Data Transformations

After this step, there are a couple directions one can go to create what are known as features, or the properties of data that are used to drive a BCI. For electrocorticography, these features can simply be neural spike trains; direct voltage data from a cell or population of cells (Rao, 2013). Another common feature used in both EEG and ECoG are power spectra frequency bands. Frequency bands are calculated using a technique called Fourier Transform, which decomposes the signal into a sum of waves, each with a different frequency. The power spectra result from squaring amplitudes of each wave, thus they represent the strength of a signal in square volts per frequency (v2/Hz) (Rao, 2013). Common frequency bands that are used as features, often in combination with one another, are known as delta (2-4Hz), theta (4-7Hz) alpha (8-12Hz), beta (16-25Hz), gamma (>30Hz), and mu, a sensorimotor rhythm in the alpha range that occurs with motor activity (Kilmesch, 2018). The mu rhythm is a good example of a feature used in motor imagery paradigms, where BCI users imagine moving a part of their body in order to control the device. Another common type of feature is the event-related potential (ERP), typically recorded with EEG but also used in ECoG nonetheless. As the name suggests, these patterns in brain activity occur as a result of a stimulus event response. The P300 is a robust, well-studied ERP that has been used in a number of paradigms (Wolpaw & Wolpaw, 2012). It gets its name from its valence relative to reference, positive, and its timing, around 300ms after stimulus onset (Rao, 2013). Steady-state visual evoked potential (SSVEP) is another ERP frequently used as a feature for BCI training. It occurs in reaction to stimuli that flash at a certain frequency, thus evoking the same frequency in regions of the brain associated with visual processing.

Other than the aforementioned Fourier Transform, there are other useful transformations on the data in order to make it easier to analyze. The results of these signal transformations can be used to extract features as well. Take for example the component analysis family, whose most popular members are principal component analysis (PCA) and independent component analysis (ICA). The primary goal of these algorithms is to reduce dimensionality of a given data set, effectively finding the primary properties of the signal across all electrodes, which typically elucidates either desired activity or strong artifacts (Artoni, Delorme, Makeig, 2018). Such component analyses can be used to extract ERPs as well as frequency band data (Artoni, Delorme, Makeig, 2018). So, transformations on filtered data work to bring a BCI's processing pipeline a step closer to output. Next, the resulting features must be used to train the system.

Feature Translation & Machine Learning

The feature translation step in a basic BCI system utilizes models that translate the data from features to commands. Depending on the question a researcher wants to answer, the kind of data at their disposal, and the paradigm used to get that data, different models are used. In fact, there are an infinite number of models one can apply to any given observation (Kieseppa, 2001). The models used in BCI systems are either regressive, with output on a continuous spectrum, or discriminant/classifying, with output divided into distinct "classes." Models interact with user input to create output using three main approaches: 1) the model learns to create the proper output through machine learning, 2) the user learns how to create the input that gives the desired output, or 3) a hybrid approach known as "co-adaptation" (Wolpaw & Wolpaw, 2012).

When it comes to brands of machine learning models, there are supervised learning models and unsupervised learning models, both tasked with the job of decoding brain activity. With supervised approaches, a model is given training data with labels (e.g. "Left Hand" or "Right Hand") attributed to the output. After learning from the training data, these models can be used to determine to which label the features extracted from novel data belong. Unsupervised learning approaches, on the other hand, do not use labels. Models using this technique are more left to their own devices to connect trends of input data to types of outputs. ICA and PCA are examples of these, as they calculate the most principal features in the data, which can be used as output parameters (Rao, 2013). Linear least-squares classification functions are a commonly used discriminant, supervised learning model. They use the linear formula:

$$Y = b_1 * x_1 + b2 * x2 + \ldots + bn * xn + a \qquad (1)$$

where b is a weight, a is a constant, each x is a feature, and the output is Y. Using the output Y provided in a training session, the b weights can be calculated by a separate equation and saved to be used for novel data (Wolpaw & Wolpaw, 2012). One limitation of models like this one is that they assume linearity of the relationship between the data and the output. There are also nonlinear approaches like artificial neural networks, a regression approach which mimics the decision-making capabilities of neurons using weighted inputs that are summed together and outputted based on an activation threshold (Rao, 2013). Feature translation can be done either online (during a session for live feedback) or offline (anytime after a session's data has been collected). Once the features have been translated into commands, they are ready to be externalized into the world through the device.

Output & Feedback

In general, the purpose of BCI outputs is to either choose a goal or control a process (Wolpaw & Wolpaw, 2012). Choosing a goal could mean something as simple as switching on or off a lightswitch, or something as complex as moving a robotic arm to a location in 3D space. Once a goal is chosen, the interface does the work to produce whatever processes lead to that goal. In the robotic arm example, these processes would include any necessary rotations and translations required to reach the outputted goal state. An output that controls a process, however, involves the user in every step required to reach the goal state. Using the same example, the outputs would be the rotations and translations themselves. This gives the user more control over the path that reaches the goal state, but can be more demanding on both the user and the BCI (Wolpaw & Wolpaw, 2012).

The inner workings that drive BCI usage from end-to-end is a closed-loop system. As we have now explored, the user's input is processed translated into commands that are outputted to the interface, which then performs a function that is externalized to the user, who subsequently updates their input according to the new state of the system. Now that we know how these systems work, let's look at some examples of how they've been used.

Applications of BCIs

There are BCIs that use all of the neurotechnology covered above and more. The first known brain-computer interface was used as far back as the 1960s! Remember our friend Grey Walter from earlier? He performed an experiment in which he asked a patient who was undergoing brain surgery to press a button to advance the slides on a slide projector whilst he recorded the corresponding brain activity with an electrode (Graimann, Allison, & Pfurtscheller, 2011). After finding the ideal recording spot, Walter connected the other end of the recording electrode to the slide projector, and found that the slide would advance even before the patient's intention to press the button. Despite this early discovery, the term "brain-computer interface" itself wasn't actually used until Vidal coined the term in the 70s, for his "Brain Computer Interface project," which sought to use EEG-acquired visual evoked responses for input into a computer program (Vidal, 1973). Following an uptick in DARPA funding around that time, the field of brain-computer interfaces slowly grew. The 1990s saw the pioneering studies of Wolpaw, McFarland, and colleagues, who successfully developed a BCI for one-dimensional cursor control using sensorimotor rhythm activity (Wolpaw, McFarland, Neat, Forneris, 1991). This allowed completely paralyzed patients to communicate by moving a computer cursor "with their minds." Even more than twenty years ago, non-invasive BCI were reaching levels of 90% accuracy and greater, but at the cost of long selection periods up to 5 seconds (Doris, Wolpaw, Pfurtscheller, McFarland, 1997).

At their current stage, BCIs have become most useful as drivers of assistive technology (AT) in cases of stroke, muscular atrophy diseases like amyotrophic lateral sclerosis (ALS), cerebral palsy, spinal cord injury, all of which tend to be causes of locked-in syndrome -- a state of complete or near-complete loss of muscle movement, but normal cognitive function. Examples of assistive technologies are wheelchairs, communication boards, and text-to-speech software.

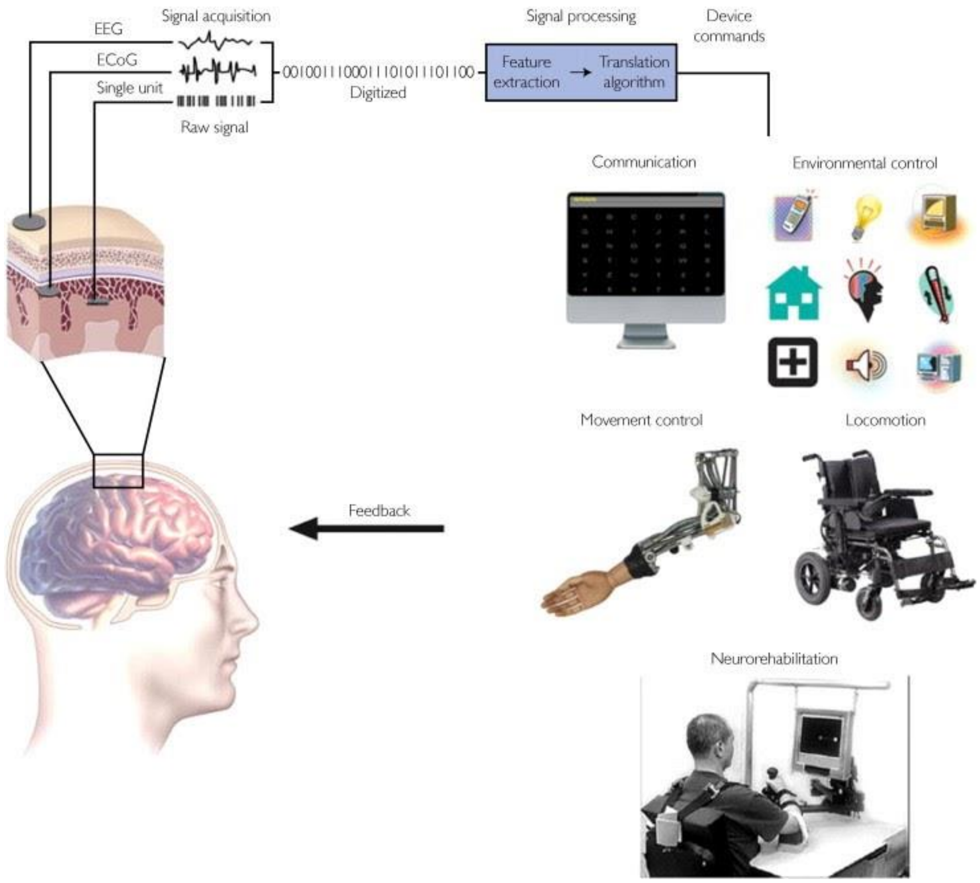


Figure 3: Another outline of a BCI pipeline, with various examples of BCI applications on the right side.
© 2012 IEEE.

BCIs have been paired with movement-related assistive technologies in several paradigms using wheelchair control as well as robotic arm control simply with brain activity (Achic, Montero, Penazola, & Cuellar, 2016; Bousseta et al., 2018). Beyond replacing (loco)motor capabilities, BCIs have also aided in speech rehabilitation via what are known as BCI spellers. These are systems that use various brain signals in order for the user to type words on a computer. One popular paradigm uses the P300, the ERP mentioned previously. In this paradigm, letters are shown on a screen in rapid succession, also known as rapid-serial visual presentation (RSVP). When the user sees the letter they want to type, the surprise or "aha!" feeling associated with detecting a target typically elicits a P300, which can be recognized by the BCI and outputted to the application (Oken et al., 2018). There have also been video game- and VR-related applications to BCIs, such as the Pacman-like BCI created at the Fraunhofer Institute in Germany (Krepki, Blankertz, Curio, & Müller, 2007; Coogan & He, 2018). BCIs have also been used for recognition of other cognitive and perceptual phenomena. For example, multiple studies have used EEG to classify a user's emotions (Nafjan, Hosny, Al-Olahi, & Al-Wabil, 2017). Another group was able to classify a user's perception of a Necker cube, an illusion that can be seen as having different orientations depending on one's perception (Hramov et al., 2017). This classification of more abstract mental states spells quite a versatile future for BCI applications, as they can be used in more than just motor-related contexts. It is important to note that a BCI is not the same as its application, rather it is a component of the application that is used for control (Wolpaw & Wolpaw, 2012). ATs, for example, exist outside of BCIs, but bringing them together opens up a whole new world of interaction for a user.

