The Potential of the BCI for Accessible and Smart e-Learning

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Abstract. The brain computer interface (BCI) should be the accessibility solution "par excellence" for interactive and e-learning systems. There is a substantial tradition of research on the human electro encephalogram (EEG) and on BCI systems that are based, inter alia, on EEG measurement. We have not yet seen a viable BCI for e-learning. For many users for a BCI based interface is their first choice for good quality interaction, such as those with major psychomotor or cognitive impairments. However, there are many more for whom the BCI would be an attractive option given an acceptable learning overhead, including less severe disabilities and safety critical conditions where cognitive overload or limited responses are likely. Recent progress has been modest as there are many technical and accessibility problems to overcome. We present these issues and report a survey of fifty papers to capture the state-of-the-art in BCI and the implications for e-learning.

Keywords: Brain-computer-interface, e-learning, accessibility, disability, artifacts

1. Introduction

It has been argued that the potential of e-learning has never been fully recognized. There are, perhaps, many reasons why this may be so, such as (a) a lack of flexibility or ability to detect and reflect the differing requirements of individual users and (b) problems with accessibility such that some learners may be excluded (e.g. those with disabilities). Recent work has focused on the construction and deployment of simple user models (based on a validated theory of human cognition) to improve the flexibility and accessibility of e-learning systems [1].

Applications of the concept of the brain computer interface (BCI), if shown to be valid, could offer partial solutions to these problems. It has the potential to facilitate e-learning systems with the ability to provide flexible, accessible and adaptive learning solutions. One very significant benefit of the BCI approach is that it has the potential to elicit information on the 'state of mind' of an individual learner (e.g. alert, attentive, drowsy, etc.) and hence to tailor the learning activities to the changing requirements of that individual. Also, the use of BCI would allow users with, for example, limited psychomotor performance or cognitive disabilities to participate more fully in education and training.

Most BCI systems rely on non-invasive measurements of the human EEG (electroencephalogram). Technologies, such as psychophysiological measurements in general and electroencephalograms (EEG) in particular, are not new. Ever since

Hans Berger [2] showed that the electrical activity of the brain could be monitored by electrodes placed on the scalp, attempts have been made to link these signals to the underlying activity of the brain. Berger went on to discover that EEG activity was abnormal in epilepsy which, combined with the work of Walter [3] who showed that slowly varying voltages arose near brain tumours, lead to the widespread use of the technique for routine clinical diagnosis. Debate has continued over the years as to whether this gross, averaged and distorted signal conveys any meaningful information or is merely an interesting phenomenon [e.g. 4]. However, recent advances have shown that Brain Machine Interfaces (BMIs) are becoming a practical proposition [5]. Future technologies built on them promise to revolutionize the emerging Information Society through the development of effective and acceptable brain-computer interface, virtual, augmented realities and augmented cognition. This paper begins with a critical review of psychological and pragmatic issues that must be understood before these technologies can deliver their full potential. Current work has shown that the concepts of usability and accessibility have rarely been applied explicitly to BCI and augmented cognition research. This is changing and while this suggests an increased awareness of these concepts and the related large research literatures, the task remains to sharpen these concepts and to articulate their obvious relevance to BCI work [6].

The concept of the brain computer interface (BCI) presents some startling possibilities for enhanced communication and accessibility: BCIs have the potential for helping individuals with severe communication and control problems due to disability or extreme circumstances, as well as giving anybody who requires or desires non-traditional human-to-system communication tools with additional input/output channels. The notion of BCI may be simple, but the underlying science is complex. Hence, an effective application of BCI necessitates an adequate appreciation of the underlying science. For this reason, this paper sets out to consider the artifacts, the psychology and the rehabilitation engineering underlying BCI, with particular reference to its use for education and e-learning.

There are at least four serious problems that must be faced if the potential of BCI is to be realized. First, the viability of the BCI to deliver a valid reflection of the activity of the human brain must be assured. A normal EEG record contains various artifacts such as the influence of gross motor movements, eye movements, external electro-magnetic influences, etc. Second, the BCI must provide enhanced accessibility and the ability to identify certain parameters associated with the individual learner necessary to support the adaptive customization of education and e-learning systems. Third, different populations of users will have different requirements, so the system must be adaptable (i.e. can be altered before running). Fourth, the requirements of modern users, in the Information Society, are much more nuanced and demanding. The system must not collapse when faced with unfamiliar user requirements. It should be adaptable and capable of adapting whilst running. The overall purpose of this paper is, therefore, to review the current state of the art, with a particular focus on the above.

