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Plug in the Brain: Evaluating the Usability of Brain Computer Interfaces

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ABSTRACT: Over the past few decades Brain Computer Interfaces (BCIs) have moved from the realm of science fiction to commercially available products. There is now a large body of research available on BCI – from different techniques for detecting brain activity to trials on implementations. Advances in neuroscience have provided understanding on how our brains work and technological improvements have made real-time monitoring possible. Now that BCI is starting to become a reality there is a growing awareness of other issues affecting BCI systems beyond just the "how". One of these areas is the usability of BCI systems – how can/should they interact with them, what are the limitations and what benefits do they offer.

Current techniques can be grouped two main ways – the type of technology used and the interaction paradigm used. Technology approaches include invasive surgery and non- invasive approaches (e.g. EEG, MEG, fMRI and NIRS.) Interaction paradigms are divided into evoked potentials and spontaneous invocation. While the main research in BCI is around speed and accuracy there is some research into usability. Examples include the learnability of BCI systems, investigating possible interactions and evaluating commercial products. While BCI has become possible it still has a long way to go before it becomes an everyday technology. Improving speed and accuracy, reducing learning times, minimizing cognitive work, enhancing equipment and providing feedback are all rich areas for improvement.

KEYWORDS: Brain-computer interface (BCI), usability, interaction styles

ACM Classification Keywords
H.5.2 **[INFORMATION INTERFACES AND PRESENTATION]**: User Interfaces - *Input devices and strategies, Interaction styles*; H.1.2 **[MODELS AND PRINCIPLES]**: User/Machine Systems - *Human factors, Human information processing*;

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I. INTRODUCTION

Brain-computer interfaces (BCIs) have been researched for over three decades now. What once was purely in the realm of science fiction is now an emerging discipline with great potential. Potential uses for BCI systems include com- munications, controlling the environment (including mobility), recreation (e.g. games, music, art, etc.), aug- menting cognition and detecting emotional and mental state [7, 12].

Research into BCI started in the 1970s at the University of California Los Angeles [3]. The initial idea of BCI was to "read" the brain and use these signals to control prosthetic or robotic devices, especially for those who by reason of disability are unable to do so themselves. However the potential of BCI has grown and researchers are now investigating a wide range of other areas – both for normal and disabled people – from recreational use to assisting in space [7].

These advances have been possible because of improve- ments in many different areas. For example, advances in neurology have allowed a greater understanding of how the brain works. Advances in technology have allowed for improved or new types of equipment for detecting brain signals. And improvements in algorithms and processing techniques have allowed converting the mass of raw data into recognisable input. Today BCI is no longer a question of is it possible, but instead how can it be used.

Most research in BCI looks at the technical issues in BCI. How can brain signals be detected? How can these signals be converted into input that a computer understands? How can speed and accuracy be improved? Early research has provided many avenues of investigation that are still being explored in these technical areas of BCI.

However now that BCI is possible an interest is growing in going beyond just the technical "how" of BCI. A growing area of BCI research is the usability of BCI [5]. Over the years many different technologies have used to interact with computers – from punch cards to keyboards to mice to touch screens. Just because something is possible does not mean that it is usable – there may be limitations on what it can do, possible side-effects or disadvantages. So some current usability questions in BCI are is it beneficial? How can it best be used? And what are the limitations? The answers to these questions will provide a better under- standing of BCI.

This paper starts with an overview of some BCI techniques and interaction paradigms. This is followed by a review of current usability studies around BCI – including learnability, interaction approaches and current commercial products. Finally this report closes by summarizing the current state of usability of BCI and looks at some future directions for research.

II. CURRENT TECHNIQUES

Two ways of classifying the different BCI systems are by the input techniques used and the type of interaction paradigms. Input techniques are divided into invasive and non-invasive techniques, and the current interaction para- digms are evoked potentials and spontaneous invocation.

Invasive techniques are when electrodes are surgically implanted directly into neural tissue. They can be directly attached to single neurons or merely inserted into a general region of the brain. While invasive techniques offer the highest quality signals they require surgery to implant and tend to degrade over time. The degradation of signal requires further surgery to replace electrodes and can lead to a build-up of scar tissue. Currently most research using invasive techniques only uses rats or monkeys as subjects due to these limitations [3, 7, 10].

One variation on invasive techniques is to implant the electrodes into the skull instead of the neural tissue. This reduces some of the risks involves in surgery, including the problems with degradation. However this approach suffers from some of the same issues as EEG including not being able to identify activity in specific areas of the brain [7].