Usability

An important aspect of the application side of BCI is usability, the relationship between the user and the application. Feedback, or what the user experiences from the interface as a result of their actions, is one facet of usability that is studied in BCI research. Better feedback helps to better control and understand a device and how it can be used to reach goal states. If a user tries an input and it leads to the wrong output that is clearly shown (e.g. the robotic arm moves in a direction that is just slightly off), this feedback helps the user understand how to interact with the interface. Cognitive psychologist Donald

Norman, who has extensively developed design and information theory for decades, puts the idea of feedback into perspective using the examples of both auditory and visual feedback: "Imagine trying to talk to someone when you cannot hear your own voice, or trying to draw a picture with a pencil that leaves no mark: there would be no feedback" (Norman, 1988). Proper feedback drives our usage of systems, be they cognitive or physical. Thus, the effects of a BCI system's output on the application or on itself must be unambiguous to the user. Two other facets of usability that are considered in BCI research are the practicality of the mode of acquisition and the interface design (Baek, Chang, Heo, & Park, 2019). Aspects of the device experience like how comfortable the headset is, how practical the interface is for daily life, and the longevity of its use are all important to how the application itself is designed in accordance with the BCI.

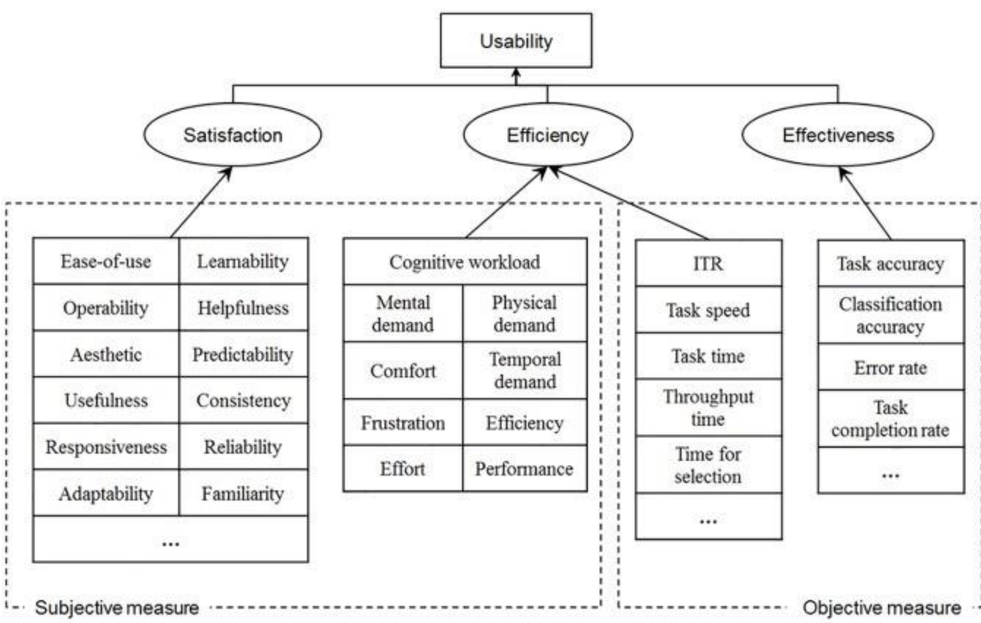


Figure 4: Usability factors in BCI.
(From Nam et al., 2017)

An invaluable asset to both biomedical research and the healthcare industry, BCIs have seen numerous applications in the past few decades. While they have grown considerably with time, like any relatively new technology, there are still areas on both the computational and the usability sides that are under constant improvement.

Current Limitations

As we now know, each approach to building a BCI has its limitations from the signal acquisition level to the output and application levels. The following section will explore some of the main limitations of BCI research and the practical use of BCI applications.

Limitations of Signal Processing & Classification

The issue with many signal processing algorithms is that they only work for specific problems (Rashid et al., 2020). For example, algorithms like empirical mode decomposition (EMD), and independent vector analysis (IVA) are good for small numbers of features, but suffer drawbacks of artifact detection in certain frequencies. Other approaches that work better for a higher dimensionality of features sometimes do so at the cost of being too slow and are thus impractical for live use (Rashid et al., 2020). Furthermore, "tried and true" techniques like PCA and some implementations of ICA have been found to cause "eigenspectors," artifacts that cause a misallocation of spectral density (Leichter, 2013). Moving forward, researchers seek to create signal processing algorithms that are both sensitive to artifacts, while also working efficiently and accurately enough to be used in live sessions.

In terms of classification, one of the main issues is the information transfer rate (ITR) of BCIs. ITR, also known as bit-rate (bit/min), is a common metric that synthesizes classification accuracy, the number of classes, and the time that it takes to make a selection (McFarland, Sarnacki, & Wolpaw 2003). BCIs that use P300 spellers are known to have poor ITR, which is even lower for those that are used in virtual reality and gaming applications. One solution to this has been the use of hybrid BCIs, which utilize the higher ITR of activity like SSVEP alongside those with lower ITR in order to boost the net ITR of the system (Achic, Montero, Penazola, & Cuellar, 2016). Higher ITR systems also have a decreased calibration time, so it means all the more to user experience to increase classification speed and accuracy.

Limitations of EEG Signal Acquisition & Interface Design

As we have seen before, modalities of signal acquisition have strengths in some areas but suffer from weaknesses in others. Despite its wide availability, the lower signal to noise ratio in EEG makes it harder to develop BCIs that use finer movements. ECoG can alleviate this, but at the cost of a timely and expensive surgery. Another end of EEG's limitation is the timely and often uncomfortable process required to apply "wet" EEG systems, which use conductive gel to increase signal quality. The introduction of "dry" EEG systems have erased the need for conductive gel and are, therefore, easier to use but possibly at the cost of signal strength and quality (Mathewson, Harrison, & Kizuk, 2017). The advent of mobile or wireless EEG systems also exemplify a development toward more portable EEG recording. Traditional wired systems are typically considered a reliable gold standard in research, though there is increasing evidence that wireless systems are equally as reliable (Kam et al., 2019).

In terms of interface design, some paradigms like the RSVP paradigm mentioned earlier require a great deal of focus on rapidly displayed letters, which may be tiring to a user over a long period of time (Oken et al., 2018). One direction could be to display the letters more slowly, but this would turn typing a word into a much longer process. When it comes to interaction design, tradeoffs like these are common issues that are considered deeply to find the best attributes to a system for ideal user experience.

The technical and design realms are not the only areas for improvement. There are other factors that limit the current capacity for BCIs in daily use, such as the price accessibility of such a system and the generalizability of usage (e.g. the availability for a single device to be used at different levels of fatigue, or by multiple parties). Each approach to improving BCIs is unique and focuses on different levels of the overall system, but all aim for the same goal: “to provide a direct link between the inductive mental processes used in solving problems and the symbol-manipulating, deductive capabilities of the computer” (Vidal, 1973).

Mental Imagery

As you read these words, imagine a piece of paper in your mind. Now, have you got it? Chances are your paper is rectangular and white. This is likely due to the fact that most leaves of paper you have seen in the past have been white, like the one these sentences are written on (Kosslyn & Moulton, 2009). Now take that piece of paper from your mind and bring it outward. Let it fly around you, flutter right in front of your face, even go behind you. Now, you can not see behind you but, somehow, you may now have an image of what this "something behind you" is. Finally, imagine yourself grasping that paper, crumpling it. Can you hear the crackling? Feel the light material bend? Let the paper dissolve, now, into nothing. Or was it anything to begin with?

This thought experiment, an extended reimagining of one given in Kosslyn & Moulton's paper on mental imagery as emulation, is meant to exemplify mental imagery's multifunctionality as a process involving memory, visuo-spatial reasoning, and multisensory emulation (Yates, 1966; Kosslyn & Moulston, 2009). Beyond this exercise, in daily life outside of experimental paradigms, mental imagery does so much more. It is a central part of our interaction with the world. Thus, as with psychological science in general, the concept of mental imagery has been a subject of study, and profound debate, for millennia. Looking into its history, it is clear that contemporary theories of mental imagery and its role in cognition have well-alive roots in ancient theories from ages ago. As we will explore, what has changed over time alongside these theories are the empirical evidences that are used to support or refute them.

A History of Debate

What philosophers and scientists of today may call “mental representations” Aristotle knew as “phantasma,” or residue from actual, stimulus-driven perception (Thomas, 2014). He believed that these images of the mind provided us with the energy and direction required to reach goal states in the world (McMahon, 1973). Aristotle also held the idea that semantics, the meaning behind language, was related to imagery (Thomas, 2014). Though ancient in comparison to the developments in modern psychology that have occurred since, Aristotle’s early conceptions of mental representations in the human mind have analogs to comparatively more recent theories of mental imagery.

One of these analogs came in the form of Thomas Hobbes’ argument for materialism, which theorizes an answer for a fundamental question of mind itself: is there a difference between the physical properties of the brain and the inscrutable phenomenon of conscious experience? In the scope of mental imagery, this question asks about the necessity of the separation between perception, actually seeing a stimulus, and imagination, seeing a stimulus from an internal source, i.e., “in the mind’s eye”. The nature of mental imagery was, and still is, cause for metaphysical debate. Indeed, materialists like Thomas Hobbes defended the idea that images were nothing but “decaying sense,” which can be thought of like a “pendulum swing gradually decreasing in amplitude” (Leviathan I.2; Thomas, 2014). This bears much similarity to Aristotle’s “phantasma” which he thought were also remnants of exogenous sensation. Hume was another one of the materialists who backed the indistinction of perception and imagination. He compared percepts, which he called “impressions,” to images in that they “did not differ in kind, only in their degree of [vivacity]” (Thomas, 2014). Non-materialists like Renee Descartes, Jean-Paul Sartre, and Thomas Reid, on the other hand, made a clear distinction between stimulus-driven perception and imagined experience. Descartes tended to embrace the distinction between the two, believing that mental images began as material in the brain but were passed onto mind, which was of a different, non-material quality (Descartes' Optics, 1637; Thomas, 2014).