We propose that an effective BCI system must satisfy the following three axioms:

(1) It is possible to take sensitive and reliable measurements of aspects of human brain activity on a non-invasive basis;

(2) Aspects of human brain activity can be controlled systematically and dependably by the individual;

(3) These measurements of human brain activity can be readily used to control or communicate with interactive systems or to communicate with other people [7].

In addition, we suggest that there are at least three generic requirements that apply to any communication and control system:

- Functionality [8], i.e. does it support important, useful and desirable tasks;
- Usability [9], i.e. is the system too difficult to use;
- Accessibility [10] i.e. are there any barriers that prevent or disadvantage users when using the system?

2. The Human Head and Electrical Signals

The human head has three main layers, namely skull, scalp and brain. There are also many thin layers between them. In the skull area, signals are attenuated by approximately one hundred times [11]. The resultant signal that reaches the surface of the skull is in the order of a few tens of microvolts and represents the average of the activity of a large number of individual neurons firing in the underlying area. Different levels of activity can be picked up depending on the position of the electrode on the surface of the scalp. This, in part, reflects the activities associated with different regions of the brain. The human brain is basically divided into three parts. The cerebrum initiates behaviour such as movement, conscious, sensation, complex analysis, expression and motion. The cerebellum is responsible for the co-ordination and control of voluntary movement and balance of muscle and body. Finally, the brainstem controls involuntary function such as heart regulation and hormone section [12]. The human body can generate a range of different signals but the primary sources are the brain and the muscles. The electroencephalogram (EEG) and magnetoencephalogram (MEG) are generated by the brain. The electromyogram (EMG) originates from the nerve impulses to the muscles. Of these, the electrooclugram or electrooptigram (EOG) generated from the optical nerves and electrocardiogram (ECG) generated from the heart, are of particular importance. Both can lead to a serious disruption of measurement of the EEG and hence can seriously compromise a BCI. The signals from these other sources may be hundreds of millivolts, i.e. several orders of magnitude greater than that of the EEG signal.

The majority of current BCI applications are concerned with the classification of EEG signals from the brain and their translation into control signals. These control signals give power to the human participant to control the environment and communicate with the outside world by thought alone, without the intervention of physical movement. For example, this could allow control over a computer screen cursor, or an electric wheelchair, just by thinking and imagining left or right-related movements and receiving feedback from any consequent movements (of cursor or wheelchair, etc). Different EEG patterns can be obtained and identified, depending on the type of motor or imaginary motor responses [13]. EEGs can be recorded (i.e. BCI data acquisition) by sets of electrodes that are placed in standard positions on the scalp surface (i.e. this is a non-invasive system). Other, more invasive systems may rely on implanted electrodes, but that is not the focus of our work.

The simple act of collecting the EEG signals for BCI presents enormous practical problems. In a clinical environment, the person undergoing an EEG recording would do so within a very controlled environment, with dimmed lighting and with movements kept to a minimum. For a practical BCI system, neither of these conditions can be assumed and indeed, depending on the type of system, may precipitate activity, e.g. looking at flashing images, moving eyes to look at certain positions on a screen, etc. As previously mentioned, the signals picked up by the scalp electrodes from EMG will swamp those resulting from normal EEG activity. Any BCI system that is to be of practical use must be able to cope with EMG and other spurious pickup in an efficient manner, hence much effort is expended in techniques designed to reject and/or remove artifacts (i.e. any signals that are not the direct result of EEG activity). In a clinical environment, artifact rejection is generally quite simply accomplished by ignoring sections of the signal that appear to be contaminated. This is a valid approach since only small sections of the EEG recording would normally be affected in this way. However, for BCI this is generally not a satisfactory solution. It is likely that large segments of the EEG record will be 'contaminated' and to simply ignore them would render as useless, any attempt to make a real-time classification.

