

Brain Computer Interfaces & Human Computer Interaction

AISB 2008 Proceedings Volume 5

AISB '08



UNIVERSITY
OF ABERDEEN

AISB 2008 Convention
Communication, Interaction and Social
Intelligence
1st-4th April 2008
University of Aberdeen

Volume 5:
Proceedings of the
AISB 2008 Symposium on Brain Computer Interfaces
and Human Computer Interaction: A Convergence of
Ideas

Published by
**The Society for the Study of
Artificial Intelligence and
Simulation of Behaviour**

<http://www.aisb.org.uk/convention/aisb08/>

ISBN 1 902956 64 8

Contents

The AISB'08 Convention	ii
<i>Frank Guerin & Wamberto Vasconcelos</i>	
Symposium Preface	iii
<i>Slawomir J. Nasuto & Faustina Hwang</i>	
Brain Computer Interfaces: Psychology and Pragmatic Perspectives for the Future	1
<i>Ray Adams, Gisela Susanne Bahr & Benigno Moreno</i>	
Toward Construction of an Inexpensive Brain Computer Interface for Goal Oriented Applications	7
<i>Anthony J. Portelli & Slawomir J. Nasuto</i>	
Single-Trial Event-Related Potential Analysis for Brain-Computer Interfaces	13
<i>Nicoletta Nicolaou, Slawomir J. Nasuto & J. Georgiou</i>	
Adaptive Brain-Body Interfaces	20
<i>Paul Gnanayutham & Jennifer George</i>	
Towards natural human computer interaction in BCI	26
<i>Ian Daly, Slawomir J Nasuto & Kevin Warwick</i>	
BrainGain: BCI for HCI and Games	32
<i>Anton Nijholt, Jan B.F. van Erp, Dirk Heylen</i>	

The AISB'08 Convention: Communication, Interaction and Social Intelligence

As the field of Artificial Intelligence matures, AI systems begin to take their place in human society as our helpers. Thus it becomes essential for AI systems to have sophisticated social abilities, to communicate and interact. Some systems support us in our activities, while others take on tasks on our behalf. For those systems directly supporting human activities, advances in human-computer interaction become crucial. The bottleneck in such systems is often not the ability to find and process information; the bottleneck is often the inability to have natural (human) communication between computer and user. Clearly such AI research can benefit greatly from interaction with other disciplines such as linguistics and psychology. For those systems to which we delegate tasks: they become our electronic counterparts, or agents, and they need to communicate with the delegates of other humans (or organisations) to complete their tasks. Thus research on the social abilities of agents becomes central, and to this end multi-agent systems have had to borrow concepts from human societies. This interdisciplinary work borrows results from areas such as sociology and legal systems. An exciting recent development is the use of AI techniques to support and shed new light on interactions in human social networks, thus supporting effective collaboration in human societies. The research then has come full circle: techniques which were inspired by human abilities, with the original aim of enhancing AI, are now being applied to enhance those human abilities themselves. All of this underscores the importance of communication, interaction and social intelligence in current Artificial Intelligence and Cognitive Science research.

In addition to providing a home for state-of-the-art research in specialist areas, the convention also aimed to provide a fertile ground for new collaborations to be forged between complementary areas. Furthermore the 2008 Convention encouraged contributions that were not directly related to the theme, notable examples being the symposia on “Swarm Intelligence” and “Computing and Philosophy”.

The invited speakers were chosen to fit with the major themes being represented in the symposia, and also to give a cross-disciplinary flavour to the event; thus speakers with Cognitive Science interests were chosen, rather than those with purely Computer Science interests. Prof. Jon Oberlander represented the themes of affective language, and multimodal communication; Prof. Rosaria Conte represented the themes of social interaction in agent systems, including behaviour regulation and emergence; Prof. Justine Cassell represented the themes of multimodal communication and embodied agents; Prof. Luciano Floridi represented the philosophical themes, in particular the impact on society. In addition there were many renowned international speakers invited to the individual symposia and workshops. Finally the public lecture was chosen to fit the broad theme of the convention – addressing the challenges of developing AI systems that could take their place in human society (Prof. Aaron Sloman) and the possible implications for humanity (Prof. Luciano Floridi).

The organisers would like to thank the University of Aberdeen for supporting the event. Special thanks are also due to the volunteers from Aberdeen University who did substantial additional local organising: Graeme Ritchie, Judith Masthoff, Joey Lam, and the student volunteers. Our sincerest thanks also go out to the symposium chairs and committees, without whose hard work and careful cooperation there could have been no Convention. Finally, and by no means least, we would like to thank the authors of the contributed papers – we sincerely hope they get value from the event.

Frank Guerin & Wamberto Vasconcelos

The AISB'08 Symposium on Brain Computer Interfaces and Human Computer Interaction: A Convergence of Ideas

Brain-computer interfaces (BCI) and human-computer interaction (HCI) have overlapping goals – to enable more seamless communication between human and machine. This symposium aims to bring together researchers from both the BCI and HCI communities, to investigate how they can inform each other and to foster interaction between the two research communities. With its focus on improving communication between humans and machines, this symposium fits very well with the main theme of the AISB convention – Communication, Interaction and Social Intelligence.

A brain-computer interface uses signals from the brain as a mode of communication and control. Traditionally, BCI research has focused largely on creating methods for the efficient extraction of user intentions from EEG signals. However, the overall effectiveness of a BCI depends not only on successful processing of the input signal, but also on the design of the interface that is being used to achieve a goal.

At the same time, human computer interfaces strive to improve communication between users and computers and to make interaction more intuitive and effective. From this perspective, there is great potential for work in the domain of HCI to improve BCI interfaces. Equally, in addressing some of the key challenges faced in BCI, there is also the potential to stimulate new directions of research in the wider HCI context.

To date, there have been few workshops that aim to bring together the BCI and HCI communities. The need for increased dialogue has been recognised by workshops such as the PASCAL Workshop 2007 – BCI Meets HCI in April 2007 in Martigny, Switzerland, the International Workshop on Brain-Computer Interface Technology & 2nd BCI2000 Workshop at HCI International 2007 in Beijing, China, and the workshop on Brain-Computer Interfaces for HCI and Games at CHI 2008 in Florence, Italy.

The programme for our one-day symposium comprises a good balance of talks from both the BCI and HCI communities. Therefore, we anticipate that it will continue the work of other initiatives towards increasing communication between the disciplines.

We would like to acknowledge the help of our International Programme Committee and the AISB Convention organisers. We are grateful for the support of the EPSRC-funded Complex Cognitive Systems Initiative, University of Reading and the School of Systems Engineering, University of Reading.

*Slawomir J. Nasuto
Faustina Hwang*

Symposium Chairs:

Slawomir J. Nasuto, University of Reading
Faustina Hwang, University of Reading

Programme Committee:

Dr. Ray Adams, Middlesex University, UK
Dr. Adriano O. Andrade, Biomedical Engineering Laboratory (BioLab), Federal University of Uberlandia, Brazil
Dr. Jinjuan Heidi Feng, Department of Computer and Information Sciences, Towson University, USA
Dr. Faustina Hwang, School of Systems Engineering, University of Reading, UK
Dr. Christopher James, Signal Processing and Control Group, ISVR, University of Southampton, UK
Dr. Simeon Keates, ITA Software, USA
Dr. Slawomir J Nasuto, School of Systems Engineering, University of Reading, UK
Dr. Nicoletta Nicolaou, Department of Electrical & Computer Engineering, University of Cyprus, Cyprus
Professor Peter Robinson, Computer Laboratory, University of Cambridge, UK
Dr. Alcimar B. Soares, Biomedical Engineering Laboratory (BioLab), Federal University of Uberlandia, Brazil

Brain Computer Interfaces: Psychology and Pragmatic Perspectives for the Future

Ray Adams¹, Gisela Susanne Bahr² and Benigno Moreno³

Abstract. Whilst technologies, such as psychophysiological measurements in general and electroencephalograms (EEG) in particular, have been around and continually improving for many years, future technologies promise to revolutionise the emerging Information Society through the development of brain-computer interfaces and augmented cognition solutions. This paper explores critical psychological and pragmatic issues that must be understood before these technologies can deliver their potential well. Within the context of HCI, we examined a sample ($n = 105$) BCI papers and found that the majority of research aimed to provide communication and control resources to people with disabilities or with extreme task demands. However, the concepts of usability and accessibility, and respective findings from their substantial research literatures were rarely applied explicitly but referenced implicitly. 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.

1 INTRODUCTION

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 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 psychology and rehabilitation engineering underlying BCI.

An effective BCI system is based on 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) These 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 [1]. These are the specific requirements for effective BCIs. In addition, we suggest that there are at least three generic requirements that apply to any communication and

control systems: Functionality [2], i.e., does it support important, useful and desirable tasks? Usability [3], i.e., is the system too difficult to use? and Accessibility [4] i.e., are there any barriers that prevent or disadvantage users when using the system?

This paper is structured in four sections to present and discuss (a) important psychological factors for BCI, (b) practical factors for BCI, (c) the implications of BCIs for the future of Human Computer Interaction and (d) a futuristic BCI vision.

2 PSYCHOLOGICAL FACTORS FOR BCIs

We propose that any consideration of psychophysiological measurements must include the rigorous scrutiny and interpretation of these measurements in a human centred context. This includes a popular measurement approach for BCI, the scalp-recorded electroencephalographic measurement (EEG). EEG refers to the placement of electrodes on the head of a human or animal in order to measure the electrical consequences of brain behaviour. The conventional view of BCI is that EEG will enable severely disabled individuals to communicate with and control their environments through control of screen displays, prosthetic devices and robotic systems. This conventional view is changing, however, particularly as are the results of the emerging psychological and pragmatic issues. The following four factors provide not an exhaustive but comprehensive set of psychological considerations for analysis.

They are (a) the types of cognitive function reflected in the EEG, (b) the nature of feedback and the modalities involved, (c) the types of intended users and (d) the types of tasks and environments chosen.

The first consideration is that different patterns of the brain activity may be mapped to respective cognitive functions. If so, then different aspects of the EEG may reflect different functions to a greater or lesser extent. One of the most obvious areas is that of motor – related EEG. Since voluntary movement control already exists as an internal control system in humans, it is natural to use voluntary movement-related potentials (VMRPs) to drive a BCI [5]. Thus it is possible to detect actual index finger flexions in an individual's EEG records. Furthermore, imagined voluntary movements with able-bodied persons can be reliably detected and measured [6]. This opens some major opportunities for individuals with significant psychomotor impairments.