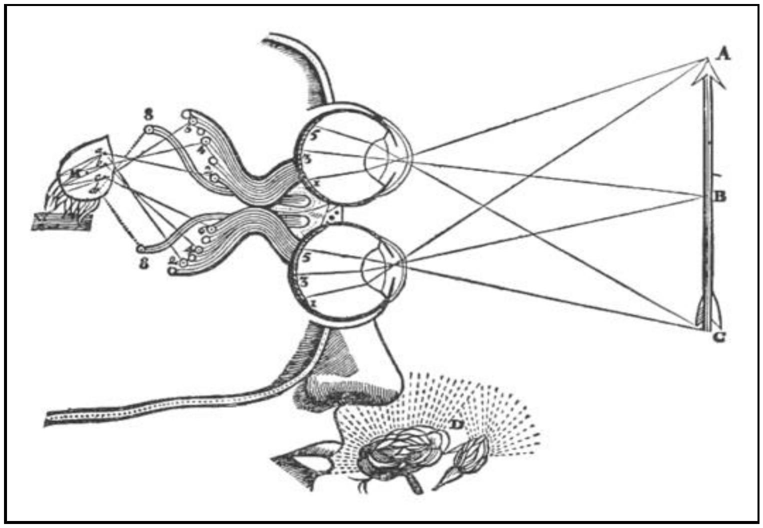


Figure 5. Descartes' depiction of human visual perception.
Descartes believed that the pineal gland (left) was the part of the brain that bridged perception from the senses to images of the soul. (from *Traite de l'homme,* Descartes, 1648)

Through its discussion in the philosophy of mind, mental imagery became of great interest in the budding field of psychology in the late 19th century. Because of the field's beginnings, which relied heavily on introspective analysis, the veracity of mental imagery was implicit among early psychologists. Most of us, after all, are quite familiar with our own mental imagery. This implication was, however, deeply shaken upon the results from a 1901 experiment at the Wurzburg School in Germany. There, researchers found evidence for what they called "Bewusstseinslage," imageless thought (summarized by Humphrey, 1951). Though the original study methods would be considered deeply flawed by contemporary standards due to the fact that the experimenters themselves were participants, a series of follow-up studies confirming the existence of imageless thoughts began to pop up (Buhler, 1907-08, from Humphrey, 1951; Marbe, 1901).

With these experimental results, the study of mental imagery that seemed so certain became less credible. The rise of behaviorist psychology - - the theory that psychology can be understood from the observation of a subjects behaviors (think Pavlov's dog) -- in the early 20th century, marked the final turning-away of most researchers from mental imagery studies. In fact, behaviorist dogmatists considered it completely foolish to look within one's psyche and try to develop theories based on their subjective reports.

It was not until the rise of cognitivist theory in the 1960s and 1970s that mental imagery slowly became of interest again. Researchers like Paivio, Piaget, and Holt re-emboldened into psychology the importance of cognition, the internal mental processing that defines psychological phenomena. And with this rebirth rose another debate, this time about the very nature of mental images, rather than their difference from stimulus-driven perception. At the forefront of this debate -- known in relevant circles as "the imagery debate" -- were Kosslyn and Pylyshyn. Kosslyn favored the "pictorial" side of the debate, which held the idea that mental images were depictive in nature (Tye, 1991). By depiction, this stance did not argue that imagery takes the form of exact photos, rather it is represented in a similar way to how external pictures have visuo-spatial features (Thomas, 2014). Because of its similarity to actual pictures, but being mental in nature rather than external, Kosslyn called this theory a quasi-pictorial theory. Pylyshyn, on the other hand, leaned toward the "descriptive" side of the debate. This side held that mental images were propositional in nature, in that they were represented by a system that used syntax, structure, and semantics, much like language. This was similar to Fodor's theory of "mentalese," the inner, unspoken language of conceptual representation of the mind (Thomas, 2014). Of course, some theorists preferred a more holistic approach that included aspects from both sides of this debate. Kosslyn and Pylyshyn's Imagery Debate is, though, a paramount example of the debates that have driven forward the study of mental imagery.

So, we've now seen that the definition of mental imagery has experienced a multitude of formulations, many a cause for debate. Though most of these theories focus on visual mental imagery, primarily because vision plays such a central role for humans, some are generalizable to images of all sensory modalities. Beyond introspection and subjective reporting, the advent of neurotechnology has given rise to numerous neuroscientific studies that have paired brain activity with a number of mental imaging paradigms. Thus, these studies have been used as evidence to elucidate the physical mechanisms and subsequent subjective effects of mental imagery.

Mental Imagery and the Brain

Given the window into the brain that neurotechnology has provided, researchers have explored a number of sensory modalities and their neural correlates. In general, it has been found that mental imagery in a given sensory modality activates the same brain regions related to the actual perception of that modality (Moulton & Kosslyn, 2008). Visual mental imagery, for example, has been found to elicit activity in V1, the primary visual cortex, even to the point of modulating the activity as a function of how vivid the image is (Nanay, 2018). This overlap between brain activity related to imagery and that of perception has been used as evidence for the pictorial side of the imagery debate. According to Kosslyn, this connection suggests that mental images are depictive in nature; seeing that we perceive the world in a depictive manner, activating the same brain region in imagery is evidence for the depictive nature of mental images (Kosslyn, 2005).

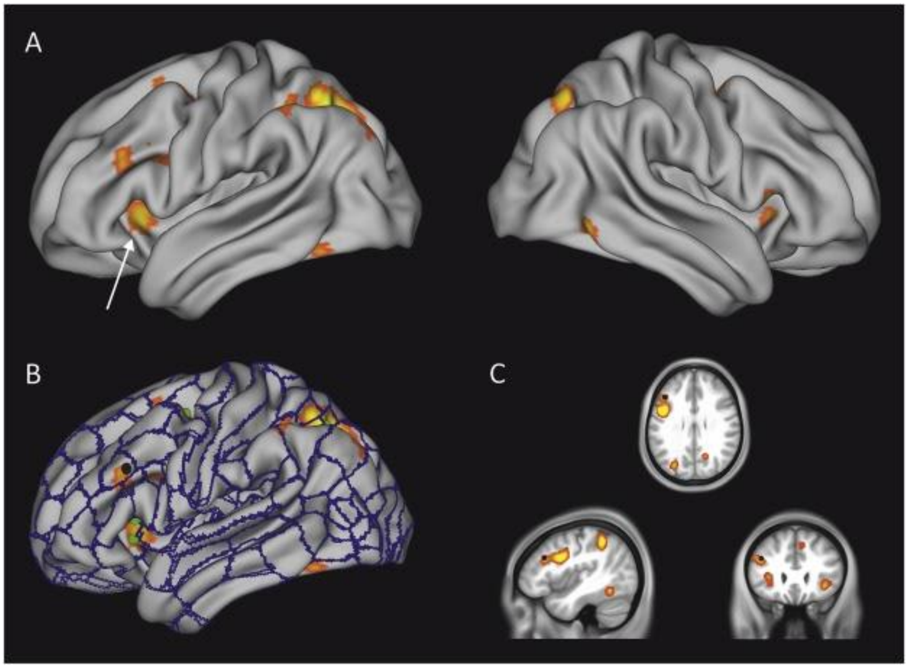


Figure 6: fMRI data across 40 different studies showing brain regions most frequently activated during mental imagery.
A) and B) show the intraparietal area 1 (IP1), intraparietal sulcus 1 (IPS1), and dorsal and ventral lateral intraparietal (LIP) areas; C) shows the greater activity in the left hemisphere than the right. There is also bilateral visual cortex activity (in the 'back' of the brain) because all studies tested visual mental imagery (from Winlove et al., 2018)

Other than V1, parts of the parietal lobe and occipitotemporal cortex have been found to be correlated with mental imagery in humans. A recent meta-analysis of forty different neuroimaging studies observing visual mental imagery of scenes or objects found consistent activation in the superior parietal lobe -- specifically in the left hemisphere -- across all studies (Winlove et al., 2018). Interestingly, the same meta-analysis found some studies with activation of rostral area 6 and the inferior frontal sulcus, which have been found to be related to the semantic processing of language and decision-making. This could suggest mental imagery is semantic in nature as well, providing support for the descriptive side of the imagery debate. However, as the authors of the meta-analysis note, to attribute a single anatomical area of the brain to a single function is a challenge due to the human brain's complexity. Thus some studies have employed more network-oriented approaches to neurophysiology, studying interconnected circuitry of activation that is correlated with mental imagery, rather than just isolated regions. One such study used ECoG to observe connected activity in both the frontal and temporoparietooccipital in relation to the decision process in rotating mental images of 3D shapes (Nikolaev, 1995). Though it is prevalent in most discussions of imagery, visual mental imagery is not the only sensory modality that has been studied in experimental paradigms. Parietal regions of the brain have also been found to be activated for both spatial, motor, and tactile imagery (Sack et al., 2008; Jeannerod, 2001; Schmidt, Ostwald, & Blankenburg, 2014).

In general, the parietal cortex is considered to be part of a network for mental imagery representation that includes the prefrontal cortex at the higher level, and the relevant sensory region at the lower level (Jeannerod, 2001). Oftentimes, regions of the occipitotemporal cortex are found to be active in this network as well. A study in spatial imagery, for example, found that motor-related information from sensory brain areas send signals to the parietal cortex, which are routed to the prefrontal cortex (Sack, 2008). Similarly, there is evidence of a "construction network" that involves activation in the primary and secondary somatosensory cortices (responsible for tactile sensation) followed by the lateral occipital visual-tactile area (Schmidt, Ostwald, & Blankenburg, 2014). Imagery of different sensory modalities, of course, likely do not use the exact same circuitry. But the locality of regions activated across modalities points to a common network for mental imagery, which bears striking similarities to the network for actual sensory perception. Beyond just their spatial similarities, even the temporal qualities of actual movement and imagined movement are nearly identical (Jeannerod, 2001). The reason for the experiential difference of mental imagery despite near identicality to actual perception is still relatively uncertain.

A discussion of mental imagery by French neuroscientist Marc Jeannerod points to a couple of theories for this difference in the context of motor activity. For one, it could be that neural activations due to mental imagery are not strong enough to elicit actual muscle activity. On the other hand, there could be an inhibitory mechanism at play during mental imagery (Jeannerod, 2001). Jeannerod also proposes a synthesis of the two, offering that, perhaps, there could be "subthreshold preparation to move" paired with a "parallel suppression of overt movement by inhibitory influences." This discussion, though specific to motor studies and corticospinal activity, can also be generalized to other sensory modalities. This could explain why mental imagery both facilitates later perception in the same modality, and suppresses perception if an individual attempts to exercise both at the same time (Chang & Pearson, 2018; Zvyagintsev et al., 2013).

Though the neural substrates of mental imagery are continuing to be studied, the general activation of the relevant sensory brain region during mental imagery is a well-established finding in the field. The extensive research done on mental imagery has not only aided the development of underlying theories, but they have also had a tremendous impact on BCI research, due to the use of mental imagery as a primary input method for BCI applications.