In contrast non-invasive techniques detect brain signals without using surgery. The first studied and most widely used today of these techniques is the electroencephalogram (EEG). Other techniques include magneto encephalography (MEG), functional magnetic resonance imaging (fMRI) and near infrared spectroscopy (NIRS) [3].

Using EEG involves attaching electrodes to the surface of the head and detecting the electrical signals produced by the neurons firing. This approach is generally easy to use as the equipment is lightweight and can be non-intrusive, but it does have some limitations [3, 9, 17]. First an EEG only detects the summation of neural activity – it cannot detect the activity of individual neurons. Depending on the locations of the electrodes it has some limited ability to detect which region of the brain is active, but this is very general. EEG tends to be better at detecting whole brain activity, e.g. level of attention, arousal or consciousness, etc. Second most EEG techniques require direct skin and need the electrodes to the precisely placed – requiring some time to set everything up [9, 17]. Finally EEG signals are sensitive to external noise (e.g. muscular and cardiac electrical signals, movement artefacts, equipment noise, etc.) [7]

Investigating how to overcome some of the limitations in EEG input is currently an important area of research. The EEG setups that are used in laboratories or clinical settings are often impractical for other settings. For example, applying the electrodes can require precise placement, direct contact with the skin, applying a gel, etc. Different groups are trialling different approaches to overcoming these issues. For example Fernandes, *et al.* have developed a "brain cap" that does not need exact placement [9]. Most commercial BCI products use a headset that helps provide the exact placement needed [16, 17].

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MEG involves detecting magnetic signals given off by electrical activity in the brain [2]. It provides better spatial resolution to detect which areas of the brain are active, is able to detect deep neural activity and is less sensitive to external electrical interference. However MEG requires expensive bulky equipment, limited the locations where it can be used. And it is very sensitive to external magnetic noises (e.g. from urban environments.)

fMRI is similar to MEG in that it uses a magnetic field to detect blood flow within different regions of the brain. The regions of the brain that are active have a higher blood flow which can be detected by fMRI. Like MEG it offers a high spatial resolution, the ability to detect deep activity and can detect real-time changes. And like MEG it also suffers from needing expensive bulky equipment [3]. Another limitation is due to the large magnetic field generated by the scanner – it is not possible to use it around metal (e.g. inside the subject or in close proximity.)

NIRS is a recent approach to detecting neural activity. Like fMRI it detects cerebral blood flow as an indicator of neural activity [3]. Instead of using magnetic imaging it uses an infrared monitor to detect an increase in surface blood flow. This increase in blood flow can then be mapped to the underlying brain region. Unlike fMRI it is a low-cost and portable approach [1, 14]. Initial evaluations comparing NIRS to EEG have indicted both are roughly comparable for some types of task (e.g. mental state [18].) The main disadvantage of NIRS is it is not a direct measure of neural activity. And like EEG it suffers from a lack of spatial resolution.

A second way of grouping BCI systems is by the interaction paradigm used [7, 18]. The two primarily paradigms currently being investigated are evoked potentials and spontaneous (or intentional) invocations.

An evoked potential is when some external stimulus is presented to the subject and the subject responds to it. Typically the subject is presented with a range of options and told to focus on the desired option (e.g. a picture or sound.) The various options are then selected randomly (e.g. the picture highlighted or sound played.) When the desired option is selected the subject's brain has a peak in activity which can be detected. Currently the two most common triggers are visual and auditory stimuli [23]. Common variations on this approach is the P300 signal (a peak in neural activity 300ms after the desired option is selected), μ and β rhythms (different types of brain rhythms) and steady-state (when the brain settles into a specific pattern) [23].

In contrast spontaneous invocation is when the subject initiates the command. The BCI system then detects the command and performs some action based on the thought patterns of the subject [7, 21]. In this approach the interface either detects a change in overall neural rhythm or an increase in activity in a specific area of the brain.

Most research focuses on evoked potentials as these signals are easier to detect with the current technology available. However the main limitation of this approach is the need for the external stimulus. The stimulus requires a certain amount of space, depending on the type of stimulus, and can interfere with other interaction modalities [4, 7]. In addition there is a limit to the rate at which the stimuli can be presented. This has the effect of limiting the amount of options that can be presented or in reducing the accuracy of detection.

III. USABILITY

Currently there are few studies looking at the usability of BCI systems; most studies on BCI systems look at different techniques used to detect input from the brain. Commonly they are interested in the accuracy and speed of BCI interfaces.

