Brain Computer Interaction: State of the Art

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ABSTRACT

This paper attempts to provide an insight into current Brain-Computer Interaction (BCI) research, and review the state of the art. It provides a general overview of the methods of data acquisition (primarily focussing on non-invasive EEG BCI technology), detailing specific studies into pivotal experiments in BCI research, such as experimentation performed into the "Common Spatial Pattern" analysis technique popularised by C. Guger (cited by 55 other papers, according to Google Scholar). Further, it attempts to explain in non-scientific terms how the data obtained from an EEG is analysed in a useful manner. Finally, the paper describes some practical applications of BCI technology, such as aiding physically disabled persons and as an input device for computer games.

ACM Classification Keywords

H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION

With the recent announcement of the OCZ "Neural Image Actuator" (NIA) in 2008 [OCZ, 2008], media attention has been directed towards the BCI community, and the potential it presents. While BCI technology is still in very early stages, research has been ongoing from as early as 1994 [Wolpaw and McFarland, 2004], and is now reaching a more mature level. Research completed at the Pontifical Catholic University of Peru indicates that commodity hardware with as little as 256MiB of RAM can now approach real-time BCI translation [Tupayachi et al., 2006], and OCZ make note of the proliferation of multi-core CPUs in modern hardware as one of the reasons their product has become commercially viable. There are still several complications in the path forward for using BCIs as viable input mechanisms, but research continues at an extremely rapid pace.

Due to the clinical risks associated with invasive BCIs, most current research focusses on non-invasive methods of interacting with the brain. Ostensibly, the most popular non-invasive BCI technology is Electroencephalography (EEG), in which electrodes are placed on the scalp of a person in order to measure brain activity. While not as accurate as invasive BCI technology, EEGs can still provide interpretable data to researchers.

However, non-invasive BCIs preclude any form of computational output being fed back to the brain (as in neurofeedback). Non-invasive BCI technology means that the brain is viable as an input device. This has led to applications across several domains, including as an assistive technology for disabled persons (replacing joysticks on wheelchairs, for instance), for video-gaming, or even to aid in musical input. Mention that this focusses on input only.

READING THE BRAIN

The core focus of current BCI research is how best to use data obtained from Electroencephalogram (EEG) readings, and standardisation of practises involved in obtaining this information. Consequently, several academic papers (such as [Blankertz et al., 2004]) revolve around the use of different algorithms for decreasing errors found in data, and increasing the accuracy of EEG readings while increasing the efficiency of algorithms used.

Methods of Reading the Brain

Methods of reading the brain broadly fall into two categories: invasive and non-invasive. Invasive methods of obtaining data from the brain involve physically attaching electrodes to the brain of the subject, and carry a large amount of risk. The two prominent fields of research in this regard involve inserting electrodes into the brain [Gopal et al., 2006], or inserting electrodes onto the brain, in the subdural space (the space between the skull and the brain) as used in Electrocortographical readings [Leuthardt et al., 2004].

The data obtained from invasive BCI technology is of a substantially higher spatial resolution than that obtained from non-invasive methods; [Leuthardt et al., 2004] estimates the spatial resolution of ECoG technology to be as small as tenths of millimetres, as opposed to centimetres in EEG technology. However, the substantial clinical risk involved with directly attaching foreign objects to the brain means that invasive BCI research is primarily executed on "non-human primates" (as discussed in [Wolpaw and McFarland, 2004], [Gopal et al., 2006]). Figure 1 displays a picture obtained by [Leuthardt et al., 2004] during ECoG research (subjects in this case were healthy human patients who vol-

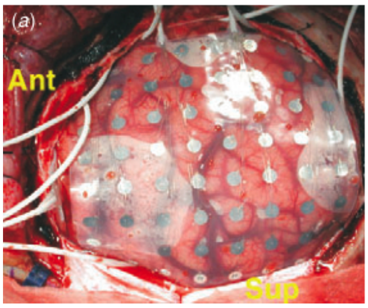

Figure 1. An image obtained from a report by [Leuthardt et al., 2004], depicting electrodes attached to a human brain during ECoG based BCI research. The clinical risks of such research cannot be understated, and other invasive research at this stage focusses on "non-human primates" [Gopal et al., 2006].

unteered and consented to the trial), illustrating how ECoG systems are deployed.

Non-invasive BCI interfaces typically revolve around the use of EEG technology, however, there has been some success recently using functional Magnetic Resonance Imaging (fMRI) [Wang et al., 2005]. Most commonly referenced academic papers (such as [Wolpaw and McFarland, 2004], [Guger et al., 2000], [Tupayachi et al., 2006], [Blankertz et al., 2004]) make use of the substantially more mature EEG technology, and this paper focusses on the current state of EEG research. This attention is spurred by participants at the 2005 BCI conference voting non-invasive EEG research "more desirable" [Birbaumer, 2006].