A BCI system thus needs a reliable method to separate noise and artifacts from the incoming EEG signal (i.e. pre-processing), a means of enhancing and/or isolating the features of interest (e.g. specific frequency bands) (i.e. signal conditioning), a method to identify the presence of specific features (i.e. feature recognition), a decision making process (i.e. classification) and finally a suitable output channel to send control an appropriate signal to the application interface (e.g. a wheelchair or computer). The components of the BCI system are connected together as a sequential chain, such that reliable detection of EEG signals forms the start of the chain. So if this step fails, the whole system will fail! It is therefore not surprising that much recent effort has been expended in the search for suitable pre-processing and signal conditioning techniques.

The detection of 'signals buried in noise' has been a major pre-occupation for those involved in signal processing, for many years. Numerous techniques are available to choose from, but the most successful for EEG artifact rejection are currently based on some form of decomposition and/or cancellation. One particularly powerful method is based on Independent Component Analysis (ICA) which has been shown to be effective in detecting and removing artifacts in EEG, arising from a variety of sources (e.g. ECG, EOG, line noise, etc.) [14].

The majority of signal conditioning methods involve some form of filtering, either spatial, temporal or a combination of both. The Common Spatial Patterns (CSPs) algorithm has proved to be successful in the design of spatial filters, suitable for example, in the discrimination of rhythmic brain activity (e.g. beta and theta activity, associated with 'creative thinking'). It has not proved particularly effective when it comes to non-periodic, or temporal, activity (e.g. imagined motor movements). In these cases, the Independent Residual Analysis (IRA) has been applied with good results. For many applications (e.g. e-learning in our case) both methods are important and the most successful implementations to date, incorporate both techniques (e.g. [15]).

BCI however, is not just about finding solutions to the technical difficulties, the types of people who will use the systems are of equal or even greater importance. In order to operate a BCI system, a user must be able to produce brain activity that can be detected and classified with a high degree of reliability and reproducibility. There is a general consensus, based on experimental results, that a user must learn to operate a BCI system. This will require the development of suitable training mechanisms, and has been liken to the experience of a child learning to walk. We expect our focus on e-learning based on BCI to make a significant contribution in this particular aspect of research. There is already evidence that subjects exhibit a high degree of variability in terms of their ability or otherwise to master the necessary control of their thought processes. This is not necessarily a surprising finding and could be considered as akin to learning to master a musical instrument. However, a number of potential BCI users can be broadly classified into one of three main Groups, as defined below, each with a common set of demands or requirements.

3. BCI User Groups

3.1 Severely Disabled People

Severely disabled people and those who are totally paralyzed or have little or no control over their motor functions, such as spinal cord injury and lock-in-syndrome patients often have involuntary eye-blinks, eye-movements as well as facial or behavioural mimicry, producing EEG contamination. (Lock-in-syndrome patients are usually aware and awake, but cannot move or communicate due to an almost complete paralysis of nearly all voluntary muscles in the body. However, they often display strange mimicry behaviour, such as crying, yawning, stretching, etc. Actions that are not considered to be within their normal repertoire of behaviours.) These people are usually isolated from the outside world. Here, EEG-based channel communication (BCI) has the potential to be a form of assistive technology that provides new communication channels for them to communicate with and control their environments. But can current BCI systems fulfil all the requirements of these groups? Can BCI systems support writing, arithmetic, spelling, and imaginary mental tasks? The answer is that this can usually be achieved where these tasks are based on binary and simple responses (on/off, yes/no, and left/right, up/down, etc). A good example is the "Dasher" system [16]. This system allows an individual to type letters, papers, etc, simply by navigating a moving cursor up or down on the screen. Thus, this interface design is mediated by the simple binary responses ("up" versus "down") but still allows the individual to work their way through the letters of the alphabet to create whole words and sentences. The system uses dependencies between letters to present the user with the most likely options first. With practice, performance speed can show significant improvement. Of course, for some individuals, it may be the only way yet that they can communicate by writing! (It should be added that Dasher is more than just a BCI system and supports a range of response modes). Such systems are not yet able to replicate complex mental tasks that are without the mediation of binary responses by the individual.