BCIs for Mental Imagery Classification

Now we know that imagery is a type of mental representation that plays an important role in our thought processes via emulation of actual perception. Despite the debate, it is generally accepted that 1) images refer to something out in the world, and 2) are produced at the voluntary will of a mind (with some exceptions, like intrusive or instinctive imagery). Thus, in a way, mental imagery is a mapping from our internal world of expectation, representation, and intentionality, to the external world of actions and outputs. This viewpoint highlights why imagery is so useful to BCI research: the neural activity that roughly encodes our internal world is a window into that world, or at least how it is represented. This is how we use tools beyond BCIs, afforded by their functions and constrained by their limitations. Using pencils, we are able to map our intentions through the function of making markings on a surface. Using a guitar, we map our intentions through the strings and strumming patterns to create the desired output. Now what makes BCI so unique is the fluidity of this mapping. Because of its prevalence in human cognitive processes, mental imagery can be further explored as a heuristic for mapping intentionality at an even more complex level in BCI systems. Although imagery-based paradigms are notoriously less salient than others (due to the lack of an actual stimulus), especially in non-invasive brain recording, researchers have still been successful in using imagery as a reliable input.

Motor Imagery

The overwhelming majority of imagery-based BCI have to do with motor imagery. In fact, searching Pubmed, a world leading database for published clinical studies, for the terms "BCI" AND "Imagery" yields 995 results, while a search for the terms "BCI" AND "Imagery" AND "Motor" yields 953 results, which roughly exemplifies the sheer presence of motor imagery as a use for BCI research. There are a few reasons for this, one of which being a primary reason for clinical BCI research in the first place: to restore or replace motor activity. It is a more natural effort for an individual to map the movement of a robotic arm to imagined muscle movement of their own arm than to, say, their emotional state. Thus, BCI applications like cursor and arm movement studies have benefited most from motor imagery paradigms.

In general, motor imagery BCI systems utilize the power of two frequency bands -- mu, or the sensorimotor rhythm (8-12 Hz), and beta (18-30 Hz) -- for input. As we already know from the previous section, motor imagery yields the most activity over the sensorimotor cortex. BCI applications using motor imagery have a long history, some of which have been discussed in earlier sections. The late 1980s and 1990s studies of Wolpaw and McFarland utilized motor imagery as for EEG-controlled cursor movement (Krusienski, McFarland, Wolpaw, 2006; Wolpaw, McFarland, Neat, Forneris, 1991). The high accuracy rates of their participants only further solidified motor imagery as a gold standard in BCI. Since then, motor imagery has been used in increasingly complex cursor movement studies, as well as wheelchair and prosthetic limb applications (Yu et al., 2018; Gannouni et al., 2020). Recently, BCIs have even been used for the control of quadcopter drones, further exemplifying the diversity of possibilities for applications (Xie et al., 2016; He et al., 2013). Usually, binary classification (left or right hand/foot motor imagery) is used for commands, but a growing number of systems are achieving more complex levels of classification. In the case of one wheelchair application, for example, researchers were able to classify four motor imagery tasks at 94.2% accuracy to accelerate, decelerate, turn, and stop the wheelchair (Yu et al., 2018). As computation and technology become more powerful, even more complex actions are foreseen to be possible with the use of BCIs.

The use of motor imagery (and imagery in general, for that matter) for BCIs is, however, not without its limitations. The most common of these limitations arises from the fact that the strength of mental imagery can be weak to nonexistent for some individuals. For those without any mental imagery, possessing a neurological condition known as aphantasia, tasks that require it can be, understandably, very difficult to follow. Thus, for this group, mental imagery may not be the easiest form of mapping intention to external action. Interestingly, the vividness of a mental image may not be correlated with BCI-illiteracy, a condition describing the estimated 10-30% of BCI users who are unable to achieve accuracy levels necessary for adequate control (Vasilyev et al., 2017). Multiple studies have, instead, found that the resting state amplitude of the sensorimotor (mu) rhythm, an individual's ability to suppress this rhythm, and attentional and spatial abilities are better predictors of BCI-illiteracy (Vasilyev et al., 2017; Blankertz et al., 2010; Jeunet, Kaoua, & Lotte, 2016). In other words, the strength of a person's experience of motor imagery is different from the classifiability of the resulting EEG activity, pointing to another limitation of mental imagery for BCIs: brain activity is an approximation of an actual mental state; it is not an exact mapping, but a rough representation with the goal of accurate output. This is not to say that vividness of a mental image is not important. The strength of one's mental image plays a key role in their feeling of control, which is vital in any interface. Finally, mental fatigue, a limitation of any paradigm, is often seen in motor imagery studies. It has been found that, with increased fatigue, the power of lower frequency bands is affected, thus dampening the system's ability to classify with accuracy (Talukdar, Hazarika, Gan, 2018).

Other Forms of Imagery

Though the most prevalent, motor imagery is not the only form of imagery that has been used as an input for BCIs. Mental object rotation has also been used in a few BCI studies (Friedrich, Scherer, & Neuper, 2012; Abibullaev, An, & Moon, 2011; Hwang, Lim, & Im, 2014) with significant classification accuracy. A few studies have also used BCIs to detect mental arithmetic, where participants are tasked with simple math to do in their heads (Im, Shin, & Kwon, 2018). Another group of studies have classified mental singing, either alone or in combination with mental arithmetic, in participants using BCIs (Power, Kushki, & Chau, 2012). In many cases, in fact, these BCIs were tested on multiple forms of imagery (motor vs. mental arithmetic vs. mental singing, for example), with the non-motor imagery trials sometimes being more consistently classifiable than the motor ones. This classification difference could actually provide an individualized solution to BCI-illiteracy; individuals who struggle to produce satisfactory output using motor imagery could find more success in other forms of imagery.

Non-motor forms of imagery as input for BCI open up the field to an array of potential forms of interaction that exist beyond physical activity. They can give individuals with communication disorders an avenue for expressing their more complex, inner thoughts. They can provide concept-specific classification (i.e. is this person wanting food, or assistance with their chair?) that allows for a more direct mapping of intentions to output than a selection screen can. Much like language allows us to approximate our internal concepts via lingual outputs, BCI, especially by use of the imagery that we use to represent these internal concepts, can offer an approximate mapping via brain activity classification.

Shape Imagery

The use of BCIs in design software has increased as its potential grows with emerging research (Folgieri et al., 2016). One form of imagery classification with particularly notable implications for design-related applications is shape mental imagery classification. A most relevant application for shape imagery classification, especially for three-dimensional shapes, is computer-aided design (CAD) software, which has, in its development over the past couple decades, provided engineers, designers, and artists with a powerful modality for object and structural modeling. Many studies have observed the intuitive use and multipurpose capabilities of BCI in CAD software, opening up possibilities for more complex and in-depth implementations (Bhat et al., 2013, Rahul et al., 2013, Lang, 2012).

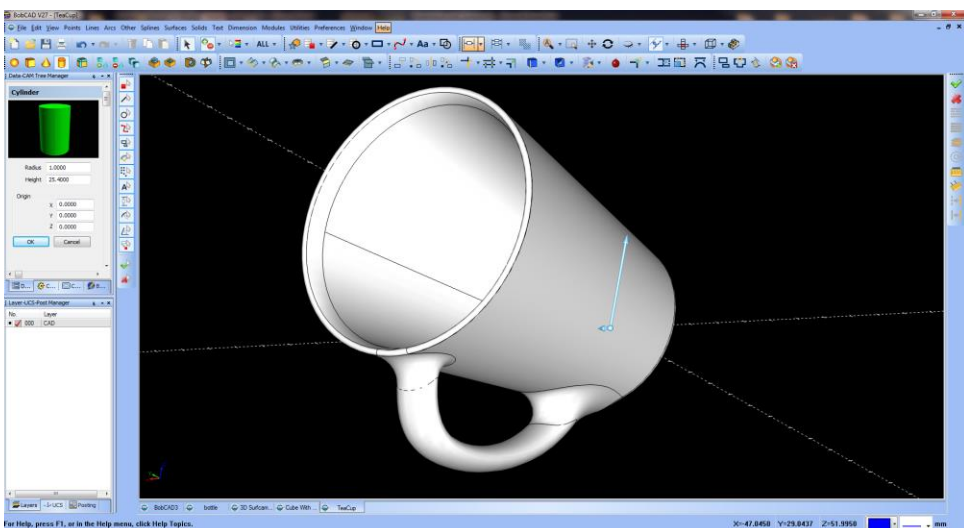


Figure 7: An example of CAD software.

Courtesy of BobCAD-CAM, Inc.

These studies have used, in general, two principal approaches to explore applications of BCI in CAD software: 1) replacing typically mouse-controlled spatial functions (e.g. lateral translation, rotation) with brain-activity-controlled implementations, and 2) classification of geonic structures from mental imagery with the goal of shape generation in the virtual space. What these two approaches, in essence, aim to do is decode the mental state of the user and provide output into the world, or, in this case, the software. In the first approach, BCI researchers typically use activity in the sensorimotor or temporal cortices (imagined hand movements) or visual activity (SSVEP, eye movement) as the general paradigm for mapping brain-activity to existing software controls. On the other hand, classification of shape mental imagery, is an approach that attempts to classify the imagination to a congruent output. In other words, the user imagines a shape, and the computer outputs that shape.

As stated before, what this potential modality for BCI use in CAD software can add is a more direct mapping of user's intent and the actions required to realize that intent in the world; a relationship that is called the gulf of execution in human-computer interaction (Kirkpatrick, 2002; Norman, 1988). In a traditional interface, a user must map their intent to a series of cursor movements and buttons (e.g. Insert -> Shapes -> Cube -> Isometric) to produce an output in the program. This paradigm is known as WIMP -- Windows, Icons, Menus, Pointers (Hinckley, 1996). While this method of input requires precise physical movements that are memorized over time with the occasional erroneous action, a BCI interface replaces that physical cursor control with brain activity, erasing the need for such gestures and allowing individuals with neurodegenerative disorders to interact more easily with such design software. What previous research using this approach has lacked, however, is the ability to generate entire shapes (rather than just gestures) using only BCI. The addition of shape mental imagery classification, the second of the two approaches to BCI in CAD software, can grant this ability. This approach allows the user to intend a specific object, which is then efficiently recognized by the machine and outputted onto the screen. Although the present study focuses on this approach, we believe that a holistic implementation that combines the two is ideal.

Shape mental imagery has a history of study, but hardly any in BCI research. Though its use in the field is relatively new and unexplored, the exploration of shape mental imagery can be a pivotal addition to both BCI development in general, and the intuitive use of such technology. Design and simulation in CAD software is a practice in which fluidity of control is key. The implementation of BCI in CAD software is a key step toward the ability to spatially translate, rotate, and generate, and morph virtual objects in an intuitive manner that is accessible to all. We hope to contribute to the work that reaches that point and beyond.