How Electroencephalograms Work

EEG data is obtained by placing electrodes on the scalp of a subject. These electrodes measure the electrical potential at the positions they have been placed, which is indicative of brain activity. In turn, based on the positions and patterns of brain activity, useful data is obtained.

One of the major issues associated with using data obtained from EEGs as opposed to data obtained from invasive methods is that the spatial resolution, and the accuracy of the data obtained is decreased. Typically, electrodes used in EEG based experiments can only obtain amplitudes of 10µ V to 50µ V (as found by [Leuthardt et al., 2004], [Tupayachi et al., 2006]) compared to an electrical earth, meaning that equipment providing amplification of significant magnitude is required to obtain useful data. According to one experiment, [Tupayachi et al., 2006], equipment capable of approximately a 50,000 level gain was necessary to obtain useful data. This can introduce significant noise to the signal. Conversely, data obtained via ECoG can have an amplitude of up to 100µ V [Leuthardt et al., 2004]. In order to address this problem, typically a form of conductive gel is placed between the EEG electrode and the scalp (in order to reduce electrical impedance). While this provides some success (in one experiment, the reduction in impedance is measured to be in the range of 5kΩ [Wang et al., 2005]), it cannot

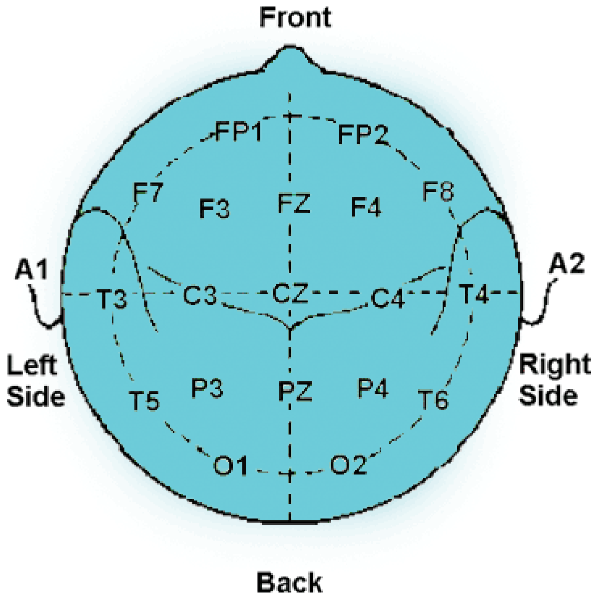

Figure 2. An image describing the international "10-20" system for the placement of electrodes, designed so that EEG researchers could easily describe the locations of electrodes placed on the scalp of a subject. All odd numbered electrodes are on the left hemisphere, and all even numbered electrodes are on the right hemisphere. The name "10-20" is derived from the fact that the distance between electrodes is either 10% or 20% of the horizontal or vertical length of the skull.

be denied that invasive BCIs provide substantially more viable data, and the larger BCI community does recognise this fact [Birbaumer, 2006].

However, data obtained via EEG is still perfectly usable. Figure 2 shows the locations of electrodes placed according to the international "10-20" system. Typically, current BCI techniques involve obtaining data from the primary sensorimotor cortex, and thus several experiments focus on data obtained from electrodes in positions C3 and C4. Figure 3 shows the positions in which electrodes were placed in one of the seminal papers in BCI research [Guger et al., 2000].

The sensorimotor cortex is used as a primary source of information in several BCI experiments due to the viability of sensorimotor rhythms as a control mechanism. This is because when imagining physical movement (for instance, moving your left or right hand), sensorimotor rhythms display an "event-related de-synchronisation" close to contralateral primary motor areas. That is, when one imagines physically moving, a notable difference in electrical rhythms the brain produces can be observed, especially close to sections of the brain we now recognise as governing movement - in both hemispheres.