Perceptual and cognitive brain processes can also be detected. We know from primate studies that decision making involves at least two general phases of neural processing, namely the depiction of sensory information and the accumulation of evidence from decision-related regions. Recent research [7] deployed a cued paradigm plus single-trial analysis of electroencephalography (EEG) and found temporally specific components related to perceptual decision making. They then went on

¹ CIRCUIA, Collaborative International Research Centre for Universal Access, School of Computing Science, Middlesex University, The Burroughs, Hendon, London NW4 4BT Email: ray.adams@mdx.ac.uk

² Gisela Susanne Bahr, Florida Institute of Technology, Florida, USA. gsbahr@gmail.com

³ Benigno Moreno, Fundació Ave Marí, Engineering R&D, ing-it@terra.es

to conduct further analyses of their EEG recordings to understand their analyses of fMRI data collected for the same behavioural task to identify the cortical locations of these EEG components. They found evidence of a cascade of events associated with perceptual decision making that takes place in a highly distributed neural network. Of particular importance is activation in the lateral occipital complex supporting the view that perceptual persistence is a mechanism by which object-based decision making in the human brain takes place.

In addition to EEG and FMRI, consider event related potentials (ERPs). These are electrophysiological responses to internal or external stimuli, including perceptions or thoughts. Event-related potentials (ERPs) are seen in the electroencephalogram (EEG). Since ERPs may be used to measure brain activities associated with human related information processing, they may be able to indicate variations in cognitive load [8] [9]. The measurement of ERPs in a laboratory setting is relatively easy, but much more difficult in the real world, due to all manner of uncontrollable factors such as eye movements, switching of attention, continuous as opposed to discrete sensory inputs. [10]. These researchers reported a range of techniques that they could produce significant single trial ERPs in such circumstance, leading to the generation of useful averaged evoked potentials (AEPs) over multiple trials. They were able to locate the spatial origins of these ERPs. Finally they were able to observe minute by minute changes in cognitive load and overload, using (back-propagation) neural networks to do so.

A second psychological factor is the nature of the feedback given to the individual using the BCI. In particular, choosing the modality for feedback is perhaps the most obvious choice. It is often assumed that the feedback modalities of choice are visual, auditory or their combination. However, researchers [11] have reported a system that uses vibrotactile biofeedback to supply haptic information. They found that six, healthy, young, male participants could use a mu-rhythm based BCI within a motor imagery paradigm to control the position of a virtual cursor. The cursor position was shown visually as well as transmitted haptically by varying the intensity of a vibrotactile stimulus to the upper limb. The six subjects operated the BCI in a targeting task, receiving only vibrotactile biofeedback of performance. They were able to control the BCI using only vibrotactile feedback with an average accuracy of 56% and as high as 72%. The results of this study show that vibrotactile feedback works as a possible feedback modality to operate a BCI using motor imagery.

A third psychological issue is the choice of intended users. Whilst much of the above work has been conducted with the support of non-disabled participants, these are often tests of the feasibility and practicality of the proposed methods. The authors often state their aims are to be to assist individuals with high levels of disability, particularly psychomotor disabilities. However, we can also be disabled by our circumstances and by the excessive demands that tasks place on us. In particular, cognitive overload occurs when the information throughput of our tasks / circumstances become too high or complex for us to cope [12]. In such cases, augmented cognition through modality specific input scheduling is a potential solution. If BCI is a progressively more viable option, as current research suggests, then BCI can provide another communication channel as a basis for augmented cognition. The difference between augmented cognition and BCI approaches is in the intent of the user. In the former the

system senses user state and engages task dependent mitigations to optimize performance; conversely, the latter accepts deliberate, intended, cognitively articulated input from the user. For example some researchers [13] state their research question as "How can BCI be used to assist neurologically healthy individuals in specifically demanding tasks?"

A fourth psychological consideration is the choice of tasks and context of use that are chosen. Many of these studies make use of simple tasks such as the control of screen cursors to demonstrate the impressive potential of BCI; few of the studies have based their insights on an analysis of user requirements. Future BCI investigations require the systematic evaluation of user requirements to improve the user-sensitivity of the chosen designs of such BCI systems. Where individuals have substantial psychomotor deficits, any opportunity to communicate and control the environment appears to be beneficial, but, as science moves on, these individuals may wish to enhance their quality of life through the control of screen displays, prosthetic devices, robotic systems etc. If so, the consideration of more user sensitive design could be beneficial. However, BCI is likely to be beneficial to a wider range of intended users and beneficiaries. Individuals with reduced sensory, psychomotor or cognitive attributes may also benefit and would surely want more than the basic functionality of BCI based control of simple systems. However, the increasing work on augmented cognition demonstrates that there will be individuals who are working in high information or high stress environments and could use BCI communication (active or passive) to indicate a need for changes in the task / information configurations that they must face. Considering all these potential, intended users, it is clear that the tasks and environments supported by BCI will soon need to become much more enriched and interactive than at present. Of course, the tasks / environments must not only be functionally enriched, they must also be perceived as positive and welcoming. In the past, assistive technology has sometimes proved to be functionally valuable but aesthetically inadequate. People with disabilities and indeed all potential users may be discouraged from using unattractive technology that seems to stigmatise its users. If this argument is correct, then the BCI systems of the future must be acceptable to intended users in the gestalt of a sophisticated industrial design that meets functionality needs and user requirements whilst affording usability, accessibility, aesthetics and personae.

In summary, we have proposed four psychological factors that are of practical importance to BCI developments and applications. They are all important if BCI methods are to be effectively understood and applied. The following four factors are of highest face validity. They are; (a) the types of cognitive function reflected in the EEG, (b) the nature and modalities used for feedback, (c) the types of intended users and (d) the types of tasks and environments chosen. However, these factors have been chosen on the basis of face validity. How can such factors be identified on a more conceptually robust basis, without creating cognitive overload for the BCI scientist or practitioner? Elsewhere, it has been suggested that nine factors can be used to capture the essentials of human cognition. Research [12] has proposed nine factors that have been validated by two, large sample validation studies. Those nine factors are (from a user perspective); input processing, feedback management, executive functions, working memory, long term memory, emotions and motivations, mental modelling, output and learned, complex

output sequences. Episodic memory has also been suggested as an extra factor, but it has been argued by leading researchers [14] that this is best seen as part of working memory.

3 SOME PRACTICAL ASPECTS OF BCI

BCI can be seen from a number of distinct perspectives. Above we considered a psychological perspective and the nature of the psychological processes involved. Here, we look at BCI from the perspective of rehabilitation engineering.

Traditionally, EEG has been the measurement of popular choice and, within that, EEG related to the motor cortex and thus to psychomotor processes. As discussed above, simple psychomotor responses (e.g. finger flexions) are feasibly detected in an individual's EEG. This would be helpful for an individual with limited movement to control a system with minimal physical effort. In addition, improving technology now allows for the cortical electrophysiological correlates of imagined movement (e.g. imaginary finger flexions) to be detected and that is much more promising for people with severe limitations. There are a significant number of ways to extract measurements from an EEG record, of which the event-related potential (ERP) or evoked potential (EP) and the averaged evoked potential (AEP) are perhaps the best known. However, current and recent work shows how many variations of this theme are possible and so the race is on to determine the most effective options.

Continuing the focus on evoked potentials and averaged evoked potentials (AEP), researchers [15] explored the measurement of the P300 component of the human EEG, with a new and unsupervised algorithm for P300 estimation, thus improving the raw EEG records. They proposed and tested a new method to detect the P300 potentials in the human EEG by a P300 based BCI. The results were favourable to this new approach over a selection of older methods.

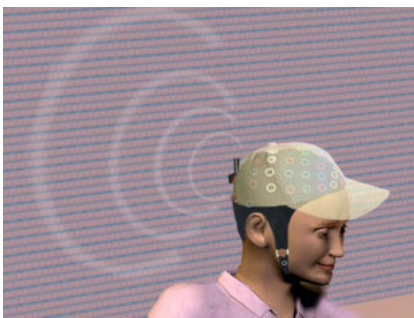
Other researchers [16] explored the use of flash onset and offset visual evoked potentials (FVEPs) to activate a BCI system. Flashing stimuli displayed on a screen are used to produce onset and offset FVEPs when the users look at them. By shifting their visual attention to different items, users can produce strings of letters or numbers with which to communicate or to control useful systems. They also produced averaged evoked potentials from their data, including the differences between the N2 and P2 peaks and the N1 and P1 peaks. In two experiments with five subjects in two experiments, they found an accuracy level of 92.18%, showing that the onset and offset FVEP-based BCI can achieve a high information transfer rate. In contrast, other researchers [17] explored steady state visual evoked potentials (SSVEPs) with overlapping stimuli that can evoke changes in SSVEP activity without the need for shifting gaze. They found that half of their subjects could achieve a suitable level of control of a BCI. Though further work is needed to improve this percentage, the authors argued that this method might be very suitable for severely disabled users.

One way to improve the effectiveness of EEG based BCIs is to develop more advanced measures. Some researchers [18] explored the use of energy density maps derived from EEGs in ten healthy volunteers, comparing two real as well as between two imaginary movements. They were able to identify the most discriminative features based on statistically significant differences between the energy density maps. They concluded that these types of analyses could provide a larger number of com-

mand signals to control the external systems via a BCI. In addition, researchers [19] explored the potential of machine learning methods for compensating for the high variability in EEG data when analyzing single-trials in real-time. They concluded that such methods contributed to the creation of cleaner data and thus more effective BCI systems.

Of course, there is no need to use EEG measurements in isolation. It can be put to joint use with the respiratory heart rate response, induced by brisk inspiration [20]. They investigated the ways in which a BCI could be turned on or off by the user. They found that ten healthy subjects were able to switch on and use a steady-state visual evoked potential-based (SSVEP) BCI using one ECG (electrocardiogram) and EEG channel, after only 20 min of feedback training. In addition, the subjects made very few false positive errors. On this basis, the combination of EEG and ECG promises to be very useful in the future. A further methodological improvement is based on the concept of the "quasi-movement" [21] defined as voluntary movements that have been minimised as to be virtually undetectable, making them rather like imagined responses. In fact, quasi-movements are consistent with the proposed continuity between real and imagined movement. They found that in healthy subjects quasi-movements work well in brain-computer interface, being associated with significantly smaller classification errors when compared conventional imagined psychomotor responses. It is also feasible to consider the potential role of near-infrared spectroscopy (NIRS) for BCI [22]. They concluded NIRS that instruments are only small-scale and can be used to make noninvasive measurements. They were able to show that they could measure regional cerebral blood flow effectively by NIRS during a tapping task (preferred hand) and reported methods to evaluate NIRS measurements by use of an artificial neural network.

So far, we have assumed that the BCIs will be based on hard-wired systems. This is a reasonable assumption given current experience of wired and wireless Internet interfaces. However, wireless systems offer potentially greater flexibility given a suitable wireless environment. Thus it is important to consider wireless BCIs. Thus wireless systems for BCIs could make use of subcutaneous transmitters with little loss of signal strength! [23]. Such wireless systems can be strengthened further by the effective use of compact, operational amplifiers that require little power and can support implantable systems [24]. Such an amplifier has only a power consumption of only 736 nW and a chip area of only 0.023 mm². Another, non-invasive option is the application of wireless principles to EEG using an electrode cap with a wireless link. A study of the Armoni Project [25], using non-invasive criteria, designed an EEG cap that made the EEG system become invisible to the wearer (see graphics pictures below).