A Novel BCI System for 3D Shape Imagery Classification

To date, there have only been two shape imagery classification studies: Esfahani & Sundararajan (2012) and Korik et al. (2018). Esfahani & Sundarajan created an EEG-based BCI that was able to classify five primitive shapes (cube, sphere, pyramid, cone, cylinder) from the brain activity of participants (Esfahani & Sundararajan, 2012). The goal of the research was to explore possible computer-aided design software implementations of BCIs, with the hope that the technology could eventually utilize shape mental imagery classification to inform object generation in a CAD interface. The present study seeks to replicate the shape imagery classification accuracy results of Esfahani & Sundararajan (chosen over Korik et al. due to higher classification accuracy), particularly Experiment 1.2, in which researchers were able to classify the five shapes with a 44.6% average accuracy across all participants (n = 10). We performed an extension to this study that employs the similar preprocessing, feature extraction, and classification methods, but using a wet EEG system with 64 electrodes, as compared to the dry 14-electrode system used in the original study. Although wet electrode systems are less portable and take more time to apply, the conductive gel used in wet systems has been found to significantly decrease electrode impedance, and analyze a wider frequency range (Mathewson, Harrison, & Kizuk, 2017; Waldert, 2016). Furthermore, the sheer increase of electrodes from 14 to 64 is also likely increase accuracy, as it has been found that higher density electrode systems have increased capability for accurate source localization (Song et al., 2015). At the same time, there is growing evidence of the reliability of the dry systems, even compared to wet systems (Kam et al., 2019).

Still, wet systems remain a golden standard in the field of neuroimaging. Our goal was to test this gold standard, for which we hypothesized that the addition of a wet electrode system with an increased number of electrodes would significantly increase classification accuracy of the five shapes.

Methods

Experimental Design

The design of the present study follows that of the original paper, with the five shapes from the original study (cube, sphere, cone, pyramid, and cylinder) used as the primary visual imagery targets. The first two sessions included examples of the isometric shapes that participants would be asked to imagine. These examples, however, were later omitted in later sessions due to the fact that participants could be attempting to remember them exactly throughout the experiment, thus making the task more relevant to memory than imagery. Participants were also asked to imagine the shapes at the same color, position, and orientation during each mental imagery portion of the trials.

Each trial displayed a word cue for 2s (ex. “Cube”, “Cone”), denoting the shape that the participant would be asked to imagine, after which there was a 5s blank screen (with a constant fixation cross in the center) during which the participant was to imagine the shape as if it were on the screen. Then, for a random interval between 2s and 5s, a ready screen asking the participant to prepare for the next cue was shown, and the next trial began. Every shape was randomly cued (without replacement) once in each block. Halfway through the session, each participant was allowed to take a quick break to rest. During this time all participants remained seated, and moved minimally. After the break, the user was prompted to press the spacebar to begin the next half.

In total, this study had two main experiments, differing in number of blocks. In Experiment 1 (n = 6), there were 10 blocks where each shape was presented once, creating a total of 50 trials. After some consideration about the potential effect that the number of trials may have on the classification accuracy, Experiment 2 (n = 1) was designed to observe if any changes in accuracy correlated with an increased number of trials. This experiment had 20 blocks with the same each shape presented once per block, creating a total of 100 trials.

Finally, all participants were compensated monetarily for the 2-hour session. After signing a consent form, participants were fitted with the EEG device in a low-light, soundproof recording room. All experimental sessions were run after the study design received International Review Board (IRB) approval.

EEG System & Signal Acquisition

The experiment utilized a custom 64-electrode EEG cap to acquire electrical activity, applied to the scalp with Ag-AgCl gel to keep impedance below 10kΩ. The signal acquired by the cap was amplified by two 32-channel amplifiers (Brain Amp Standard; Brain Products), which were then digitized by a recording computer. The system sampled the data at 500Hz with an online filter that employed .1Hz low and 150Hz high cutoffs.

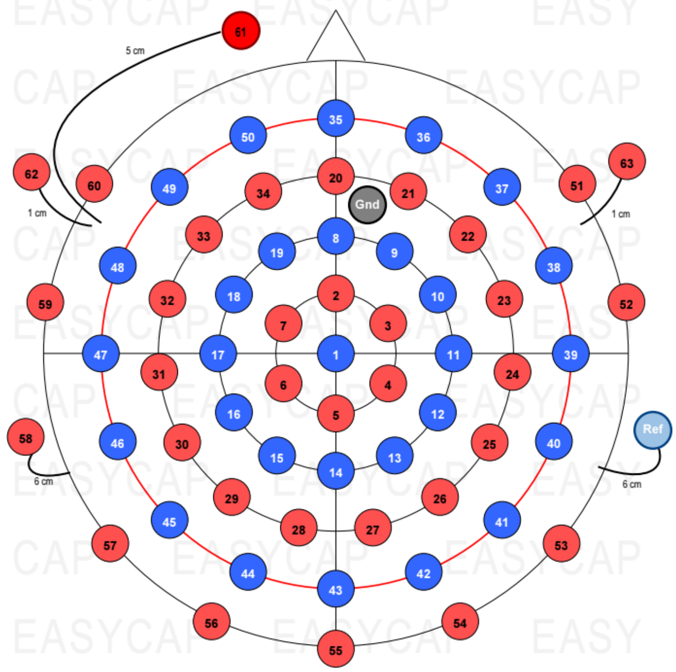


Figure 8: EEG Cap Electrode Layout and Channel Numbers
(From EASYCAP GmbH)

Preprocessing & Feature Extraction

A custom MATLAB script using MATLAB's Signal Processing Toolbox and the package EEGLAB was used to perform the necessary preprocessing and feature extraction after experimental sessions (Delorme & Makeig, 2004). First, the signal was re-referenced to the same two electrodes, 26 and 29 in Figure 8, corresponding to the two reference electrodes used in the original study. This left 61 channels of signal for processing (64 electrodes minus the ground electrode and the two reference electrodes). The raw signal was then downsampled to 128Hz, lowpass filtered at 83Hz, and notch filters were applied at 50Hz and 60Hz. The resulting data was separated into the baseline data (2 to 5 seconds of passive brain activity between trials) and trial data (5 seconds of continuous brain activity starting with the word cue). The first 10% of the signal from each trial was cut in order to eliminate residual activity from the baseline period, leaving 4500ms of signal (shown in Figure 9).

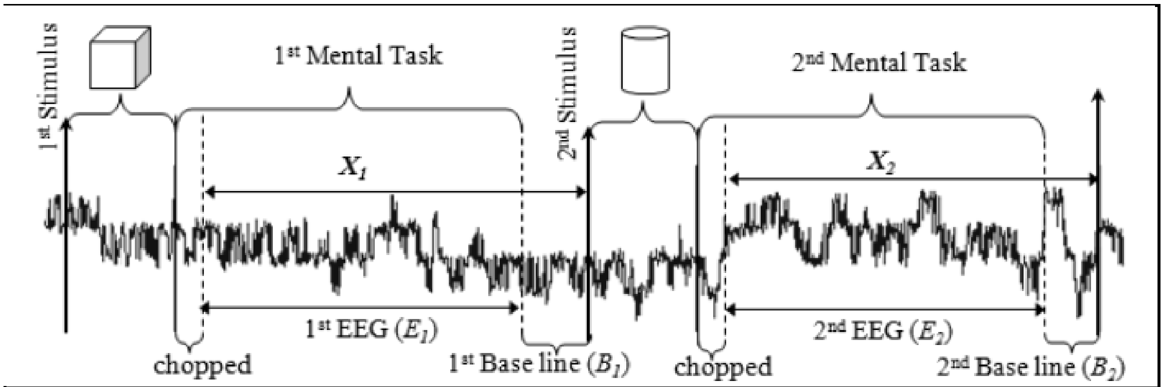


Figure 9: Raw EEG signals and how they were cut for preprocessing and analysis.
(From Esfahani & Sundararajan, 2012)

For artifact rejection, signal deconvolution via an INFOMAX Independent Component Analysis (ICA) was applied to the data in order to find the strongest components in the signal (Makeig et al., 2000). The resulting artifactual components were rejected visually, using the topographical maps of spectral density for each component (Figure 10 below shows some examples of artifactual components). Once the artifacts were rejected, ICA was applied again to the pruned data, and the resulting component activations were used to calculate features. The features were generated using the power spectral density of the component activations in the beta and gamma frequency bands, as these were the most informative frequency bands in the previous study. The resulting features were normalized with respect to power spectra calculated from the baseline signal for each trial. With this feature generation, 122 features were generated per trial (61 independent component activations x 2 frequency bands). The top features for each shape in a given participant's data were selected using a chi-squared statistical test to determine the most informative features. The number of features -- 10-13 for most participants -- was decided by overall participant performance.

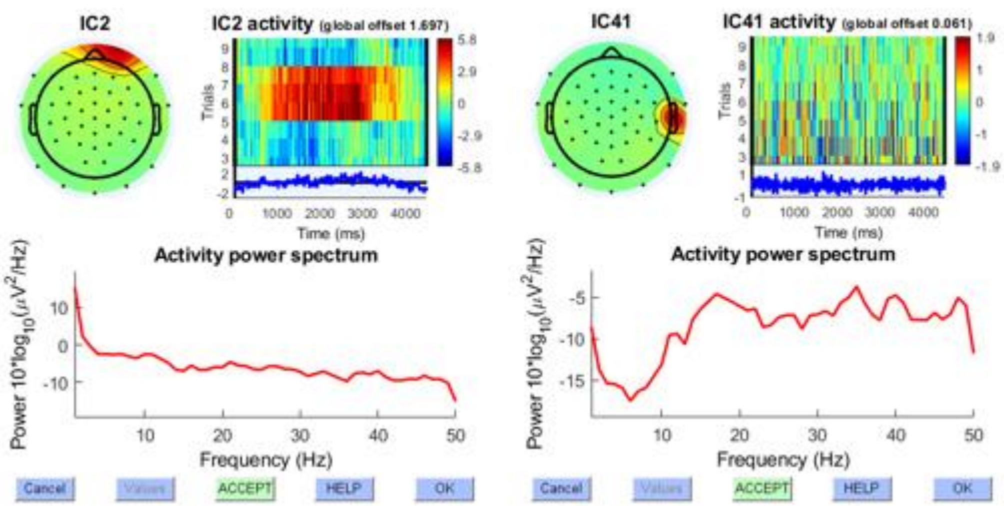


Figure 10: Examples of artifacts related to eye blinks (left) and bad channels (right).

Classification

With a custom Python script using the library Scikit-learn, a classifier was trained on the shape data using Linear Discriminant Analysis (LDA). Each trial (50 for Experiment 1, 100 for Experiment 2) was given a label, which was one of the five shapes depending on which was cued in that trial. The classifier was trained using a random 80% of the trial data, and tested on the remaining 20%. For further validation, another classifier was trained using k-fold cross-validation, a technique that shuffles the data into k groups, selecting one of these groups for testing and training on the other k-1. This process is then done until all each of the k groups have been used as test sets, to evaluate the general robustness of the model for more than just one kind of test set. The average classification accuracy across all k groups was used as a metric to estimate its cross-validation performance. All code used in this pipeline is available online in the Github repository provided in the abstract.