For example Manh, *et al.* reported on achieving an 87% accuracy rate for detecting a spontaneous invocation [15], Hongyu *et al.* achieved between 86% and 92% accuracy for a VEP system [11], Shih-Chung, *et al.* achieved 90% accuracy with a VEP system [19] and Yazdani, *et al.* achieving 80% for a P300 system [22] (all systems were used EEG.) Speed for BCI systems is typically reported in either bits per second or bits per minute – where a bit is a single binary decision. Kauhanen, *et al.* reported bits rates from 0.02 to 8.00 bits per minute [13] and Shih-Chung reported an average rate of 0.67 bits per minute [19] – both systems were detected spontaneous invocation commands. In contrast Edlinger, *et al.* reported achieving rates of up to
84 bits per second using externally evoked signals [8].

While accuracy and speed influence the usability of BCI systems they are not the only issues that need to be considered. Recent researchers have started to look at other ways that usability applies for BCI systems. Issues include

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learnability, potential interaction options, the effects of using BCI together with other input modalities and the effectiveness of current commercial products.

One important area currently being researched is learn- ability – how easy is it for a person to start with the new interface and how quickly can they become competent using it. This is especially an issue in BCI systems where significant time is needed to start using the system – both for the user and for system itself [8, 13]. This training period can go from several hours to several weeks! Part of the reason for this learning period is everybody has slightly different neural patterns; which means that a system which is accurate for one person may be inaccurate for another. To further complicate things people's brains are plastic and can adapt to different stimuli; meaning that over time a system may lose accuracy. Both of these lead to a dilemma in BCI– how can training time be minimized while still maintaining a high accuracy rate?

Kauhanen, *et al.* looked at how they could build a simple EEG system that only needed a 30 minute training period [13]. To achieve this they combined machine learning techniques together with supervised learning. This had the advantage that both computer and user were learning how the other part reacted – which in theory means they would meet on common ground somewhere in the middle. They trained several subjects using a spontaneous invocation system and then tested how accurate the system was. They reported mixed results from their experiment – some subjects were able to achieve reasonable accuracy (79%) and speed (up to eight bits/minute) others had an accuracy no greater than random chance and/or slow speeds (down to 0.02 bits per minute.) They stated that while their results were contradictory, their approach did compare favourably with other studies that took much longer to achieve similar results.

Another study on BCI learnability was performed by Edlinger, *et al* [8]. They were interested in seeing whether training could be transferred between similar BCI systems. Their approach compared two P300-based EEG systems with visual menus. The subjects were initially trained on a spelling system and then transferred to a home control system. The initial training time with the spelling system was around 40 minutes to achieve a reasonable accuracy rate; then they were transferred to the control system. They managed to achieve 83%-100% accuracy rates without needing any additional training. This showed that training can be transferred between similar BCI systems.

Another area in usability is looking at what type of inter- faces should be used. Currently most interfaces are dictated by the technology used (especially for evoked potential systems) so the question still stands as what would be the ideal interface. Given the potential popularity of spontaneous invocation systems what would be the best type of interaction? To try and answer this question Bos, *et al.* performed a series of experiments where BCI systems were connected to games [4, 5]. They used different types of games and tried different types of interactions. As well as identifying a potential "best" interaction style they wanted to know how BCI would affect other input modalities.

Their first experiments involved simple games that were directly controlled by a keyboard, mouse or Wii remote [5]. The BCI input was used to modulate the effectiveness of the main input – when the user was more relaxed they had greater control over their avatars within the game. This identified that BCI input could be used together with other input modalities and it could have a significant effect on the game.

Going one step further they then investigated what people would desire as the "ideal" interaction style [4]. To do this they looked at a popular video game (World of Warcraft) and surveyed players as to how they would like to use BCI input. This identified three potential ways of interacting – inner speech, association with the task and overall mental state. They then evaluated these three interactions against both an "ideal" implementation and an actual implementation.

For the "ideal" implementation they identified ease of use and enjoyment as the most important factors affecting usability. Inner speech was the preferred interaction to use due to its ease of use and minimal mental requirement. For the actual implementation group the main factor was the recognition rate of the system. Mental state – the method requiring the most effort – was the best trigger for the BCI system. Users preferred to expend more effort in order to achieve higher accuracy rates, although this lowered the enjoyment of the game. From this they concluded that the current focus on accuracy is important for helping BCI systems mature and as BCI systems become more accurate people will find better ways of interacting with them.