Hence, Electroencephalograms work by measuring electrical potentials across the scalp of a subject. These potentials

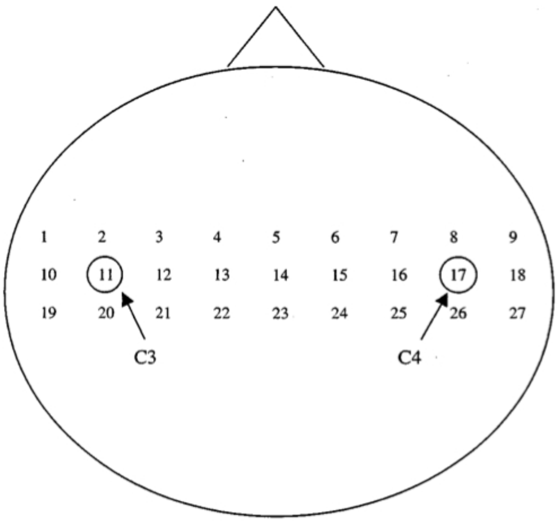

Figure 3. An image showing the locations of electrodes placed on the scalp of a subject in experiments performed by [Guger et al., 2000]. The two electrodes referenced to positions C3 and C3 are marked.

are sampled at regular intervals (which in turn allow observers to see "rhythms" in electrical activity) and amplified to a level useful for study.

Approaches Used to Obtain Useful Data for Brain-Computer Interaction

The general approach for making use of BCI data is to "train" the system for a given subject, and have the computer react to learned patterns. As mentioned, one of the most common topics of recent research papers is how to increase the accuracy of the data obtained; that is, how to correctly recognise brain activity while reducing the effects of artefacts. Artefacts in EEG data are primarily caused by electromyographic (EMG) or electrooculographic (EOG) activity in the brain. EMG signals are produced by nearby muscle activity (such as subjects blinking [Miranda and Brouse, 2005]), and EOG signals are produced by subjects moving their eyes.

Figure 4 is an image obtained from experiments performed by [Guger et al., 2000]. It illustrates a method known as "common spatial patterns", or CSP. The images represent calculated sets of CSP for a test subject; the black dots (of which there are 27) indicate the positions of the electrodes, and the crosses indicate the positions of electrodes C3 and C4 as according to the 10-20 system (Figure 2). The white areas represent weighting; the whiter the area, the more important the electrodes are for determining usable data from this particular subject. C. Guger's experiment used this information (obtained from a training session) as an approach to reducing the effects of artefacts, however, in most cases it took up to 160 trials to produce accurate data. More recent studies echo this approach, using mathematical algorithms in order to allow the BCI software to adapt to user input, recognising active areas of the brain and "weighting" them in

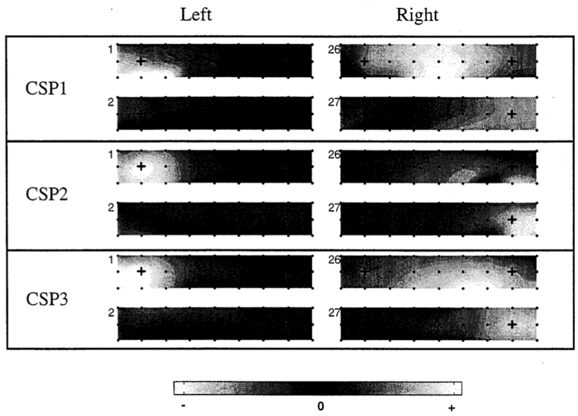

Figure 4. An image showing the weighting of electrode importance in finding useful data from 27 channels of EEG, for a particular subject. The white areas indicate more "important" regions, which receive a higher weighting. This image is obtained specifically from experimentation performed by [Guger et al., 2000].

order to obtain better data [Wolpaw and McFarland, 2004]. However, as recently as 2005 it has been noted that the extensive training sessions necessary for EEG BCI technology are actively hampering research [Birbaumer, 2006].

In [Wolpaw and McFarland, 2004] (in which an attempt at moving a cursor in two dimensions is attempted), data obtained at regular time intervals underwent mathematical analysis (an autoregressive function) in order to obtain the relevant amplitudes, and the changes in them. Pattern recognition of this data is interpreted according to the specific subject, and subsequently, the cursor is moved on the screen. [Wolpaw and McFarland, 2004] makes specific note of the significant improvement in BCI technology with respect to time; Figure 5 shows the increase in accuracy of the technology since an experiment in 1994 [Wolpaw and McFarland, 2004].

An Assessment of the State of EEG-based BCI Technology

As this paper is written from the perspective of an observer of the BCI community rather than a participant, some salient observations can be made. Chiefly is the concern with the variance in the early research completed. Clinical configurations differ widely, with participants in the 2003 BCI Competition [Blankertz et al., 2004] using from six to sixty-four electrodes depending on the situation. This indicates that while research is ongoing, it would perhaps be beneficial to the BCI community to push towards a standardised solution in order to promote the research community, and allow differing groups to accurately compare results.