Results

Experiment 1

Analysis of Spatial Activity

The original 2012 study found more activity in the right hemisphere during shape trials, a finding that was consistent with another mental imagery study (Mellet et al., 1996). In order to verify that the shape mental imagery-elicited brain activity was, in fact, in accordance with these findings, the scalp topographies across all shapes for five frequency bands (alpha, beta, gamma, delta, theta) were generated.

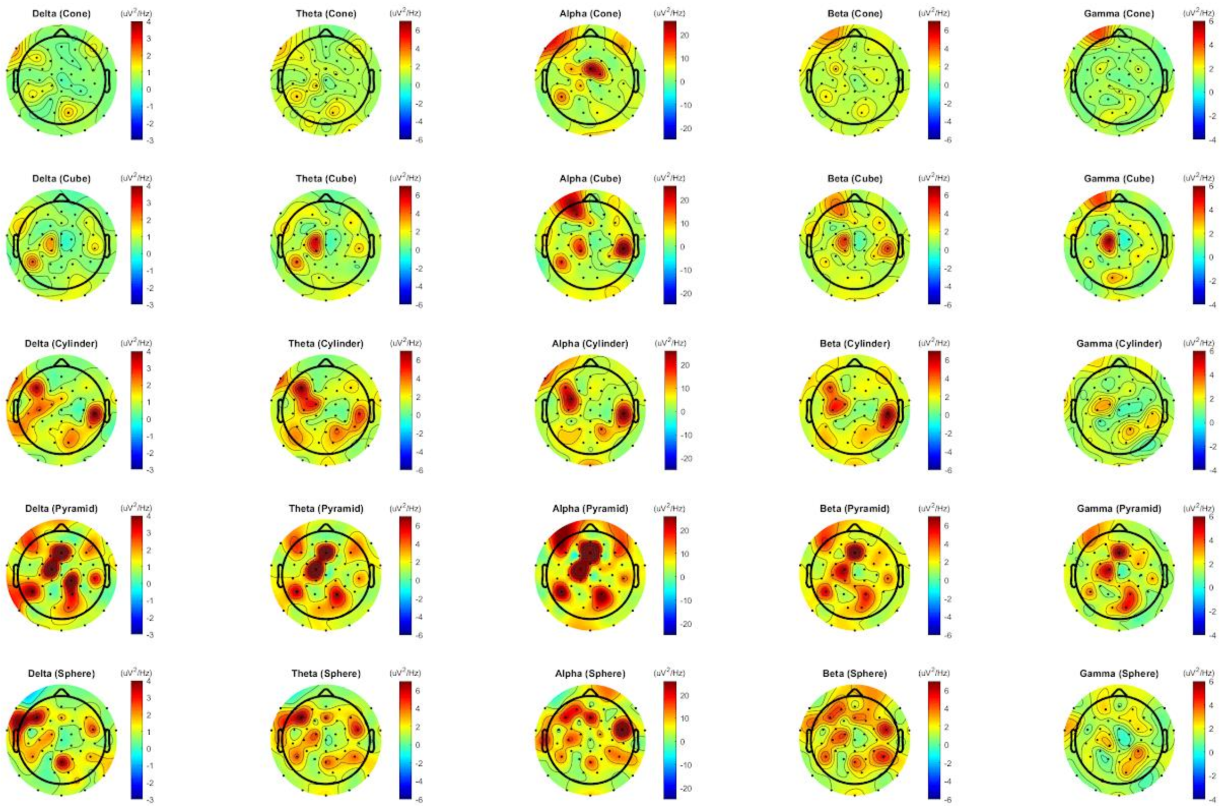


Figure 11: Experiment 1 scalp topographies per shape (row) and frequency band (column), averaged across all six participants.
Darker red denotes higher bandpower, or more activity in that frequency band.

In general, the activity in Figure 11 is either bilateral (most clearly in the Cylinder trials, and somewhat in the Sphere and Cube trials), quite sparse (Cone trials and most of the gamma band column), or central and noisy (Pyramid trials). Regarding the bilateral activity, those topographies are more in line with earlier findings from Winlove et al. (2018), shown in figure 6, rather than those from Esfahani & Sundararajan (2012), who found a right hemisphere-dominant pattern. In their meta-analysis of visual mental imagery studies, Winlove et al. found most consistent activity bilaterally in parietal areas, which closely match the beta, alpha, and theta maps of the Cylinder trials, as well as some of the Cube and Sphere trials.

The noisier aspects of the plots are likely some residue of other artifacts (there is some evidence of blink artifacts, even after performing the artifact rejection step). It could be that the visual heuristic for rejecting ICA components was not sufficient for reducing the presence of artifacts. As mentioned before, ICA is a standard but imperfect artifact rejection method, and can be improved with modifications or using a hybrid technique (Leichter, 2013).

The sparse overall activity found for most of the Cone class could be shape-specific, a possibility that is supported by the results in the next subsection on classification. At the same time, however, because activity can have some variation between participants for the same task, it is also likely that the averaging process actually erased some of the clearer signals within individuals, which (See: Appendix A). This also explains the disappearance of gamma activity in Figure 11, which is more present in the individual plots.

Classification Results

In total, the average classification accuracy across participants was 43.3% (compared to the 44.6% found in Esfahani & Sundararajan), ranging between a maximum of 70% and a minimum 30%. Table 1 shows the average accuracy of the classifier's prediction versus the true class across all participants. Most of the hit rates for each class were well above chance (20%), peaking at 53.8% for Cube. The hit rate for Cone, however, was around chance level. Similar to Esfahani & Sundararajan's findings, the classifier more often confused Cone for Pyramid than correctly guessing Cone. This confusion could be explained by the perceptual similarity between cones and pyramids. This low accuracy is also in line with the sparse band power activity within the row for Cone trials (Figure 11). Interestingly, the classifier did not once guess Pyramid for Cylinder, Cylinder for Sphere, nor Cone for Cube. In the original study, there were no zero rates in the confusion matrix, so this could simply be unique to the analysis used for this experiment.

		Classification Result (%)				
		Cube	Pyramid	Cylinder	Sphere	Cone
True Class	Cube	**53.8**	23.1	7.7	15.4	0.0
	Pyramid	20.0	**50.0**	10.0	10.0	10.0
	Cylinder	11.1	0.0	**44.4**	11.1	33.3
	Sphere	14.3	14.3	0.0	**50.0**	21.4
	Cone	14.3	35.7	21.4	7.1	**21.4**

Table 1: Confusion matrix of classification results, averaged across participants. Because of the randomization of the training-test sets, there are different numbers of observations of each true class in each test set. Hence, the columns do not add up to 100%, but the rows do. The bolded percentages are hit rates (correct guesses).

Contrary to the initial classification results, the k-fold cross-validation (k=5) yielded an average classification accuracy of about 24.3%, a near-chance level. This discrepancy very possibly occurred because of the randomness that the first classifier training method performed to split the data 80:20. When randomizing training and testing data, it is entirely possible that a single class appeared once in the test set (especially given that each test set has only 10 trials), thus making a single correct prediction yield 100% accuracy entirely for that shape. K-fold validation is there to make sure that *all* test set combinations are accounted for. Thus, the classifier performed well on randomized trials, but not as well for validation. Moving forward, a solution to this would be to simply have more trials, in which case the randomization would be less likely to falsely represent the model's actual fit, which is what was done for Experiment 2.

Lastly, in order to check for any outliers between shapes, another LDA-based classification was performed in a one-vs-all fashion (each class vs. the rest as a single group). The average one-vs-all classification accuracy across participants is presented in Table 2 below, which does not show a particular shape with a significantly lower classification accuracy than the others.

Shape	**One-vs-All Classification Accuracy**
Sphere	71.7
Pyramid	76.7
Cube	73.3
Cone	76.7
Cylinder	83.3

Table 2: One-vs-all classification results for all shapes, averaged across participants.

Experiment 2

Classification Results

In the second experiment with an increased number of trials, the classifier reached an accuracy of 25%, barely above chance, and slightly below the lowest accuracy from the first experiment, 30%. Table 3 shows a clear drop in hit rates compared to Experiment 1, with the exception of the Cone class, which remained around chance level. Interestingly, k-fold cross-validation did not yield a different classification accuracy, most likely because of the increased number of trials. The more trials, the less likely a random selection is to create a false representation of the model.

	Classification Result (%)					
		Cube	Pyramid	Cylinder	Sphere	Cone
True Class	Cube	**33.3**	33.3	16.7	0.0	16.7
	Pyramid	33.3	**33.3**	0.0	33.3	0.0
	Cylinder	0.0	50.0	**0.0**	0.0	50.0
	Sphere	0.0	20.0	20.0	**20.0**	40.0
	Cone	0.0	50.0	0.0	25.0	**25.0**

Table 3: Confusion matrix of classification results in Experiment 2

The one-vs-all classification performed on this participant's data shows no shape that stood out significantly from the others to cause the extreme drop in accuracy, leaving factors outside of shape-specificity to be potential causes.

Shape	**One-vs-All Classification Accuracy (%)**
Sphere	65.0
Pyramid	70.0
Cube	70.0
Cone	70.0
Cylinder	80.0

Table 4: One-vs-all classification results for all shapes in Experiment 2

One of these potential causes was fatigue. It is known that increased fatigue during BCI use can negatively affect classification accuracy (Talukdar, Hazarika, Gan, 2018). In order to check for potential effects of fatigue, the classifier was subsequently trained and tested on only the first 50 trials. This yielded a classification accuracy of 30%, showing little but not particularly significant evidence for the effect of fatigue. Though this accuracy was slightly higher, Table 5 shows that most of the classes were at-chance-to-zero in their hit rates (with the exception of Pyramid and Cone).

		Classification Result (%)				
		Cube	Pyramid	Cylinder	Sphere	Cone
True Class	Cube	**25.0**	25.0	50.0	0.0	0.0
	Pyramid	0.0	**50.0**	0.0	0.0	50.0
	Cylinder	0.0	100.0	**0.0**	0.0	0.0
	Sphere	0.0	0.0	0.0	**0.0**	100.0
	Cone	0.0	0.0	0.0	50.0	**50.0**

Table 5 Confusion matrix of classification results of first 50 trials in Experiment 2

To check, again, for the potential effect of a single outlier class, one-vs-all classification was run on the first 50 trials of Experiment 2, shown in Table 6. this analysis, like the earlier one-vs-all classifiers, shows no particular outlier shape to cause the drop in accuracy.

Shape	One-vs-All Classification Accuracy (%)
Sphere	60.0
Pyramid	70.0
Cube	60.0
Cone	60.0
Cylinder	80.0

Table 6: One-vs-all classification results for all shapes in the first 50 trials of Experiment 2

With little evidence for fatigue being a significant cause of such poor classification accuracy, the scalp topography was also checked for anomalies.