3 BCI IMPLICATIONS FOR HCI

The brain computer interface (BCI) should be the instantiation of access “par excellence”. Current work, as discussed above, has established the feasibility, in principle, of communication and system control through a BCI. It is clear that a range of psychophysiological measures can be used either singly or in combination. Intended users range from individuals with virtually no disabilities to those individuals with severe psychomotor impairments. BCIs can also be used by individuals facing cognitive overload or inappropriately high stress levels. Such systems can now be set to detect such problems and provide cognitive augmentation through task or information sharing. For example, a task can be carried out jointly by a system and a person. Alternatively, the person could take one task and the system could be given another task. It is also increasingly possible to identify those aspects of human cognition that are reflected in different components of the EEG. This would allow BCIs to focus on the most relevant cognitive functions, perhaps capturing the most accessible or usable. Whilst visual feedback is the most common form, as discussed above, BCIs can use a range of different modalities to guide the user. Finally, it is important to add that powerful data analysis methods can be used to extract the maximum informational value from psychophysiological data with consistency and reliability.

The above summary demonstrates the successes of current BCI research and development and points to their use to solve accessibility problems, particularly for people with severe psychomotor deficits, but also much more widely. However, it is remarkable when we considered a large sample ($n = 105$) of BCI

related papers, very few made reference to, or use of, the extensive research literatures covering universal accessibility or usability. Yet these should be central to the development of this field. This is undoubtedly due to the current state of the art and the necessary focus upon demonstrating validity and feasibility.

However, such systems are not themselves immune to usability and accessibility problems. Whilst these two topics are much too big to be discussed in depth here, some simple links can be suggested. Usability is defined in terms of the level of task difficulty that a system requires. There are many experts on usability, but for our focus on BCI, references to the work of Nielsen [3] and Shneiderman [26] will have to suffice. The point is that there are simple ways to conduct usability evaluations for interactive systems. Accessibility is defined here as the lack of barriers between a system and a user that would otherwise degrade or prevent the effective use of system.

Universal accessibility is equally large as a topic. Here the work of [27] can be singled out. The accessibility of an interface depends on at least four factors: the technology platform, the intended users, the tasks and the context of use. All of these four factors have been discussed above, but their contributions to accessibility need a more explicit treatment. For a system to be truly accessible, it can also be said that depends on (a) the chosen hardware, (b) the quality of the connection, (c) the users’ ability to perceive incoming information and feedback, (d) the making of appropriate responses with sufficient ease, (e) cognitive accessibility i.e. the ability to navigate efficiently (with few errors) and to comprehend the information given and (f) the achievement of their objectives through the use of an interactive (BCI) system [28]. If BCI research and development can achieve these twin goals of usability and accessibility, then BCI promises to become a mainstream technology and a substantial contributor to the global Information Society.

A new application of BCI is discussed by the Armoni Project [25]. The low levels of motivation that people with intellectual disability often experience during long periods of their daily life when they are without adequate cognitive, sensory and motor stimulation is an aggravating circumstance that can have a detrimental impact on their moods [29], their well-being and, therefore, their quality of life. These cognitive, sensory and motor decrements can be mitigated by systems based on ICT technologies, using feedback with indicators based on BCI (Brain Computer Interaction), EEG pickups of the real-time emotion states of the users of such a system.

To meet these needs, a BCI related PC station has been constructed, which can be assembled in groups of two, three or four unit’s ensembles. BCI (Brain Computer Interaction) techniques are used, with technically advanced and conventional peripherals, as well as state-of-the-art software with auto-adaptive capacities. They are designed for dependent-disabled people and allows access to and interaction with more than 100 activities, with systems that, from the point of view of the user, are significantly: easy to use, accessible (according to the different degrees of disability), cognitively interesting for all types of people considered here, recreationally funny, easy to learn and to use for learning, rehabilitation and maintenance activities.

There is a substantial amount of research that demonstrates emotional monitoring in people with EEG [30], with evoked emotions [31], cerebral laterality-emotion and EEG [32], recognition of emotions [33], emotion assessment [34] frontal EEG asymmetry as a monitor of emotions [35] and depression meas-

ured through EEG [36]. This development of an appropriate EEG methodology, allows for a baseline to be established for each user, in terms of his/her emotions plus the map of the EEG, particularly of the ventromedial frontal zone of the human brain cortex [37].

All this feedback, coming from standard peripherals, as well as from advanced systems, particularly the EEG cap, can be formally processed. BCI provides an objective and real time interaction and supplies us with feedback relating to the mental state of the cortex of the user through real-time evaluation of the correlative EEG, with order-disorder states of the brain (polarity of emotion and probably intensity, [38], and customized emotion performance and identified for each user by therapist in institutions. State-of-the-art BCI (Brain Computer Interaction) technology, and the specific case adopted here of BCI by EEG (electroencephalogram), has developed systems that are very focused on the ability to control peripheral elements and devices (for example, moving a cursor, moving a wheelchair etc). The Armoni project immerses the user in a new perspective, focussing on the emotional personal state of the user, capturing it in the main-frame computer of the stimulation station through wireless based EEG (This has been supported by clinical trials).

4 THE FUTURISTIC VISION OF BCI

Imagine a situation in which you are working in your home study. You notice that the room temperature is slightly too high, so you turn your gaze to the temperature display and think it down a few degrees. The room cools to a more acceptable level. Your next task is to send a package to a colleague by 3Dmail. You had prepared the package the night before, so all you have to do is to think yourself through the process. A copy of the package goes and you are rewarded by feedback in the form of a brief passage from Mozart. Suddenly, you find that you have a home visit from a colleague, a rare treat these days. You both exchange archived information via your systems and exchange pleasantries. She shows you her new system, which is not based on the familiar hat system but on subcutaneous units, set almost flush the skull. You make a cognitive note to explore the options sometime, but not sometime soon. You both agree that sometimes it is nice to get out.

Later, you inspect your news feeds, filtering out those items that do not accord with your religious views. This reminds you to switch on your background prayer mode. You notice the item in which some criminals have adapted their BCIs so that they can control other peoples' robots and wireless enabled property and down load it for immediate inspection. Before you have a chance to read, you receive a handwritten, hence highly secure text message from your daughter saying that she is on the inter-continental bus and needs you to send some credits as she is over-extended

This view of BCI future may be in turn, attractive or repellent, depending on your world view, but in the nearer future, we can surely look forward to BCIs that make usable, accessible contributions to universal accessibility.

REFERENCES

- [1] Wolpaw, J.R. Birbaumer, N. Heetderks, W.J. McFarland, D.J. Peckham, P.H. Schalk, G. Donchin, E. Quatrano, L.A. Robinson, J. Vaughan, T.M. (2000). Brain-computer interface technology: a review of the first international meeting: IEEE Transactions on Rehabilitation Engineering [also IEEE Trans. on Neural Systems and Rehabilitation, 8, 164.
- [2] Szykman, S., Racz, J. W. and Sriram, R.D. (1999). The representation of function in computer-based design. Proceedings of the 1999 ASME Design Engineering Technical Conferences September 12-15, 1999, Las Vegas, Nevada, DETC99/DTM-8742.
- [3] Nielsen, J. (1994). Usability engineering. N.Y., Morgan Kaufman.
- [4] Lawrence, S. and Giles, C. L. (1999). Accessibility of information on the web. *Nature* 400, 107
- [5] de Jong, R., Gladwin, T. E. and Hart, B. M. (2006). Movement-related EEG indices of preparation in task switching and motor control. *Brain Research* doi:10.1016/j.brainres.2006.03.030.
- [6] Bozorgzadeh, Z., Birch, G. E. and Mason, S. G. (2000). The LF-ASD brain computer interface: on-line identification of imagined finger flexions in the spontaneous EEG of able-bodied subjects. *Acoustics, Speech, and Signal Processing*, 2000 Vol 4. 2000 IEEE International Conference.
- [7] Philiastides, M. G. and Paul Sajda (2007) EEG-Informed fMRI Reveals Spatiotemporal Characteristics of Perceptual Decision Making. *J. Neurosci.*, Nov 2007; 27: 13082 - 13091; doi:10.1523/JNEUROSCI.3540-07.2007.
- [8] Schultheis, H. and Anthony Jameson, A. (2004). Assessing Cognitive Load in Adaptive Hypermedia Systems: Physiological and Behavioral Methods. *Lecture Notes in Computer Science*. 3137, 225-234.
- [9] Ullsperger, P., Freude, G., Erdmann, U. (2001). Auditory probe sensitivity to mental workload changes - an event-related potential study. *International Journal of Psychophysiology* 40, 201 - 209.
- [10] Tang, A. C., Sutherland, M. T., McKinney, C. J., Liu, J., Wang, Y., Parra, L., Gerson, A.D. and Sajda, P. (2006). Classifying Single-Trial ERPs from Visual and Frontal Cortex during Free Viewing. 2006 International Joint Conference on Neural Network. Vancouver, BC, Canada. July 16-21, 2006.
- [11] Chatterjee, A., Aggarwal, V., Ramos, A., Acharya, S and Thakor, N V. (2007). A brain-computer interface with vibrotactile biofeedback for haptic information. *Journal of NeuroEngineering and Rehabilitation* 2007, 4:40doi:10.1186/1743-0003-4-40.
- [12] Adams, R. (2007). Decision and stress: cognition and e-accessibility in the information workplace. *Universal access in the information society*,
- [13] Parra, L. C., Christoforou, C., Gerson, A., Dyrholm, M., Luo, A., Wagner, M., Philiastides M. G. and Sajda, P. (2008) Spatio-temporal linear decoding of brain state: Application to performance augmentation in high-throughput tasks. *IEEE Signal Processing Magazine*, January 2008.
- [14] Baddeley, A. D. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, 4, (11): 417-423.
- [15] Rivet B. and Souloumiac A. (2007). Subspace estimation approach to P300 detection and application to Brain-Computer Interface. *Conf Proc IEEE Eng Med Biol Soc*. 2007; 1: 5071-4.
- [16] Lee PL, Hsieh JC, Wu CH, Shyu KK, Wu YT (2007) Brain computer interface using flash onset and offset visual evoked potentials. *Clin Neurophysiol*. 2007 Dec 27
- [17] Allison BZ, McFarland DJ, Schalk G, Zheng SD, Jackson MM, Wolpaw JR. (2008). Towards an independent brain-computer interface using steady state visual evoked potentials. *Clin Neurophysiol*. 2008 Feb; 119(2): 399-408.
- [18] Vuckovic A, Sepulveda F (2008). Quantification and visualisation of differences between two motor tasks based on energy density maps for brain-computer interface applications. *Clin Neurophysiol*. 119(2): 446-58.
- [19] Müller KR, Tangermann M, Dornhege G, Krauledat M, Curio G, Blankertz B. (2008). Machine learning for real-time single-trial EEG-analysis: from brain-computer interfacing to mental state monitoring. *J Neurosci Methods*. 2008 Jan 15; 167(1): 82-90.
- [20] Scherer R, Müller-Putz GR, Pfurtscheller G. (2007). Self-initiation of EEG-based brain-computer communication using the heart rate response. *J Neural Eng*. 2007 Dec; 4(4): L23-9.