3.2 Older Adults

The older adult (over 60) may often present multiple, minor motor and cognitive function impairments or have slow control over their motor functions. EEG shape changes often occur in the older adult through increasing slow delta wave and are associated with slow EEG rhythms. They may also have slower control over muscle activities of the hands, fingers, etc. Decision-making may also be slower. For this group, the motivation to use BCI is completely different from the first group. The second group may need a system that is based on slower reaction times. Such a system could provide long-term or medium-term control over their living environments, but could not be relied upon yet for emergency responses in safety-critical situations. The design of a BCI for older adults should reflect their non-typical EEG profiles or slower response times.

3.3 Able-Bodied People

Able-bodied people, by definition, have normal or near-normal control over their psychomotor functions and have typical brain activity rhythms. Thus they should be able to use BCI systems well. However, even in this group problems may arise. At first, the BCI may be enjoyed as a new experience, as a game or as a stimulating new way to learn. For example, imagine the ability to navigate through a virtual reality environment by deploying imaginary movements. However, perhaps this group would require the system to be both fast and accurate. We suspect that current EEG-based BCIs are too slow to maintain their interest. Imaginary game direction (left/right imaginary depend on the mu rhythm of EEG) is very slow. However, this type of group can use other signals such as EMG detection (finger flexion), EOG detection (Eye tracker) or some combination of them. This population of users are also likely to be accustomed to fidgeting causing problems for the detection system. Finally, BCIs may require significant time in the "make-up room", i.e. require a substantial amount of time to adapt to a participant in order to obtain a good-enough signal strength. This group of users may lack the necessary patience. If so, a new generation of BCIs may be needed that are faster and much more robust to such problems.

4. The current state of the art

One of the primary attractions of the BCI is its potential to create much better access to interactive systems, particularly for people with significant disabilities such as the locked-in syndrome. Other potential benefits include the ability to monitor an individual for health problems, their emotional status and cognitive overload. Additionally, there is the appeal of being able to control a system, a computer game or an ambient environment through the power of thought alone, provided that the level of difficulty is acceptably low. There has also been research to explore the value of BCI for user authentication [17]. There are viable alternatives to the BCI, including eye-tracking, simple or binary switches, etc. In fact, at least one laboratory has abandoned the use of BCI [18]. Many applications of BCI technology, however, still face problems of signal processing and measurement artifacts such as eye-blinks and facial muscle movements (see below).

To explore the current state of the art, we surveyed a sample of fifty research papers from the ACM Digital Library that were constrained only by the two search terms "Brain Computer Interface" and "BCI". A set of papers meeting these search criteria were downloaded to a folder and fifty papers were selected at random from that set. This sample of fifty papers is available on request from the authors. The fifty papers were summarized in terms of (a) a paper ID, (b) definition of intended users, (c) artifacts and problems identified and (d) salient features of the paper. The resulting data were subject to quantitative and qualitative evaluation. However, as found in previous research [6], there was little or no overlap between the BCI and accessibility research literatures, as indicated by a significant lack of cross-referencing. However, there was some (subjective) indication that the literatures of BCI and HCI are slightly converging.