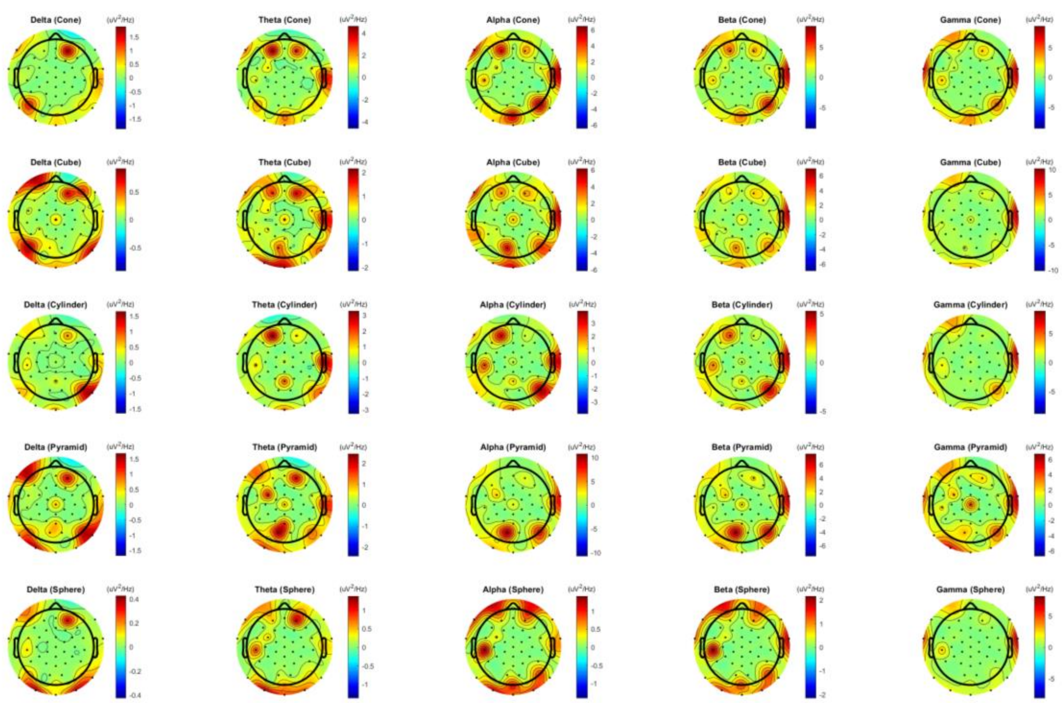


Figure 12: Scalp topographies per shape (row) and frequency band (column) for Experiment 2.

These show that there is a considerable amount of frontal and posterior activity (around the perimeter of each plot), as well as sometimes blink-related activity as opposed to the bilateral activity in individual participant data. The posterior activity could be visual cortex-related activity from the occipital lobe, which was found in the visual imagery studies from Winlove et al., but this is unlikely due to the lack of such activity in the other participants' data. Instead, this could be a result of recording error, or something participant-specific. Unfortunately, there is not enough other data to tell. In future versions of this experiment, it will be vital to have multiple participants in order to compare anomalous data to a larger pool. In summary, the cause of such poor classification in Experiment 2 is uncertain, but could be explained by some small degree of fatigue, artifacts, and possible recording failure.

Discussion

Classification

In general, the findings did not support the original hypothesis of increased accuracy given a greater number of electrodes and enhanced conductivity, having found a comparable accuracy (43.3% to the original study's 44.6%) in a randomized training/test setup, while also finding considerably lower accuracy (24.3%) when tested with k-fold cross-validation. The study's findings still, however, add to the conversation about BCI usability in wet and dry electrode systems. It is no surprising fact that dry electrode systems are more portable and comfortable for a user to wear compared to wet electrode systems. The research, however, regarding dry electrode systems being equal in reliability and, therefore, signal classifiability, is mixed, with sources posing arguments for either side (Kam et al., 2019; Mathewson, Harrison, & Kizuk, 2017). Even in this debate, wet systems are still considered a more trusted gold standard of the two in EEG research. This preference could also have to do with marketing, as dry electrode EEG systems are often marketed to more commercialized circles, and so are less trusted in having research-grade sensitivity. Now having continued evidence that a BCI using a dry electrode EEG system is able to reach a classification accuracy equal to or better than that of a wet electrode system is exciting. This suggests that these more portable options do not necessarily sacrifice accuracy for their convenience.

On this note, it is important to mention that our 4.5-fold increase of electrodes still yielded about the same classification accuracy as well. Not only is there evidence that more electrodes suggest better overall spatial resolution, but the large number of features that result from such an increase (from 70 to 305, reduced to 122 to narrow down to the beta and gamma frequency bands) also implies better classification accuracy (Esfahani & Sundararajan, 2011). One simulation study that increased electrode count did find that a higher density EEG system actually might not have increased spatial resolution (Ollikainen et al., 2000). However, this particular finding is not heavily supported by the literature. One reason for this lack of effect could be that the sources recorded by a lower density system with 14 electrodes is sufficient for adequate control, with diminishing returns as electrode count increases, thus making the smaller system comparable to the larger one. Another explanation is that the spatial resolution advantages of a higher density system are not used fully in this paradigm. Because the classifier is trained on frequency band power data of independent components obtained from ICA, which linearly transforms the original electrode space into a different vector space (known as the component space), the feature extraction process could have tempered out more sensitive spatial information. Perhaps a classifier trained specifically on spatial activity would fare better, but this is purely speculative. Nonetheless, although there are some causes left to question, these findings further support the viability of more portable BCI.

Spatial Activity

Looking at the topographical plots tells a story that is common in neuroimaging, one that is especially impactful when attempting to decode brain activity: variability between individuals makes it difficult to generalize anything, plots and classifiers alike. This is evident in the visibly variable activity between individuals in Appendix A. Of course, there are commonalities in brain activity given a similar task, but, especially in such a small group, averaging across participants can be a lossy process. Another story told in the individual spatial activity data provides support for bilateral parietal activity found in Winlove et al. rather than the right hemisphere specific activity observed in Esfahani &

Sundararajan's data. Winlove et al. also found left hemisphere specificity in mental imagery studies, which is also represented in some of the participant data as well. This is not to say that Esfahani & Sundararajan's topographical findings are inaccurate; they are well supported by findings from Mellet et al. (1995). This, instead, points to the fact that, as mentioned in the section on mental imagery and the brain, it is difficult to nail down a single anatomical area of the brain to a single function due to the human brain's complexity and variability. It is better to see data from these studies as part of a larger trend.

Mental Imagery

Might these findings add to the imagery debate mentioned earlier? They do, somewhat. The bilateral parietal activity adds to the data that certain parietal areas are involved in mental imagery, possibly supporting the representation argument as parts of the parietal cortex (See: Figure 6) are known to be involved higher cognitive functions. The lack of occipital lobe data, however, fails to support the imagery-as-picture argument. This does beg the question, however, of whether this was at all the same task for all participants. David Kirsh, a mental imagery researcher at the University of California, San Diego makes the distinction between *imagination* and *projection* (Kirsh, 2013). Projection, according to Kirsh, is the "is a mental process akin to attaching a mental image to a physical strucure." Imagination, on the other hand, "has no physical anchor, and imagined images need have no specific size or location." Although the instructions asked participants to imagine the object on the screen, it is entirely possible that some *projected* the image onto the screen's background, anchoring it to the fixation cross, for example, while others *imagined* the shape as an unattached object that just happened to be near the screen. It is, then, also possible that these two different processes have slightly different neural substrates or activation strengths of occipital vs. parietal lobe activity, thus leading to even more variability between participants for the task. Moving forward, it would be useful to use a standard test for keeping track of participants' tactics while completing the task in order to ascertain which type of imaging that was used, or if they used a mix of the two.

Conclusion

To conclude, the results of this study show that there is great potential for portable, dry-electrode EEG systems to be used in BCIs with an accuracy on par with that of higher density wet EEG systems. In order to further confirm these findings, future developments will benefit from the addition of more participants, both to train a more robust classifier that can maintain high accuracy against cross-validation, and for the averaging of topographical data to be a more informative and less noisy result. With more participants for a paradigm like Experiment 2, a more distinct mechanism behind the effect of an increased number of trials might also be observed. Additionally, more sensitive artifact rejection methods could be used in order to weed out potential artifact left over or possibly even created by ICA decomposition (Leichter, 2013).

"The dry revolution," or the introduction of dry electrode headsets as the gold standard in research, may be closer than we think (Di Flumeri et al., 2019). With improvements to these results using novel recording, feature extraction, and classification techniques, the list of applications for these portable devices is sure to grow exponentially.

Future Directions

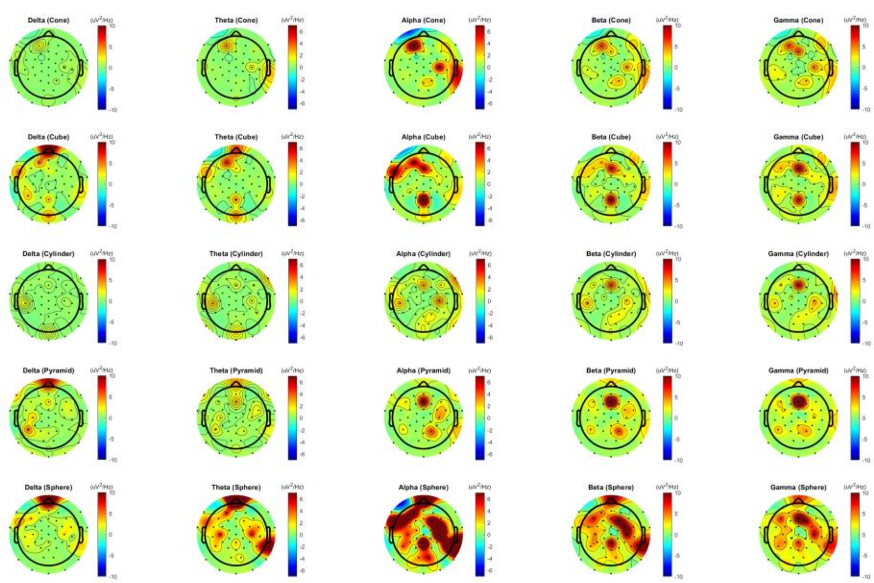
The realm of BCI applications using shape mental imagery is currently small, but has great potential. Looking forward, the same general idea used in this study and ones like it could be used to reliably generate not only common 3D shapes like pyramids and spheres, but also to create more complex shapes. These systems could even generate objects made up of multiple shapes. With better hardware, computational power, and a deeper understanding of the neuroscience of imagery, these things are possible.