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A third area of research is evaluating the usability of the commercial products currently available. Now that BCI has been proven to work outside the lab companies have started to produce mass-market interfaces. Examples of products include the Neural Impulse Actuator from OCZ, the MindSet from NeuroSky and the EPOC from Emotive systems [3, 20]. These systems are all variations of EEG- based headsets and they are all available for under US$500.

Ranky and Adamovich evaluated the effectiveness of the Emotive EPOC headset [16]. This device uses 16 electrodes, allowing some limited detection of active brain areas as well as detecting overall mental state. They connected the device to a robotic arm and attempted to control it using spontaneous invocation. Their greatest difficulty with the device was the system had difficulty detecting some of the commands. They also mentioned the need for significant training time – three days per week for two weeks.

Crowley, *et al.* and Rebolledo-Mendaz, *et al.* evaluated the Neuroskey MindSet [6, 17]. The MindSet is a simpler device than the EPOC with only three electrodes and as such can only monitor the general mental state. The headset measures the levels of attention and mediation of the subject on a scale of 0 to 100.

Both studies mentioned the device was reasonably accurate and did actually measure mental state against self-reported values. However they did find some limitations with the device. Some of the subjects were unable to correctly fit the MindSet due to either head size or hair; which meant more time was required to fit the device correctly. The batteries on the MindSet did not have a long lifespan and the device did not provide any notification that the batteries were flat. And the sampling rate was only 1 Hz with a 7-10s delay at the start of recording or after loss of signal.

Despite the various limitations mentioned all studies agreed that using BCI enhanced the user's perceptions of the computer systems. Users in the Rebolledo-Mendaz, *et al.* thought the system was more responsive to their desires with the BCI input [17] while Crowley, *et al.* found the input could accurately identify when users were becoming stressed [6].

IV. SUMMARY

The current literature shows that BCI systems have indeed moved from the realm of pure science fiction into reality – but only just! Current BCI systems tend to be slow and inaccurate, often with long training times and limitations on where they can be used. However technology is constantly improving – especially for accuracy and speed – and people are starting to investigate the actual usability of BCI systems.

Three areas of current research are learnability, interaction types and commercial product evaluation. Learnability is important as most current BCI systems have long training requirements – so anything that can reduce training time will enhance usability. With current accuracy rates the types of interactions are very limited but when accuracy improves more interaction types will become available. And now that BCI is becoming a commercial reality it is important to know the limitations of the current products on the market.

V. FUTURE WORK

Given the current lack of research on the usability of BCI systems there is a huge number of areas which knowledge in this area can be expanded. Some possible avenues for research include:

- Improving the accuracy of input. This is especially relevant for spontaneously invoked systems that detect user initiated commands.
- Improving the speed of data transfer. Again this is especially relevant for spontaneously invoked command systems.
- Investigate the different interactions styles that can be used with BCI systems. This also includes looking at which styles are best for different types of interactions and different desired outputs.
- Investigate how to provide feedback for BCI systems. Currently all BCI systems reported are input-only – other modalities are used to report feedback back to the subject. This area could include looking at direct (i.e. neural) feedback or how to best utilise other modalities to provide feedback.

- Investigate the effects of BCI systems on cognitive load. Some environments already impose a signifi- cant cognitive load on individuals. How would using BCI systems influence this load and what can be done to minimize any increases?

- Improve the learnability of BCI systems. Most BCI systems require long training times to achieve high accuracy rates. What can be done to either minimise these training times or to transfer the learning across different BCI systems.

- And finally how can the equipment be improved to achieve the above goals. This is especially important for moving BCI out of the labs and clinics and into mainstream use.