The BCI community itself also recognises this issue, particularly with regards to "the variance in BCI designs" presented at the first International Meeting of Brain-Computer Technology [Mason and Birch, 2003]. A paper released by the IEEE in 2003 notes the necessity of a "common functional model of a BCI system", in order to facilitate comparisons between

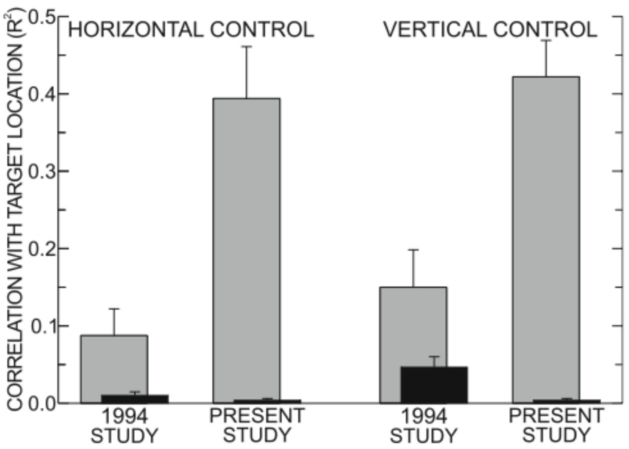

Figure 5. An image showing the relative improvement in R^2 from 1994 to 2004. R^2 measures the correlation between the input variables of a BCI to the desired outcome. That is, the correlation between, for instance, the horizontal signals read from the brain, and the desired horizontal signal for the subject to perform the required operation [Wolpaw and McFarland, 2004].

differing technologies [Mason and Birch, 2003]. The paper proposes such a functional model, defining terms necessary for a system to be classed as a BCI system, and details the creation of this framework. The framework intends to allow direct comparison of BCI systems, by separating them into separate functional areas which can be analysed.

It must be noted that since the proposal of the framework, significant strides have been made towards standardising BCI systems. The development of the BCI2000 software paid specific attention to the framework [Schalk et al., 2004], stating that "BCI2000 is based on a model that can describe any BCI system and that is similar to the one described in [Mason and Birch, 2003]". Since its inception, BCI2000 has released two major versions, and has made its source code available to contributors. It is currently used in several experiments (such as in [Cincotti et al., 2007]), and is free to non-profit organisations (as stated on their site [BCI2000, 2008]).

PRACTICAL APPLICATIONS

As mentioned, current BCI research focusses on increasing the accuracy of data obtained (and the speed at which it is processed), as opposed to how to use that data. However, there are several practical applications for BCI being actively researched, including helping physically disabled (but mentally able) persons, video-gaming, and even developing a Brain-Computer Music Interface (BCMI) [Miranda and Brouse, 2005]. The research into these areas is widely varied (but active), and the diversity of the application domains demonstrates that BCIs could fundamentally change the current HCI paradigm.

BCIs for Disabled Persons

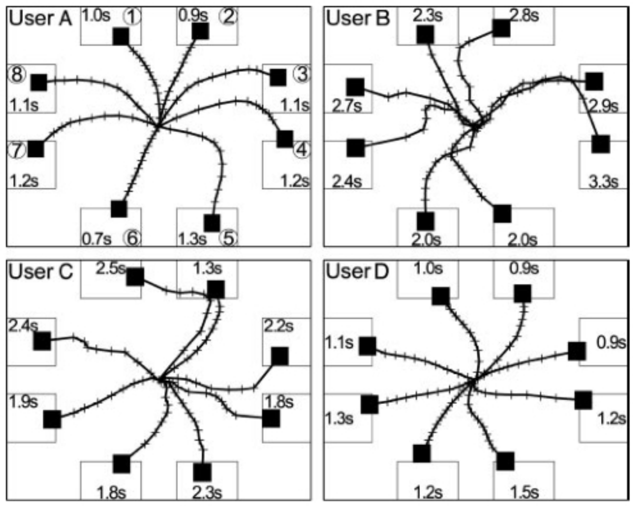

Figure 6. An image depicting the path followed by a cursor being moved in a 2-dimensional space by test subjects in recent research [Wolpaw and McFarland, 2004].

Several experiments approach this particular application domain. It has the potential to drastically increase the quality of life for persons with physical (rather than mental) disabilities; for instance, people with Spinal Muscular Atrophy type II (SMA II) or Amyotrophic Lateral Sclerosis (ALS) have been targetted by research papers as standing to benefit from a non-invasive BCI.