CAD software is a natural platform for such an interface, as it is a drawing board in a 3D space already equipped with the tools for building and manipulating complex objects. Being simulative in nature, it is easy to prototype builds with ease without the use of materials. Thus, a primary goal for future versions of this study would be to create actual output in a virtual environment. Many CAD programs, at the same time, are used for the eventual 3D printing or manual building of the virtual objects. Using a BCI interface, it could be possible to create out in the world a physical sculpture of a mental representation within minutes. In the future, it could be possible to derive a person's mental images from scratch, after, of course, some training (though there are labs that develop 'neural cryptography' methods for decoding activity without training data, see: Dyer et al., 2016). Not only would this be a game changing form of communication and physical interaction for individuals with locked-in syndrome and movement disorders, but this would be a potentially new tool to study imagery and the brain. By approximating mental representations as physical structures using a BCI, and then tuning that output to make those approximations more precise to their intended form, it is possible to create objects at an unprecedented level of fluidity beyond what we can even do with our hands. The possibilities, then, for what can be made using mental imagery are limited by one's imagination and the accuracy of what a computer can detect and generate.

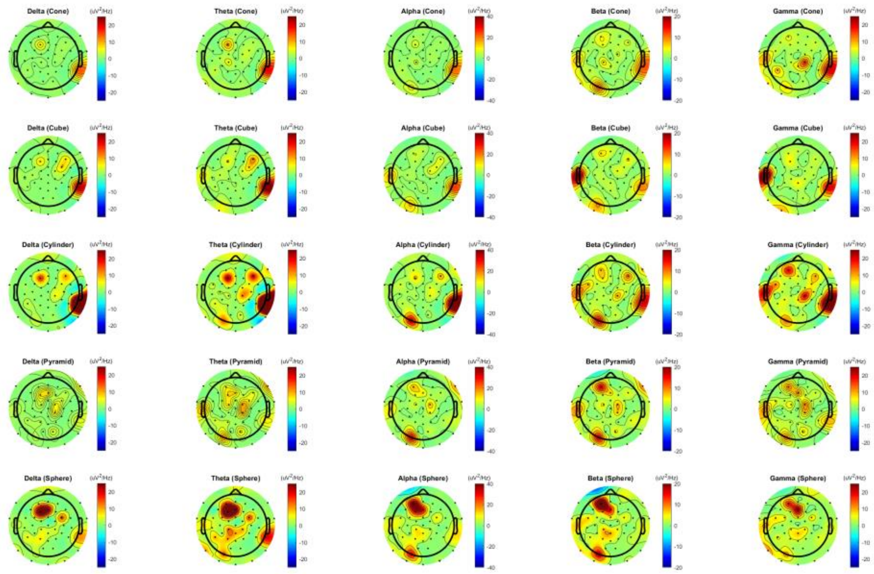
But why stop at consciously intended sculpting? BCIs provide an interface with a part of the human body that often reflects processes both conscious and unconscious. It's entirely possible create a window into human unconsciousness via sculpting, to put a visual imagery-based BCI "on autopilot" and observe what kind of formations are made from unconscious mental states, much like how one plays mindlessly with clay. Perhaps these unconscious or subconscious structures would appear as consciously generated ones do. Perhaps they would appear differently. It is possible that we use the amorphous structures as representations of mental states, which may represent those states better than even words can. This is the beauty of BCIs. They revolutionize human tool usage. There are, of course, many years of research to be done before reaching the level of complexity that fantasy can take us. Though at the rate that technology is developing and with the growing interest in BCIs, who knows what can be accomplished in the next few years?

Appendix A: Individual Topographies

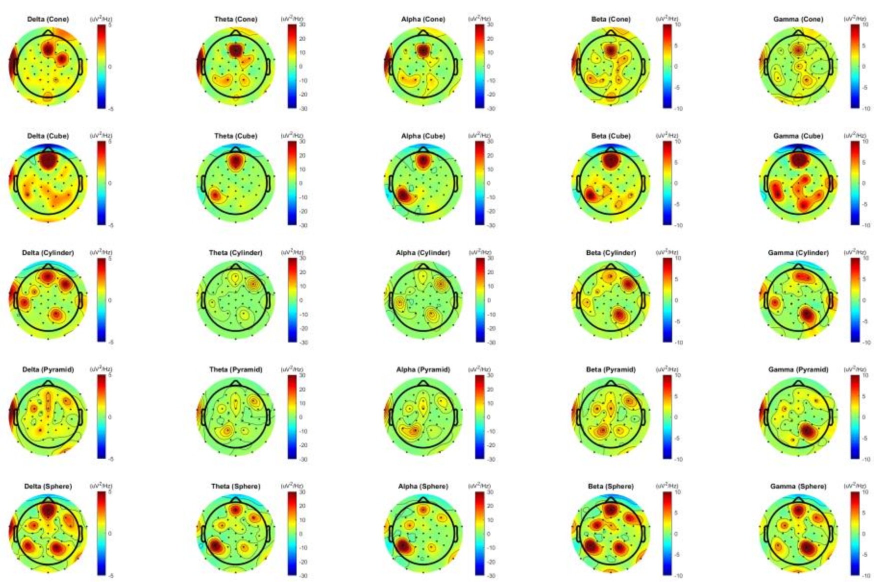
Looking at the individual scalp distributions shows a somewhat clearer activity, and it is likely that the averaging process did, in fact, conceal the more uniquely individual activity. The individual data in Experiment 2 (Figure 12), however, appears somewhat anomalous in comparison to these topographies, further suggesting a separate issue possibly related to recording, or something specific to the participant. One more fact worth mentioning is that the participant with the strongest left hemisphere activity, Participant 6, also had the highest classification accuracy (70%). Though we did not explore this, there could be a correlation between the strength of activity on this side and classification accuracy.



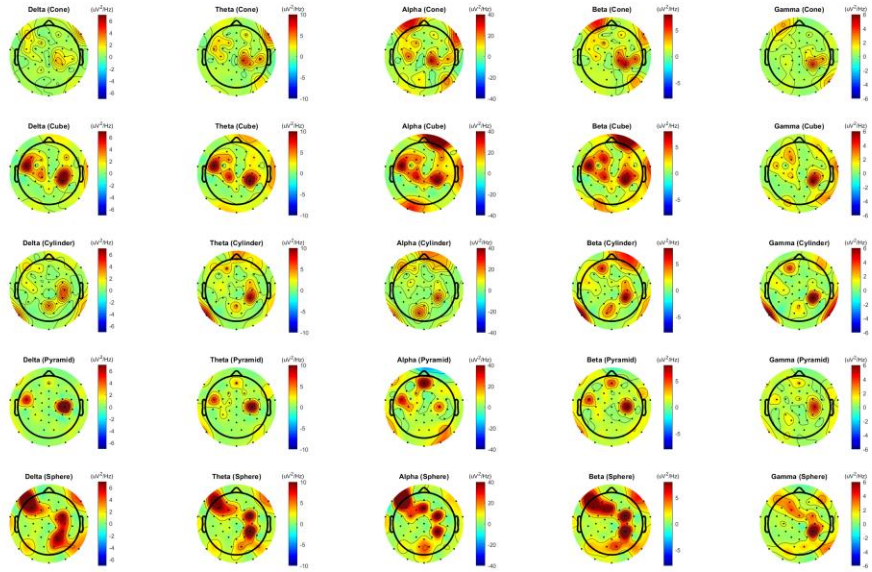
Participant 1: Avg. Accuracy = 30%



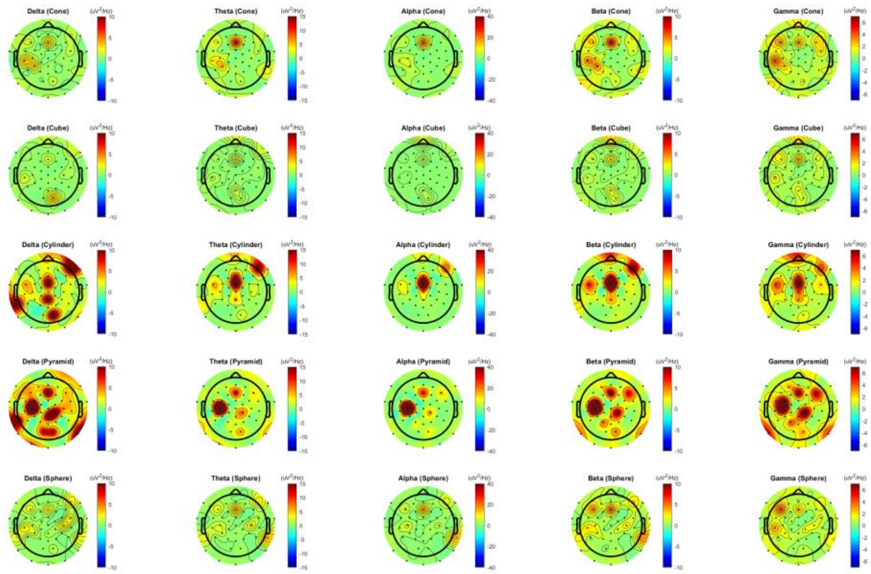
Participant 2: Avg. Accuracy = 50%



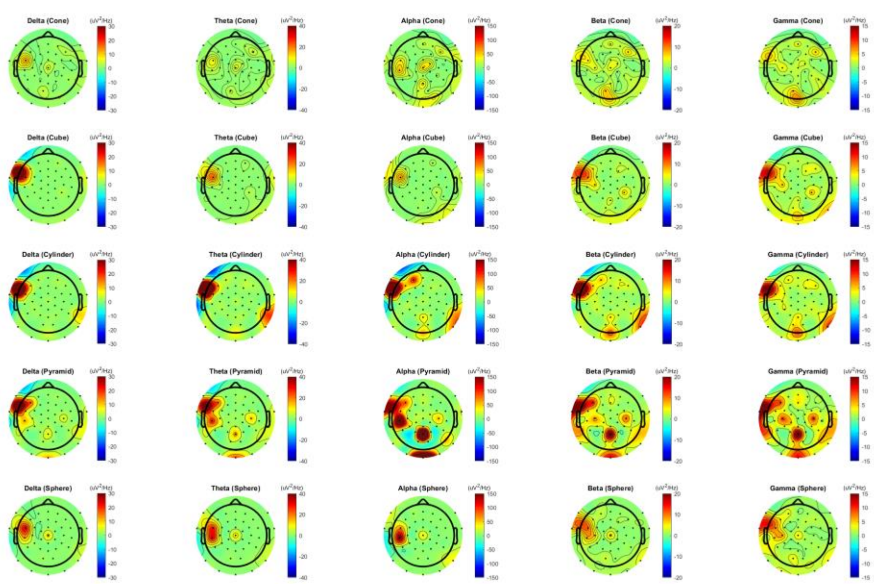
Participant 3: Avg. Accuracy = 40%



Participant 4: Avg. Accuracy = 30%



Participant 5: Avg. Accuracy = 40%



Participant 6: Avg. Accuracy = 70%

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