REFERENCES

1. Abibullaev, B., Won-Seok, K., Seung-Hyun, L., and Jinung, A. Recognition of brain hemodynamic mental response for brain computer interface. In ICCAS. (2010), 2238-2243. http://ieeexplore.ieee.org/search/freesrchabstract.js p?tp=&arnumber=5669841
2. Battapady, H., Lin, P., Ding-Yu, F., Huang, D., and Ou, B. Single trial detection of human movement intentions from SAM-filtered MEG signals for a high performance two-dimensional BCI. In EMBC 2009. IEEE Int. Conf. (2009), 524- 527. http://dx.doi.org/10.1109/IEMBS.2009.5333632
3. Biao, Z., Jianjun, W., and Fuhlbrigge, T. A review of the commercial brain-computer interface technology from perspective of industrial robotics.
4. In ICAL 2010 IEEE Int. Conf. (2010), 379-384. http://dx.doi.org/10.1109/ICAL.2010.5585311Bos, D.P.-O., Poel, M., and Nijholt, A. A study in user-centered design and evaluation of mental tasks for BCI. In 17th Int. Conf. on Adv. In Multimedia Modeling. (2011), 122-134. http://dx.doi.org/10.1007/978-3-642-17829-0_12 Bos D. .- . euderink B. van de aar B.
5. rk k . hl, C., Poel, M., Heylen, D., and http://portal.acm.org/citation.cfm?id=1852611.185
Nijholt, A. Human-Computer Interaction for BCI Games: Usability and User Experience. In CW 2010 Int. Conf. on. (2010), 277-281.
6. http://dx.doi.org/10.1109/CW.2010.22
Crowley, K., Sliney, A., Pitt, I., and Murphy, D. Evaluating a Brain-Computer Interface to Categorise Human Emotional Response. In ICALT 2010 IEEE Int. Conf. (2010), 276-278.http://dx.doi.org/10.1109/ICALT.2010.81
de Negueruela, C., Broschart, M., Menon, C., and del R. Millán, J., Brain–computer interfaces for space applications. Pers. and Ub. Comp., (2010), 1-11. http://dx.doi.org/10.1007/s00779-010-0322-8
http://dx.doi.org/10.1109/BICTA.2010.5645129 Hongyu, S., Yang, X., Yaoru, S., Huaping, Z., and
7. Jinhua, Z. On-line EEG classification for brain-
8. computer interface based on CSP and SVM. In CISP 2010 3rd Int. Cong. (2010), 4105-4108. http://dx.doi.org/10.1109/CISP.2010.5648081
9. Jackson, M.M. and Mappus, R., Applications for Brain-Computer Interfaces. Brain-Computer Interfaces, (2010), 89-103. http://dx.doi.org/10.1007/978-1-84996-272-8_6
10. Kauhanen, L., Jylanki, P., Lehtonen, J., Rantanen,P., Alaranta, H., and Sams, M., EEG-based brain- computer interface for tetraplegics. Intell. Neuroscience, (2007), 1-11. http://dx.doi.org/10.1155/2007/23864
11. Kohlenberg, J. and Chau, T. Detecting Controlled Signals in the Human Brain by Near Infrared Spectroscopy. In EMBS '06. 28th IEEE Ann. Int. Conf. (2006), 5480-5482. http://dx.doi.org/10.1109/IEMBS.2006.259877
12. Manh, N.V., Vinh, P.Q., Viet, H.A., and Thang,H.Q. A general model for digitalizing human being's thought: MiMaS. In Proc. of the 010 Sym. on ICT. (2010), 16-22.615
13. Ranky, G.N. and Adamovich, S. Analysis of a commercial EEG device for the control of a robot arm. In Bioengineering Conf., roc. of the 2010 IEEE 36th Ann. (2010), 1-2. http://dx.doi.org/10.1109/NEBC.2010.5458188
14. Rebolledo-Mendez, G., Dunwell, I., Martínez- Mirón, E., Vargas-Cerdán, M., de Freitas, S., Liarokapis, F., and García-Gaona, A., Assessing NeuroSky's Usability to Detect Attention evels in an Assessment Exercise. Human-Computer Interaction. New Trends, (2009), 149-158. http://dx.doi.org/10.1007/978-3-642-02574-7_17
15. Rutkowski, T.M., Zhao, Q., Cichocki, A., Tanaka, T., and Mandic, D.P., Towards Affective BCI/BMI,
16. Edlinger, G., Holzner, C., Guger, C., Groenegress, C., and Slater, M. Brain-computer interfaces for goal orientated control of a virtual smart home environment. In *NER '09. IEEE/EMBS Int. Conf.* (2009), 463-465. http://dx.doi.org/10.1109/NER.2009.5109333
17. Fernandes, M., Dias, N.S., Nunes, J.S., El Tahchi, M., Lanceros-Mendez, S., Correia, J.H., and Mendes, P.M. Wearable brain cap with contactless electroencephalogram measurement for brain- computer interface applications. In *NER '09. IEEE/EMBS Int. Conf.* (2009), 387-390. http://dx.doi.org/10.1109/NER.2009.5109314
18. Haifang, L., Xiaoyan, Q., Junjie, C., and Jie, X. The study of data analysis methods based on FMRI brain-computer interface. In *BIC-TA 2010*
19. *IEEE Int. Conf.* (2010), 989-993.