First, the fifty papers were divided into (a) those that defined their intended users and those that did not. Only 28 (56%) of the 50 papers defined or described these possible users. Thus 22 papers did not define the users. Fifty-six percent is a surprisingly low level, though can be understood, to some extent, by a focus on the technicalities of BCI systems. When considering EEG-based BCI systems, this sample of papers identified a number of potential artifacts and problems. This list is: eye-blinks (n=3), EEG noise (n=3), EMG (n=3), signal attenuation; associated with aging, illness and other factors (n=2), low signal-to-noise ratio (n=2), face muscle movement (n=1), eye-movements (n=1), body movements (n=1), EOG (n=1), involuntary movements, particularly with specific clinical conditions (n=1), ECG (n=1) and small sample sizes (n=1). This above list reflects the language of the individual papers, so there is some nuanced overlap. However, this would seem to be a relatively complete list of artifacts. This approach assumes a pure EEG system, but (see below) one researcher's artifact is another researcher's measure. The papers that defined their users were then examined for the groups of users. Users with severe neuromuscular disorders were the most cited group (n=9), people with physical disabilities were next (n=7), then people with cognitive disabilities were next (n=4), locked-in syndrome was an important sub-group (there are an estimated 500,000 such individuals in the world, today; n=4), gamer-players were a distinct group (n=3), people with brain injuries were included (n=3), electrical wheel-chair users (n=2), severely disabled people (n=1), people with spinal cord injuries and, finally, musicians! (n=1). Again this list reflects the language used by the authors themselves. However, there is clearly some diversity in this list. Currently, there is a debate about the merits, relative or absolute, for the use of different BCI systems for different user populations. No doubt this debate will continue, with studies of different alternative systems. Turning to the exact types of measures used, our results were surprising. We had anticipated that a significant majority of our sample would have reported EEG only based systems. This did not turn out to be so. There were a small number of cases were embedded electrodes were used (i.e. electrodes actually inserted into the human brain; ECogG) but these were infrequent (n=3). Surprisingly, less than half our sample reported the pure use of scalp electrodes for EEG (n= 20). Of those, a subset focused on averaged evoked potentials (n= 5). An almost identical number of papers reported EEG plus other measures, including EMG, EOG, heart rate, keys, pedals, buttons, heart rate and GSR (n=19). Finally, a small group used alternatives to EEG, including EMG, EOG and GSR (n=7). This may implicate a concern for the value of the EEG as a reliable and informative measure. One response to such a concern would be to combine different measures. Another strategy would be to seek to increase the signal-to-noise ratio and to filter out as many artifacts as possible. One important issue is the comparison of different measures or combinations of measures. However, the present sample of papers does not provide sufficient comparisons to allow us to do so. Clearly, further work is needed on this issue. Another vital question is the choice of the number of electrodes. Here, the number of electrodes in use varies widely. There is the 10-20 electrode placement system issued by the International Federation of Electroencephalography and Clinical Neurophysiology in 1958. However, the focus is on defining the positions of electrodes on the human scalp rather than setting an exact number of electrodes to be used in different contexts. Numbers varied from a single (implanted) electrode to 256 electrodes. Some averaging may be useful but also creates delays in the responsiveness of the system. Finally, looking at the uses to which BCIs were put, most were focused on user control of the external environment, though a small number were applied to game playing and to user authentification instead of passwords. In a few cases, the use of EEG or other BCIs to monitor the individual for health status, emotional state, cognitive state, cognitive overload, working memory load, etc. No cases were found of applications to e-learning, even though some potential learners have little or no alternatives.

These analyses have revealed a number of important collections. Whilst there has been a significant move from surgically implanted electrodes to the use of non-invasive, scalp electrodes, the cost of this move has been a reduction of signal strength. There is also a clear distinction between pure EEG (with consideration of signal to noise ratio and artifacts) and multi-measure systems. Clearly there are many agendas in operation, including a better understanding of human EEG and better, practical control being given to the user. Finally, it is emerging that the calculation of the potential benefit of BCI (and different versions of BCI) to human control of systems depends strongly on a clear definition of the intended user population. If so, we may be a step closer to the use of BCIs for the creation of more accessible e-learning systems for users who would otherwise be excluded.

5. Conclusions

We have attempted in this paper to highlight some of the potential for BCI for e-learning while at the same time recognising the enormous problems that must be overcome in order to implement even very basic functions. It is now 80 years ago that the EEG was first identified and almost 40 years since the first publications appeared on BCI type systems. Only very limited progress has been made in that time, in spite of the enormous advances in semiconductor technology, delivering ever faster and more complex processing engines, in signal processing theory and indeed in terms of our understanding of human brain function itself. Our survey has shown that the majority of current effort is focussed on the technical challenges associated with the capture and processing EEG activity and where a target application is identified, most are concerned with the use of BCI to replace motor type functions, especially for those with significant motor disabilities.

The focus of our research is on how BCI may be used to identify mental activity associated with the learning process and thereby augment and enhance the capabilities and accessibility of e-learning systems. We believe this has the potential to revolutionize education and could prove fundamental in the development of BCI itself, providing a 'bootstrap' method by which users may be trained to operate the interface. The marriage of BCI and e-learning will provide an adaptive environment through which to enhance the learning process, accessible to all members of society.

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