- [21] Nikulin VV, Hohlefeld FU, Jacobs AM, Curio G (2007). Quasi-movements: A novel motor-cognitive phenomenon. *Neuropsychologia*. 2007 Oct 22.
- [22] Tsubone T, Muroga T, Wada Y. (2007). Application to robot control using brain function measurement by near-infrared spectroscopy. *Conf Proc IEEE Eng Med Biol Soc*. 2007; 1: 5342-5.
- [23] Chow EY, Kahn A, Irazoqui PP. (2007). High Data-Rate 6.7 GHz Wireless ASIC Transmitter for Neural Prostheses. *Conf Proc IEEE Eng Med Biol Soc*. 2007; 1: 6580-3.
- [24] Drescher R. P., and Irazoqui PP. (2007). A Compact Nanopower Low Output Impedance CMOS Operational Amplifier for Wireless Intraocular Pressure Recordings. *Conf Proc IEEE Eng Med Biol Soc*. 2007.
- [25] Moreno Vidales, B. (2007). Armoni Project presented to European Commission inside FP7 Call 2007 7.2 Accessibility and Inclusion, part c) Brain Computer Interaction (BPI). Engineering R&D, Fundació Ave Maria.
- [26] Shneiderman, B. (2007). Web Science: A Provocative Invitation to Computer Science. *Communications of the ACM*. June 2007/Vol. 50, No. 6.
- [27] Stephanidis, C. (2001). User Interfaces for All. Mahwah, NJ: LEA.
- [28] Adams, R. and Gill, S.P. (2007). Augmented Cognition, Universal Access and Social Intelligence in the Information Society. HCII 2007 Beijing
- [29] Reeve, J. (1994). Activity feeling scale II [AFS II]. In Fischer J & Corcoran K (1994). Measures for clinical practice: A sourcebook. 2nd Ed. (vol. 2). New York: Free Press.
- [30] Forbes, E.H. (2003). Children's emotion regulation: frontal EEG asymmetry and behaviour during a disappointment. Doctor Thesis. University of Pittsburgh 2003.
- [31] Baumgartner T., Esslen M., Jäncke, L. (2005). From emotion perception to emotion experience: Emotions evoked by pictures and classical music. Institute for Psychology, University of Zurich.
- [32] Niemi C. P., Warren K. (2002). Studies of Emotion. A Theoretical and Empirical Review of Psychophysiological Studies of Emotion. (Department of Clinical and Social Psychology). JUR Rochester, 1, 1, 15-19.
- [33] Takahashi K. (2004). Remarks on Emotion Recognition from Bio-Potential Signals. 2^o International Conference on Autonomous robots and Agents. December 13-15, 2004 Palmerston North, New Zealand. Faculty of Engineering, Dohisha University, Kyoto, Japan.
- [34] Chanel G, Kronegg J., Grandjean D., Pun T. (2005). Emotion Assessment: Arousal Evaluation Using EEG's and Peripheral Physiological Signals. Computer Vision Group. University of Geneva-Switzerland.
- [35] Coan J. A., Allen J.J.B. (2004). Frontal EEG asymmetry as a moderator and mediator of emotion. *University of Arizona. Tucson USA. Biological Psychology* 67 (2004) 7-49
- [36] Jones, N.A., Field T., Fox, N.A., Davalos M., Gomez, C. (2001). EEG during different emotions in 10-month-old infants of depressed mothers *Journal of Reproductive and Infant Psychology*, Volume 19, Number 4, 17 November 2001, pp. 295-312(18)
- [37] Bachara A., Damasio H., Damasio A.R. (2000). Emotion Decision Making and the Orbitofrontal Cortex. Department of Neurology, University of Iowa College of Medicine. Oxford University Press 2000.
- [38] Schmidt L., Trainor L.J. (2001). Frontal brain electrical activity (EEG) distinguishes valence and intensity of musical emotions. *Psychology Press*.

Toward Construction of an Inexpensive Brain Computer Interface for Goal Oriented Applications

Anthony J. Portelli (student) and Slawomir J. Nasuto,
School of Systems Engineering, University of Reading,
Whiteknights, RG6 6AY,
Reading, UK

Abstract. The paper describes the implementation of an offline, low-cost Brain Computer Interface (BCI) alternative to more expensive commercial models. Using inexpensive general purpose clinical EEG acquisition hardware (Truscan32, Deymed Diagnostic) as the base unit, a synchronisation module was constructed to allow the EEG hardware to be operated precisely in time to allow for recording of automatically time stamped EEG signals. The synchronising module allows the EEG recordings to be aligned in stimulus time locked fashion for further processing by the classifier to establish the class of the stimulus, sample by sample. This allows for the acquisition of signals from the subject's brain for the goal oriented BCI application based on the oddball paradigm.

An appropriate graphical user interface (GUI) was constructed and implemented as the method to elicit the required responses (in this case Event Related Potentials or ERPs) from the subject.

1 INTRODUCTION

Discovered by Hans Berger in 1921 Electroencephalography (EEG) is currently one of the most heavily utilised methods for the detection and measure of brain activity, the first ever recording illustrated in Figure 1.



Figure 1. The first EEG recording made in 1921

Though it has been replaced by more contemporary methods of medical diagnosis its uses still include the identification and characterisation of neurological disorders such as epilepsy and encephalitis. The use of EEG in biofeedback systems has been showing some success in treating some cognitive conditions (sleep disorders, depression) but more recently research and implementation of BCI systems which enable opening extra communication channels for the severely disabled have come to the fore.

The EEG is the result of coherent excitation of large groups of neurons, primarily from the cerebral cortex. When electrodes are placed on the scalp voltage fluctuations between them and a reference electrode (usually positioned at the nasion or earlobes) can be observed when appropriately amplified and filtered. This reflects the operation of neuronal groups involved in cognitive processing.

Compared against alternative means of identifying activity patterns within the brain, for example Magneto Encephalography (MEG) or Positron Emission Tomography (PET), EEG prevails as the cheapest whilst offering excellent temporal resolution. In addition to a low cost, an EEG based BCI does not require extensive medical expertise, is safe (with properly tested medical grade equipment), and it is comparatively easy to use.

When examining the current market of EEG recording units and systems specifically designed for the classification of EEG signals it is clear that these components are expensive to purchase, costing upwards of £10,000 whereby a good ERP lab can be constructed nowadays for ~\$50,000 [1]. This makes the construction of an effective, inexpensive BCI platform (less than £5000) more available for research labs and potentially for patients in the future. It is hoped that such development will contribute to increase the momentum of BCI related research whereby more labs will be able to conduct BCI experiments.

The main components involved in the construction of a digital EEG recording unit are: the electrodes, the analogue to digital converters, the amplifiers, the optical isolation and the transmission into a computer for processing.

It would appear that the obvious and perhaps simplest solution would be to construct a new BCI module. However, this would introduce several problems including safety issues, prototyping and testing costs/time. These concerns are the main reasons that make the task of an independent construction less desirable as a solution.

Taking into account such considerations we have concentrated on using a low cost system that has already passed appropriate industry tests and standards [2]. The system chosen was a construction of Deymed Diagnostic costing slightly in excess of £4000.

In addition to an EEG acquisition method it is also necessary to define a cognitive paradigm leading to generation of the BCI output. Based on the results of the BCI competition in 2003 it was decided that the oddball paradigm would be applied for the elicitation of event related potentials, making this BCI goal oriented [3]. Use of this paradigm led to the classification error rates of 0% (revision of datasets made 3%) achieved by the winning group, hence this work and other ERP based approaches, [4] [5] [6], formed the basis for our ERP experiments.

2 CONCEPT

The Deymed Diagnostic Truscan32 system was designed for the diagnosis of encephalitis and the monitoring of brainwave

patterns. It is a compact unit which could easily be mounted on a mobile platform (e.g. wheelchair) as it requires minimal power consumption (six AA batteries that last for more than 120 hours of uninterrupted use), little computational power with the advantages of being able to be connected via 21 electrodes (the 10-20 system) as well as additionally placed electrodes up to a total of 32 and a standard data connection of a 25pin Parallel port found on most desktop computers. In fact, the system is scalable and additional head units can be purchased and connected together increasing a total number of available electrodes up to a maximum of 128.

The software provided with the Deymed system allows the recording, filtering and storing of EEG records as well as other useful attributes but cannot stream the data directly to any program making a direct online construction impossible.

The apparent limitations of the TruScan32 EEG capture module were a result of its primary design geared towards the diagnosis of neurological problems and not the implementation of a BCI.

For simplicity it was decided to construct a BCI system using two separate computers; one for the installation of software and acquisition of the EEG signals and the second for the administration of the target stimuli, both bridged by a separate “sync circuit”. However, it is possible to use one computer for this task as a single motherboard has all the necessary ports. This would reduce the cost of the system even further.

As a direct interaction with the hardware was not feasible, and communication of external signals to the Deymed software was required, e.g. in order to automatically introduce markers into the recording, an alternative hardware solution was engineered. This “sync circuit” design consisted of a microcontroller which was able to efficiently communicate between the two computers and provide subject-feedback where needed.

To solve the problem of synchronisation three potential methods were initially considered. The first consisted of introducing Pulse Width Modulated (PWM) signals as a timing signal and the second relied on injecting additional noise into the circuit. These were quickly abandoned due to equipment and subject safety concerns but allowed for the development of the ultimately adopted method.

Using the standard inputs of the unit to deliver a synchronising signal was not possible due to a lack of a separate ground electrode providing a reference for the external signal. The ground electrode available on the unit is connected to the subjects head hence it is unsuitable as the external signal reference because of the safety reasons (when using specific recording montages). Moreover, the TruScan32 unit would not recognise or begin recording unless the impedance was below 50KOhms.

In principle, it would have been possible to circumvent the above issues by using 2 electrodes (one effectively as a reference) and a differential montage. Although this would allow the EEG recording to be time locked to the stimulus, it would eliminate the future possibility of extending the system to online processing give the TruScan32 system operation.

The final solution adopted was based on the observation that some commands driven by the keyboard could be utilised to start, stop, pause and make rudimentary reference marks on the recording. Using a microcontroller it would have been possible to directly communicate using the PS/2 port of the keyboard.

An old keyboard was deconstructed and the main circuit board removed to be used as the link between the PS/2 port and the sync circuit. As all keyboards are simple matrix switches, it was merely a task of identifying the “columns” and “rows” which combined to give the correct key pushes.