There are several individual ways in which this particular domain can be approached, however. Experimentation in 2004 [Wolpaw and McFarland, 2004] attempted to demonstrate the viability of a BCI as a two-dimensional control interface. While fully abled persons were used as test subjects, the testing confirmed that without moving a muscle (electromyographic activity was monitored), subjects were able to move a cursor through two dimensions with a reasonable rate of accuracy (up to 92%). Figure 6 shows the paths followed by the cursor during testing; the cursor started in the middle of the screen, and patients attempted to move it to the locations displayed purely through EEG activity.

This experimentation paved the way for further research. In 2007, F. Cincotti used the previously mentioned BCI2000 software framework to further study the viability of BCI devices in order to aid disabled persons, as opposed to ocular monitors (using eye movement as a guide) or head trackers [Cincotti et al., 2007]. The experiment compared the results of able-bodied persons to those of disabled persons suffering from SMA II, and attempted to expand the possibilities of BCI software. Instead of focussing purely on the movement of a 2D entity (correlating to a wheelchair), F. Cincotti's experiment studied other aspects where a BCI may be useful - for instance, in increasing home automation (such as turning on lights in a room), reducing the reliance on a third-party caregiver for disabled persons. The experiments were completed with some success, and the paper notes that while a "larger cohort of patients" are needed in order to prove the clinical significance of the study, the "BCI application is promising in enabling people to operate an environment control system". This is a particular application domain towards which EEG BCIs are useful; [Birbaumer, 2006] asserts that they are capable in providing "binary" control - that is, for instance, turning a light off or on.

Finally, experiments completed by the Pontifical Catholic University of Peru attempt to ratify the viability of BCI research in Peru, making specific note of the significant investment traditionally required for BCI research [Tupayachi et al., 2006]. P. Tupayachi's research proves that BCI research can be completed on a computer with only MATLAB and 256MiB of RAM. The hardware external to the PC consisted of cheaper components, such as the ATmega32 (a commodity electronic chipset). The paper asserts that this particular BCI (which only collects 20 channels of EEG) is specifically oriented to the "later construction of a brain computer interface" which could "offer aid to people motor and/or communication disabilities". Again, the results (the construction of a device capable of obtaining BCI data without significant expenditure) prove promising.

BCIs in Video-Gaming

As mentioned, a commercial BCI designed for this particular realm already exists. It should be noted that while the advertising for the product claims it uses EEG activity, the device only uses three electrodes placed directly on the forehead - a significantly different location to the typical C3 and C4 positions targeted by the BCI research reviewed in this paper. As there is no documentation released for the OCZ NIA, one must assume it attempts to interpret different signals to those traditionally used [OCZ, 2008].

Regardless, the commercial viability of a BCI as an input mechanism for video-gaming is a topic that has not gone unnoticed by the wider community. A paper released by the University of Twente, in conjunction with a Microsoft employee, attempts to investigate "the possible role of brain-computer interaction in computer games" [Nijholt and Tan, 2007]. Rather than regarding a BCI input as the primary source of information on a player, however, the paper investigates the possibility of using it to augment an existing interface - by "evaluating the human" during interaction. Interestingly, the paper notes that a BCI could aid in traditional HCI usability testing, perhaps using information obtained to directly evaluate cognitive load. The paper is speculative, but presents some interesting possibilities nonetheless.

CONCLUSION

As can be seen, significant strides have been made in BCI research since its inception. Marked improvements have been made in the accuracy of data obtained, as evidenced by [Wolpaw and McFarland, 2004], in which R^2 increases as much as four times (Figure 5). Further, alongside the ever-accurate predictions of Moore's Law (that the number of transistors on processors doubles roughly every year and a half; from which a correlation can be drawn to performance), the reduction in price of hardware (and the increase in availability of hardware) has led to non-invasive EEG BCI technology becoming more commercially viable ([Tupayachi et al., 2006], [OCZ, 2008]).

Meanwhile, the BCI research community has put significant effort into standardising research. While the 2003 BCI competition [Blankertz et al., 2004] notes a wide variance in equipment used, a subsequent conference led to the development of a framework [Mason and Birch, 2003] allowing for better comparison of BCI results; in turn furthering research efforts. The consequent development of the BCI2000 software [Schalk et al., 2004] has further solidified the effort, and several recent experiments (such as [Cincotti et al., 2007]) have made use of the software.

Finally, it is worth mentioning the ever widening field of application domains. While it has been noted that research currently focusses on developing BCI technology as an aid to disabled persons (noted by [Nijholt and Tan, 2007], and evidenced by [Cincotti et al., 2007], [Guger et al., 2000]), the potential exists to apply the technology in video-gaming [Nijholt and Tan, 2007], HCI usability testing or even musical markets [Miranda and Brouse, 2005]. As research continues (and technical barriers such as cost disappear), one can only expect the practical applications to expand rapidly.

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