To synchronise the stimulus an appropriate Graphical User Interface (GUI) was designed that would allow for simple communication through a microcontroller and the graphical presentation and timing of stimulus.

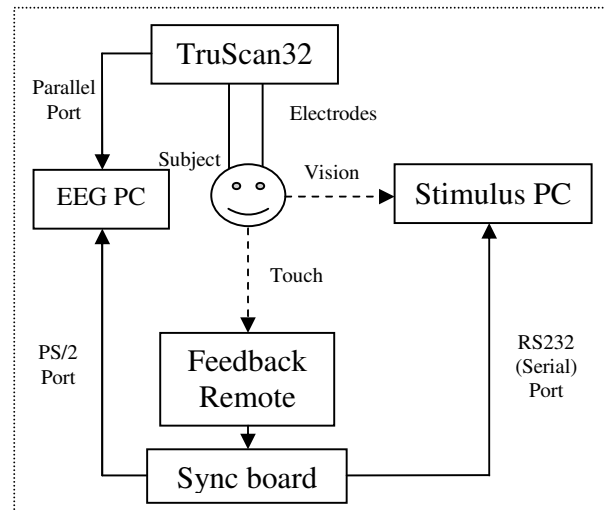


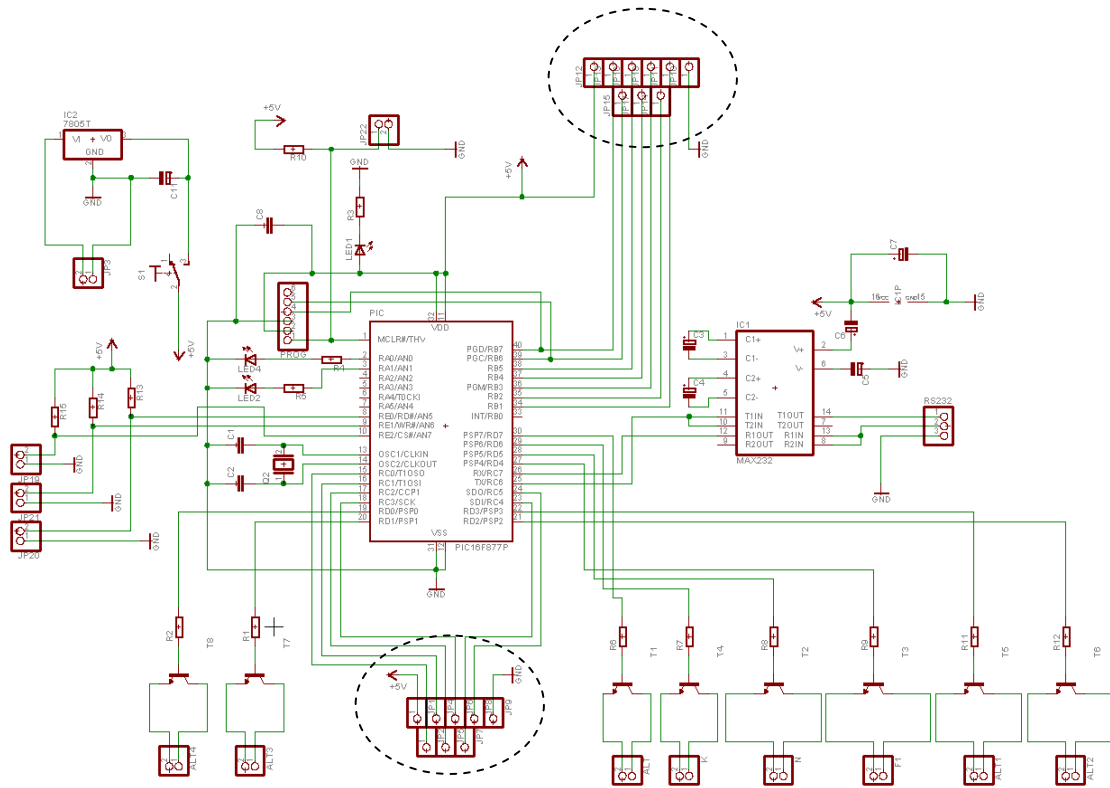
Figure 2. Final design solution showing system design

Figure 2 illustrates the suggested setup for the BCI system detailing all the components of the system.

3 IMPLEMENTATION

The microcontroller used for the implementation of the synchronisation board was a Microchip Programmable Integrated Controller (PIC) microcontroller model 16F877A. This model has all the required peripherals (i.e. Timers and a Universal Asynchronous Receiver Transmitter (UART)) and enough pins to allow for expansion and control of keyboard buttons etc.

The final schematic of the successfully tested prototype of the routed board is shown in Figure 3.



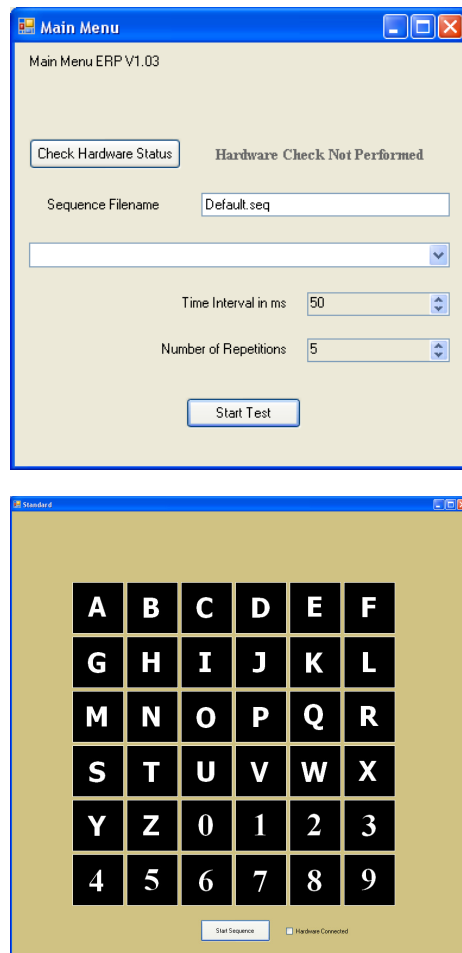


Figure 5. Main menu and standard letter grid which is the main form for providing the stimulus, in this case flashing boxes.

Figure 4 illustrates the flow of a typical experiment which can be conducted with the system using the software illustrated in Figure 5. Figure 5 shows the letter grid used for the standard ERP elicitation. The main menu form allows addition of new experiment types via the drop down menu enabling future system expansion.

4 RESULTS

The system was tested and worked correctly when used in the manner described. The delay estimates were confirmed and provided desired synchronicity between all the system components as discussed below.

The selected sampling rate of the EEG was 128Hz, resulting in the time period between two samples of 7.812ms. Thus, to achieve synchronisation of the stimulus and the EEG recordings it was necessary to ensure that the delay of the entire system was less than 7.812ms as shown in Table 1.

If the cumulative delay between the stimulus and the start of recording is below this threshold that means the start of the recording and any other data recorded will be perfectly synchronous with the stimuli allowing meaningful analysis.

The time taken for the serial port to send one byte of data appeared to be under one millisecond. Coupled with the Microcontroller instruction time and the approximate time taken for the stimulus PC to receive the data the resulting cumulative delay was still less than 1 millisecond. This is based on a microcontroller oscillator speed of 20 MHz (making it 5 MHz actual speed taking four instruction cycles per command) and a 2 GHz CPU speed on the target computer.

The keyboard circuit itself is a matrix switch which is achieved by systematically polling each column and then checking each row to ascertain the press of a button. This is a fairly slow process, however by assuming a slow clock speed of 4 MHz and making the generous assumption that each polling event takes 20 instructions with 13 row and 8 columns the cumulative delay measures at approximately 2ms.

The keyboard communication protocol states that it can run from 10 KHz to 16 KHz operating speed depending on the keyboard and what data is being transferred [7][8]. In Table 1 the conservative estimate of 10Khz was used to calculate the delay making it approximately 2.4 milliseconds add to the time it would take for the software to interpret these commands which should not be more than 1ms based on a CPU speed of 2GHz, all the delays were well below the threshold required for synchronicity.

Component	Delay Incurred (ms)
RS232 Sending	0.234
RS232 Processing	~1ms*
Keyboard circuit identifying button press	2.080
Keyboard Sending commands	2.400
Cumulative Delay in system (Sync board to stimulus)	1.234
Cumulative Delay in system (Sync board to EEG recording)	4.480
Max Possible Delay to ensure synch status	7.812

*based on 2GHz CPU speed

Table 1. Delay Elements present in the system

Figure 6 shows the final product including case and circuit connected to one of the remote controls for administering ERP experiments.

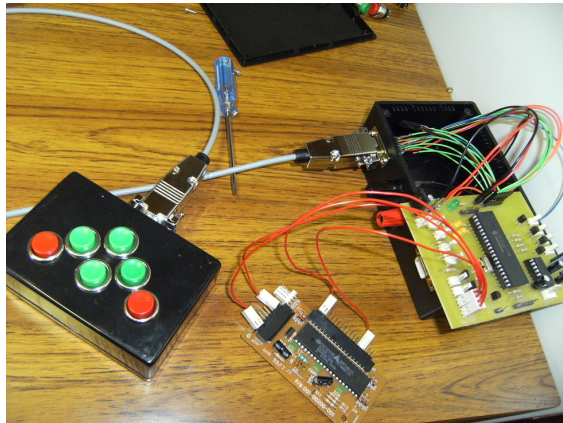


Figure 6. Finished circuit connected to its case and keyboard circuit with shielded cable connecting external remote control.

So far the system has been tested by performing several ERP experiments with the standard letter grid as shown in Figure 5. Figure 7 shows an example of a normalised waveform (p300) acquired by use of the above described system.

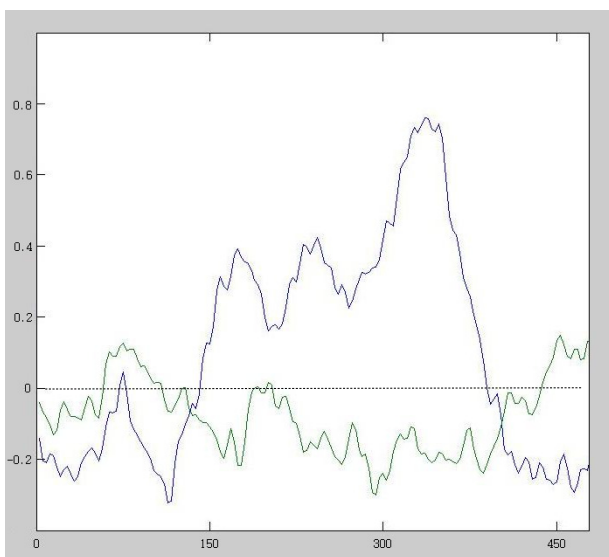


Figure 7. Shows an example p300 waveform obtained from averaged results through use of the described system. (X-axis: Time post stimulus (ms), Y-axis: Normalised Amplitude (arbitrary units)).

This waveform was obtained from EEG recordings time locked to the stimulus by the synchronisation system, aligned in time and averaged following a standard ERP approach. The electrodes used were Cz, Fz, Pz, O1 and O2 using a 50 millisecond flash interval, 20 repetitions and 128Hz sample frequency. The onset of the p300 wave is approximately 300 milliseconds after the onset of the stimulus as expected in keeping with the nature of ERPs [1].

5 CONCLUSIONS & FUTURE WORK

The system works well within the specified time limits and allows for an efficient recording of EEG stimulus data in the appropriately formatted files. Hence, the EEG data can be precisely referenced to the stimulus onset and analysed for the identification of ERP signals.

At present this platform provides an inexpensive research tool as it can be configured for study of ERP signals, or with minor modifications, for the acquisition of other EEG related signals.

Future extension of the system towards the online control of external devices is considered by taking advantage of computer system commands and Direct-Link Library (DLL) files in order to track and decode files containing the recorded EEG signals.

Thus, with an increase of accuracy, the information transfer and improvements of human computer interactions in BCIs, the costs of the proposed platform may be sufficiently low to offer a viable solution for the severely disabled by the healthcare system. This is because it could significantly increase the independence of the patients and hence could reduce the workload of the carers.

The decision to use two personal computers for the implementation of this system was primarily aesthetic. A proof of concept system has been setup successfully also on one computer thus further lowering the overall cost.

To further reduce costs and make the hardware system more compact it would be useful to implement the standard keyboard protocol to enable the connection of the PS/2 port directly to the circuit without going through a separate circuit board; this addition would also eliminate more of the delay.

It is hoped that the construction proposed in this paper will encourage more research into different methods of human and computer interaction by providing relatively easy to assemble and more affordable platforms for BCI.

REFERENCES

- [1] Luck, S. J., 'An Introduction to the Event Related Potential Technique', MIT Press, 2005.
- [2] Medical Q&A on Standards
<http://www.mdqaconsultancy.co.uk/faq%20601.html#601%20series>
- [3] Kaper, M. Meinicke, P., Grossekathoefer, U., Lingner, T., Ritter, H., 'BCI Competition 2003 - Dataset IIb: Support Vector Machines for the P300 speller paradigm, IEEE Transactions Biomedical Engineering, 51(6):1073-1076, 2004.
- [4] Rebsamen, B., Burdet, E., Guan, C.T., Chee, L., Zeng, Q., Ang, M. and Laugier, Ch., 'Controlling a wheelchair using a BCI with low information transfer rate' Proc. 2007 IEEE 10th International Conference on Rehabilitation Robotics, Noordwijk, The Netherlands, 2007, 1003-1008.
- [5] Wang, Ch., Guan, C. and Zhang, H., 'P300 Brain computer interface design for communication and control applications', Proc. IEEE Engineering in medicine and biology, 27th Annual Conference, 2005, 5400-5403.
- [6] Lotte, F., Congedo, M., L'ecuyer, A., Lamarche, F. and Arnaldi, B., 'A review of classification algorithms for

EEG-based brain-computer interfaces', Journal of Neural Engineering 4, 2007, R1-R13.

- [7] Identification of keyboard communication protocol
<http://www.computer-engineering.org/ps2keyboard/>
- [8] Page for the identification of keyboard scan codes
<http://www.computer-engineering.org/ps2keyboard/scancodes2.html>
- [9] Deymed Diagnostic Truscan 32 page
<http://www.deymed.com/truscanEEG-specifications.html>

All Web addresses referred to in this paper were verified on 7 March 2008.

Single-Trial Event-Related Potential Analysis for Brain-Computer Interfaces

Nicoletta Nicolaou¹, Slawomir J. Nasuto², and J. Georgiou¹

¹Department of Electrical and Computer Engineering, University of Cyprus, Cyprus
{nicoletta.n, julio}@ucy.ac.cy

²School of Systems Engineering, University of Reading, UK
{s.j.nasuto@rdg.ac.uk}

Abstract. Different types of mental activity are utilised as an input in Brain-Computer Interface (BCI) systems. One such activity type is based on Event-Related Potentials (ERPs). The characteristics of ERPs are not visible in single-trials, thus averaging over a number of trials is necessary before the signals become usable. An improvement in ERP-based BCI operation and system usability could be obtained if the use of single-trial ERP data was possible. The method of Independent Component Analysis (ICA) can be utilised to separate single-trial recordings of ERP data into components that correspond to ERP characteristics, background electroencephalogram (EEG) activity and other components with non-cerebral origin. Choice of specific components and their use to reconstruct “denoised” single-trial data could improve the signal quality, thus allowing the successful use of single-trial data without the need for averaging. This paper assesses single-trial ERP signals reconstructed using a selection of estimated components from the application of ICA on the raw ERP data. Signal improvement is measured using Contrast-To-Noise measures. It was found that such analysis improves the signal quality in all single-trials.

1 INTRODUCTION

“A Brain-Computer Interface (BCI) is a communication system that does not depend on the brain’s normal output pathways of peripheral nerves and muscles” [1]. In a BCI system the activity of the brain, more commonly obtained from electrodes placed on the surface of the head (electroencephalogram, EEG), is utilised directly as an input to a device, e.g. computer. The most popular application of BCIs is word spelling, achieved with the use of a “virtual keyboard” on the computer screen and mental control of the letter selection. Such systems are developed primarily as communication aids for disabled people, mainly for those who have lost the ability to communicate with their environment via conventional means (e.g. locked-in patients). BCI systems can be categorised based on their characteristics, and one such categorisation involves the type of electrical activity utilised. Different types of brain activity can be utilised to control the device, with the most popular choice being mental imagery. In such BCIs different mental imagery (e.g. motor imagery, mental arithmetic) is used to represent cursor movement in different directions (up-down and/or left-right) with the aim of directing the cursor to the letter of choice in the “virtual keyboard” in order to spell a particular word. Despite the popularity of mental

imagery-based BCIs, they are limited by the trade-off between the number of mental tasks utilised, and accuracy and speed of communication. In addition, the user must first be trained before using the system – a process which is very time consuming, with training times ranging from a few half-hour sessions a day for a few days and up to even a year [2,3].

A simpler BCI system that does not require user training and is more user-friendly is based on the use of Event-Related Potentials (ERPs). ERPs are changes in the brain electrical potential with specific characteristics and are time-locked to the onset of a motor or sensory stimulus. The study of ERP signals is not only beneficial in psychological studies of memory, language and attention [4], but the operation of many BCI systems is based on the utilisation of ERP signals, as the signals have specific characteristics that are recognisable and, thus, can be utilised successfully in a BCI. One such characteristic is the P300, a positive peak observed approximately 300ms after a stimulus presentation and is elicited upon encountering infrequent target-related stimuli interspersed with frequent target-irrelevant stimuli (“oddball” paradigm), [5]. It is more prominent at parietal electrodes, mainly at electrode Pz. An example of a way of eliciting the P300 wave in a BCI is presentation of the letters of the alphabet in a grid formation and requesting the subject to fixate on the letter of their choice while randomly illuminating columns and rows of letters in the grid, [6, 7]. The P300 is elicited once the columns and rows that contain the chosen letter are illuminated, thus allowing the subject to perform selection of letters and spelling of words in this way.

The use of the P300 as a feature in BCIs has the main advantage that the user does not require any training, as the P300 is a feature that can be elicited in everybody with presentation of the right stimulus. In addition, ERP-based BCI systems are more straight-forward to use and make the human-computer interaction aspect an easier task. However, a large number of trials must be obtained before a ‘target - no target’ decision can be made as the P300 is not identifiable in individual trials due to masking by higher amplitude background EEG (and artefact activity if no artefact removal is performed) in single-trials. As a result, common ERP analysis involves averaging over a number of trials. Using averaging for ERP analysis is based on the assumption that the ERPs invariant activity pattern is perfectly time-locked to the stimulus and is superimposed on the independent stochastic background EEG signals [8]. However,

ERP averaging causes a trade-off between the potential accuracy and the speed of communication achieved e.g. Donchin et al. report that 100% accuracy can be achieved by averaging the EEG over 40 trials, but the communication rate is 1 letter/minute; for 90% accuracy the communication increases to 4.8 letters/minute and for 80% accuracy the communication is 7.8 letters/minute, [6]. More importantly, averaging removes any information related to systematic or even unsystematic variations observed in single-trials; as a result the average waveform may not be representative of the single trial responses and important information contained in these variations will be lost. More importantly, the ability to use signals from single-trials is advantageous particularly for BCI systems mainly for two reasons. Firstly, it has the potential of increasing communication speed (by eliminating the need to perform many trials for choice of a single letter). Secondly, it may be the case that these systematic variations in single-trials carry important information for the mental processes and their utilisation may improve BCI system performance in terms of accuracy.

For these reasons, single-trial ERP analysis is gaining interest and a number of techniques are being proposed for ERP denoising [9, 10, 11]. In addition, ERP signals can be decomposed into a number of components using the method of Independent Component Analysis (ICA). Such decomposition not only allows successful denoising of the signals, but can also be used as a tool to visualise characteristics of ERP signals, such as the P300 peak, that are not otherwise visible in raw single-trial data [12].

The use of ICA for single-trial ERP analysis has a number of advantages that make it more appealing over other methods. Firstly, it allows simple and accessible visualisation of the separated components. Secondly, the assumptions behind ICA agree with certain assumptions concerning the signals recorded via EEG, e.g. the recorded EEG is a mixture of other signals that are linearly and instantaneously mixed. Thirdly, the ERP characteristics of interest can be reconstructed without inducing any spurious changes in the data, as could be the case for other methods, e.g. wavelet denoising [10].

Such ERP denoising methods are also important for BCI applications. The advantages of such decomposition for a BCI are, firstly, the increase of the speed of BCI operation, since it is not necessary to obtain many trials before a decision is made. Secondly, together with technical factors, another factor that influences the performance of a BCI system is user fatigue: performance drops when the user becomes tired. In a BCI system that is based on single-trial ERP data a single decision will not require a large number of repetitions of the same event; hence the user can operate the BCI longer before performance drops due to fatigue. Thirdly, a system that is less tiring is consequently more user-friendly at the same time. These factors make a single-trial ERP based BCI particularly from the Human-Computer Interaction perspective, as the resulting system is going to be easier, faster and more intuitive to use.

The work presented here is based on decomposition of ERP signals using ICA and reconstruction of single-trials using only components that correspond to ERP characteristics. This eliminates the need for averaging as the ERP signal is now visible in single-trial data, which can be used directly to control the BCI. The investigations were performed to assess whether such a reconstruction method is beneficial in single-trial ERP

analysis by measuring the level of improvement in signal quality achieved.

2 METHODOLOGY

2.1 Independent Component Analysis (ICA)

ICA is a technique for separating observed linear and instantaneous mixtures of random variables into a set of unobserved independent sources [13]. Let $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_N]^T$ denote the N observed variables (mixtures), with $\mathbf{x}_i = [x_{i1}, \dots, x_{iT}]^T$ a vector of T observations, $i=1, \dots, N$. Then,

$$\mathbf{X} = \mathbf{A}\mathbf{S} \quad (1)$$

where $\mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{N1} & \cdots & a_{NN} \end{bmatrix}$ is the unknown square

$(N \times N)$, instantaneous and linear mixing matrix, and $\mathbf{S} = [\mathbf{s}_1, \dots, \mathbf{s}_N]^T$, $\mathbf{s}_i = [s_{i1}, \dots, s_{iT}]^T$, $i=1, \dots, N$ are the unobserved independent sources. The goal of ICA is to recover \mathbf{A} and \mathbf{S} using only information contained in \mathbf{X} ,

$$\mathbf{S} = \mathbf{W}\mathbf{X} \quad (2)$$

where $\mathbf{W} = \hat{\mathbf{A}}^{-1}$ is the demixing matrix, an estimate of \mathbf{A}^{-1} . To solve this problem the minimal assumption of source independence is necessary and a solution can then be obtained via maximisation of a cost function that measures departure from independence or gaussianity (by utilising measures based on higher-order statistics, such as kurtosis).

Once the estimated sources and demixing matrix are obtained, it is possible to project only sources of interest back into the original signal space. This is achieved by multiplying the estimated mixing matrix, with all its columns set to zero except the ones corresponding to the chosen sources, with the estimated source matrix. In this way only the sources corresponding to the non-zero columns of the mixing matrix will be “re-mixed” and thus the signal of interest can be obtained in the original mixture space.

However, classical ICA suffers from the shortcoming that it does not take into account any temporal information since the core of the ICA estimations is based on the assumption that the sources are independent non-Gaussian random variables. The assumption of non-Gaussianity is relaxed in temporal extensions of ICA algorithms whereby the signals are treated as time-series and the temporal information of the signals is incorporated in the separation process. Such an extension also improves the quality of separation in many cases as information that is discarded in classical ICA estimations is now being utilised. This has the advantage over classical ICA methods that it allows the separation of the mixtures when more than one source is Gaussian (which is the case for EEG signals, as they have been shown to be quasi-stationary Gaussian [14]).

One such temporal extension algorithm popular for its simplicity and effectiveness is Temporal Decorrelation Source Separation (TDSEP) [15]. TDSEP incorporates temporal information in the form of time-delayed correlation matrices. Imposing decorrelation over time provides the information needed to estimate the sources without the need for higher-order statistics.

TDSEP operates on the basis that independence of the signals over time implies that all cross-correlations vanish, and hence all time-delayed correlation matrices should be diagonal. Hence, a number of stacked time-delayed correlation matrices must be simultaneously diagonalised, i.e. a matrix must be estimated which, when multiplied with the stacked covariance matrices, it rotates them in such a way that they become (as close as possible to) diagonal. In TDSEP this is achieved by:

(1) whitening the data, i.e. removing any correlations present in the data and making their variances equal to unity; and

(2) approximating the rotation matrix by a sequence of elementary rotations (Jacobi rotations), each one minimising the off-diagonal elements of a cross-covariance matrix at a specific delay. The final rotation is then the product of the elementary rotation matrices. In the special case when only 2 matrices need to be simultaneously diagonalised, the rotation matrix can simply be estimated via eigenvalue decomposition of the time-delayed covariance matrix.

The estimate of the mixing matrix is then obtained as the product of the whitening transform matrix and the rotation matrix.

One of the advantages of TDSEP is that, because separation is based on the lagged correlation of the sources, TDSEP can separate signals whose amplitude distribution is Gaussian in a very efficient and robust way. The main advantages of the method stem from the fact that the BSS problem is solved using linear algebra, thus avoiding complicated optimisation, and its operation relies on second-order statistics that can be obtained in a robust and computationally efficient manner.

There is a rapidly increasing interest in use of ICA in ERP analysis (see e.g. [16]), however the use of TDSEP is less well-studied. One of its few applications is by Lemm et al [17], who introduce a regularisation approach that linearly transforms ERP data prior to application of TDSEP in order to bias the extraction of ERP-related components from the background EEG. Each of the single-trial data is replaced by a weighted average of itself and the averaged ERP template. The weight, λ , varies from 0 to 1 and controls the amount of bias of the single-trial data towards the ERP average ($\lambda=0$ corresponds to pure raw single-trial data, while $\lambda=1$ corresponds to the ERP average). Applying TDSEP on data that is linearly transformed in this way results in improvement in the Signal-To-Noise ratio of the extracted components when the ERP component contained in the data is not very weak, i.e. a limitation of the method arises when a few number of trials is available or when the signal of interest is much weaker than the “noise” in which it is contained.

In the work presented here decomposition of the ERP signals is obtained from TDSEP. The components are then visually inspected to choose a single component, whose shape closely resembles the average ERP template. The chosen component is then projected back onto the electrode space and the “denoised” single-trial data is obtained.

2.2 Dataset

The dataset used was contributed as part of the data analysis competition of the IEEE Workshop MLSP’05 [18] and consisted of EEG recorded from 62 electrodes placed on the surface of the head (an additional 2 electrodes were placed near the eyes to record eye movements). The ERPs were recorded from a single subject (healthy volunteer) during an auditory ‘oddball’ task, which is the type of task used in ERP-based BCI systems. The ‘oddball’ paradigm involves the interspersing of frequent task-relevant stimuli with infrequent task-irrelevant novel stimuli and frequent task-irrelevant standard stimuli. In this particular case stimuli consisted of bursts of sound with low (non-targets) and high (targets) frequency. The subject was instructed to respond to a target stimulus with the press of a button. The data was presented as a continuous recording of approximately 12.5 minutes length obtained from a single subject and was sampled at a rate of 500Hz. During the recording a total of 48 target auditory stimuli were presented.

3 RESULTS AND DISCUSSION

The investigations performed utilised all 48 single-trials of target presentations to the subject. Since the data is provided as a continuous recording, the data corresponding to target presentations was extracted. A segment of the EEG recordings of length 1.1s (0.1s pre- and 1s post-stimulus) from each stimulus presentation was extracted. This gave a total of 550 samples per segment for the analysis. This particular window size was chosen for two reasons: (i) based on the sampling rate of the data (500Hz), it provided enough samples to ensure accurate ICA operation; more importantly, (ii) the window is long enough to ensure that all relevant ERP peaks elicited by the stimulus presentation, such as the P300 peak, are contained within this window. This segmentation was performed for all 48 target stimulus presentations and all 62 electrodes. TDSEP is then applied to each of the 48 single-trial data to obtain 62 independent components in each trial. In each of the decomposed trials, a single component which bore the closest resemblance to the general shape of the ERP signal obtained from averaging all 48 trials was identified via visual inspection of the estimated components. This was then projected back into the electrode space to obtain the 48 “denoised” single-trials.

In typical ERP analysis the EEG recordings are averaged over all the available trials and the averaged ERP signal is then used for subsequent processing. In order to assess whether signal reconstruction using the selected ICA component is beneficial, the quality of the reconstructed signals must be compared with the quality of the averaged ERP data, which in a standard BCI application would usually provide the input signal. This quality was assessed using the Contrast-To-Noise (CNR). The CNR measure is the difference in the Signal-to-Noise Ratio between two regions of interest [19]. Improving the CNR highlights the distinct differences between the two regions; in this specific case between the original averaged ERP template and the clean single-trial signals from projection of a single component. Two similar CNR measures can be defined as

$$CNR_{\max}(y^e) = \frac{\max_j y_j^e - \frac{1}{N_p} \sum_{i=1}^{N_p} y_i^e}{\frac{1}{500} \sum_{k=50}^{550} \sqrt{\sum_{i=1}^{N_s} (x_{ik}^e - y_k^e)^2}} \quad (3)$$

$$CNR_{\text{mean}}(y^e) = \frac{\frac{1}{100} \sum_{j=350}^{450} y_j^e - \frac{1}{N_p} \sum_{i=1}^{N_p} y_i^e}{\frac{1}{500} \sum_{k=50}^{550} \sqrt{\sum_{i=1}^{N_s} (x_{ik}^e - y_k^e)^2}} \quad (4)$$

where x^e and y^e are respectively the original and clean ERP recordings at electrode e , N_s is the number of target stimuli presentations, and N_p is the number of pre-stimuli samples (50 samples corresponding to 0.1s). $j \in [350, 450]$ and represents the maximum (eq. 3) or average (eq. 4) peak amplitude of the ERP. If we are interested in the overall improvement in signal quality, then the average CNR measure over all electrodes can be estimated,

$$CNR = \frac{1}{N_{el}} \sum_{e=1}^{N_{el}} CNR(y^e) \quad (5)$$

where CNR can be either the $CNR_{\max}(\cdot)$ or the $CNR_{\text{mean}}(\cdot)$ obtained at each electrode. Before estimating any measures, all the data is normalised by removing the mean and making the signal variance unity. This is to ensure that a correct measure is obtained by comparing signals whose amplitudes are in the same region. Estimating the CNR measures for the averaged ERP gives a “lower” bound; anything above this bound implies an improvement in the signal quality. The CNR measure is also estimated for the ERP reconstructed using the chosen IC at each single trial and is then averaged over all trials to obtain the average improvement for each trial at each electrode. The aim here is to investigate whether separating the EEG recordings using ICA and then choosing which components to use in further analysis is more beneficial than using the averaged raw EEGs. Hence, if this hypothesis holds then an improvement in the CNR for the reconstructed ERP is expected.

Figure 1 shows the reconstructed single-trial signal at electrode Pz (where the P300 feature is in general most prominent), together with the averaged ERP and the raw data recorded at that electrode. The data is obtained from the 6th stimulus presentation, for which the maximum average CNR_{\max} (reported in table 1) was obtained for the reconstructed data. The shape of the reconstructed IC closely resembles the shape of the ERP template. For comparison, figure 2 shows the corresponding signals for trial 41, which is the trial for which the minimum value of the CNR_{\max} measure was obtained for the reconstructed data.

Figures 2 and 3 show the electrode averages of the CNR_{\max} and CNR_{mean} measures respectively for each of the 48 single-trials. The dotted line in both figures represents the CNR measures obtained when the original ERP signals are averaged over 48 trials (lower “bounds”). Almost all measures estimated

for the single-trial reconstructed data exceed this lower “bound”. More specifically, the CNR_{\max} measure exceeds the bound for 47 out of the 48 trials (97.9%), and the CNR_{mean} for all 48 trials (100%). This implies that the signal decomposition using TDSEP and single-trial reconstruction from a single component improves the signal quality more than signal averaging, thus making single-trial ERP data usable.

Table 1 shows the average, minimum and maximum CNR measures of all 48 reconstructed single-trials. Comparing the lower CNR “bound” with the maximum single-trial CNR_{\max} and CNR_{mean} values obtained, an improvement of 184% and 430% respectively was obtained. However, despite the vast improvement in signal quality observed, it may be possible to improve it even further if a collection of components that correspond to other ERP features is used in the reconstruction, instead of using only a single component. In addition, it would be interesting to see whether the use of more components in the reconstruction manages to improve the signal quality above the lower “bound” values for the trial for which inadequate signal improvement was obtained.

Moreover, in interpreting these findings one must also take into account other factors which are specific to the dataset used. Firstly, data from a single subject is used. This allows to investigate the robustness of the method during fluctuations in ERP signals over time. However, it does not allow the investigation of inter-subject variability of the method, something which needs to be addressed by future work. Secondly, the data is from a healthy subject, which is appropriate if the ERP-based BCI is to be used for purposes other than an assistive device. Data from healthy subjects is usually used in the development and initial assessment of the majority of BCI systems, as it is difficult to obtain data from the target population (people with severe motor disabilities). However, for assistive BCIs it is preferable to assess the methods proposed using data from the targeted population when such data can be made available.

	Recon. ERPs			Aver. ERPs
	Mean	Max	Min	
CNRmax	0.279	0.357	0.151	0.194
CNRmean	0.090	0.198	0.006	-0.023

Table 1. Mean electrode averages of the CNR measures from the reconstructed ERPs and the averaged ERP template (for the former case the maximum and minimum CNR values are also provided).

In addition, the separation of the signals into components that correspond to ERP features and background EEG activity is also interesting for another reason. A subset of components may represent the systematic or variations observed in single-trials. More importantly, averaging removes any information related to these systematic or unsystematic variations observed in single-trials; as a result the average waveform may not be representative of the single trial responses and important information contained in these variations will be lost. It remains to be seen which component groups can offer a larger improvement in the performance of a BCI system – only the ERP-related components, the background variations or even a combination of both? As an aside, a possible explanation for obtaining a CNR_{\max} measure below the lower “bound” for this specific trial could be due to the slight misalignment in terms of

latencies between the reconstructed signal and the original data. The inclusion of more components in the reconstructed signal may correct this misalignment and thus increase the signal quality.

4 CONCLUSIONS

This paper has shown that separation of ERP signals with temporal ICA results in components that correspond to ERP features and background EEG activity. This allows us to choose a subset of ICs that correspond to ERP features and back-project them to obtain denoised signals. The improvement in signal quality in single-trials obtained using this method is large and could allow the utilisation of single-trial data for applications such as BCIs. Subsequently, this will benefit both the technical aspect (speed, accuracy) and the human aspect (usability, user performance, user-friendly) of a BCI system.

The need for averaging ERPs over a number of trials is, thus, eliminated, with benefits in terms of speed and accuracy of a BCI. In addition, this ERP decomposition opens up new possibilities in single-trial ERP analysis in general and may even offer the ability to isolate and study the variations in background EEG which could be the carrier of information whose importance is much greater than previously thought.

REFERENCES

- [1] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, "Brain-Computer Interface Technology: a review of the First International meeting", *IEEE Trans. on Rehabilitation Engineering*, 8(2):164-173, June, 2000.
- [2] A. Kostov and M. Polak, "Parallel Man-Machine training in development of EEG-based cursor control", *IEEE Trans. in Rehabilitation Engineering*, 8(2):203-205, June, 2000.
- [3] G. G. Molina, T. Ebrahimi, and J.-M. Vesin, "Joint time-frequency-space classification of EEG in a brain-computer interface application", *EURASIP Journal of Applied Signal Processing*, 7:713-729, 2003.
- [4] "Electrophysiology of mind", *Oxford Psychology Series*, 25, M. D. Rugg and M. G. H. Coles, Eds. Oxford: Oxford University Press, 1995.
- [5] T. Hruby and P. Marsalek, "Event-related potentials - the P3 wave", *Acta Neurobiol. Exp.*, 63:55-63, 2003.
- [6] E. Donchin, K. M. Spencer, and R. Wijesinthe, "The mental prosthesis: assessing the speed of a P300-based Brain-Computer Interface", *IEEE Trans. on Biomedical Engineering*, 8(2):174-179, June, 2000.
- [7] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials", *Electroenceph. Clin. Neurophysiology*, 70:510-523, 1988.
- [8] R. Quiñero, M. Atienza, J. L. Cantero, and M. L. A. Jongsma, "What can we learn from single-trial event-related potentials?", *Chaos and Complexity Letters*, 2(2/3), 2006.
- [9] G. Zouridakis and D. Iyer, "Comparison between ICA and wavelet-based denoising of single-trial evoked potentials", in *Proc. 26th Annual Intl. Conf. of the IEEE EMBS*, San Francisco, USA, pp.87-90, 2004.
- [10] R. Quiñero and H. García, "Single-trial event-related potentials with Wavelet denoising", *Clinical Neurophysiology*, 114:376-390, 2003.
- [11] N. Nicolaou, and S.J. Nasuto, "Automatic artefact removal from Event-Related Potentials via Clustering", *Journal of VLSI Signal Processing*, 48(1-2):173-183, August 2007.
- [12] T.-P. Jung, S. Makeig, M. Westerfield, J. Townsend, E. Courchesne, and T.J. Sejnowski, "Analysis and Visualisation of Single-Trial Event-Related Potentials", *Human Brain Mapping*, 14:166-185, 2001.
- [13] A. Hyvärinen and E. Oja, "Independent Component Analysis: A tutorial", *Neural Networks: ICA - Algorithms and Applications*, 1999.
- [14] F. Lopes da Silva, "EEG analysis: Theory and Practice", *Electroencephalography: Basic Principles, Clinical Applications and Related Fields*, Ch. 6, pp. 1135-1163, 1998.
- [15] A. Ziehe and K.-R. Müller, "TDSEP - an efficient algorithm for blind separation using time structure", in *Proc. ICANN'98*, pp.675-680, 1998.
- [16] Makeig S, Debener S, Onton J, Delorme A, Mining event-related brain dynamics, *Trends in Cognitive Science*, 8(5):204-210, 2004.
- [17] S. Lemm, G. Curio, Y. Hlushchuk, and K.-R. Müller, "Enhancing the Signal-To-Noise Ratio of ICA-based Extracted ERPs", *IEEE Trans. Biomed. Eng.*, 53(4):601-607, 2006.
- [18] Data contributed by Dr. V. Calhoun and is available online from <http://mlsp2005.conwiz.dk/index.php?id=30.html>
- [19] C. Westbrook, "Handbook of MRI technique", 2nd ed: Blackwell Publishing, 1999.

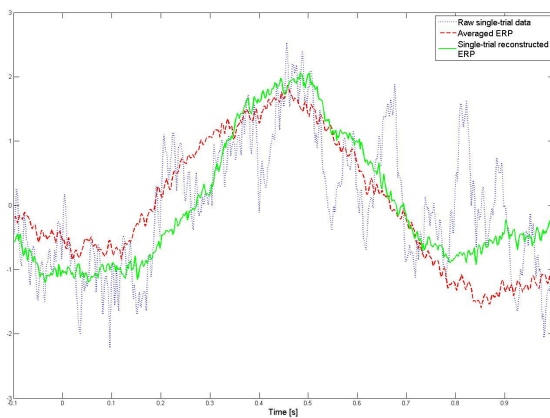


Figure 1. Raw single-trial data, averaged ERP data and reconstructed single-trial ERP data at electrode Pz. The data is for the 6th stimulus presentation, for which the maximum value of the

electrode average CNR_{max} from the reconstructed data was obtained.

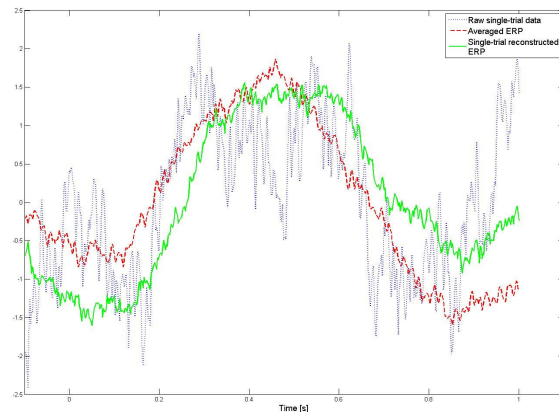


Figure 2. Raw single-trial data, averaged ERP data and reconstructed single-trial ERP data at electrode Pz. The data is for the 41st stimulus presentation, for which the minimum value of

the electrode average CNR_{max} from the reconstructed data was obtained.

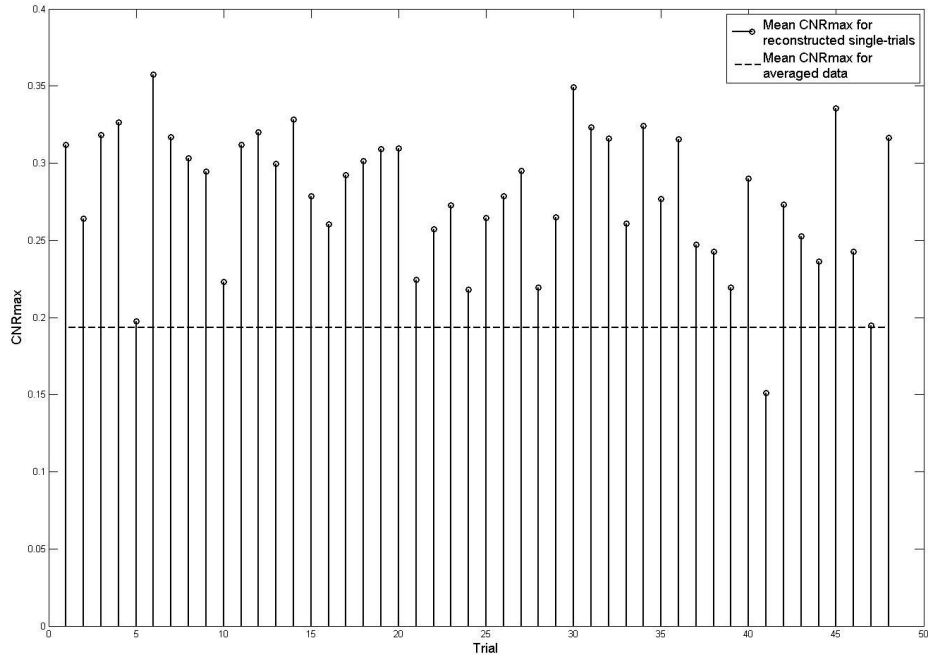


Figure 3. Average CNR_{max} over all electrodes for ERPs reconstructed using a chosen independent component. The CNR_{max} measure is given for all 48 trials. The dotted line corresponds to the mean electrode CNR_{max} for the averaged ERP template. It can be seen that an improvement in the CNR_{max} measure is obtained for the reconstructed ERPs in 47 out of 48 trials.

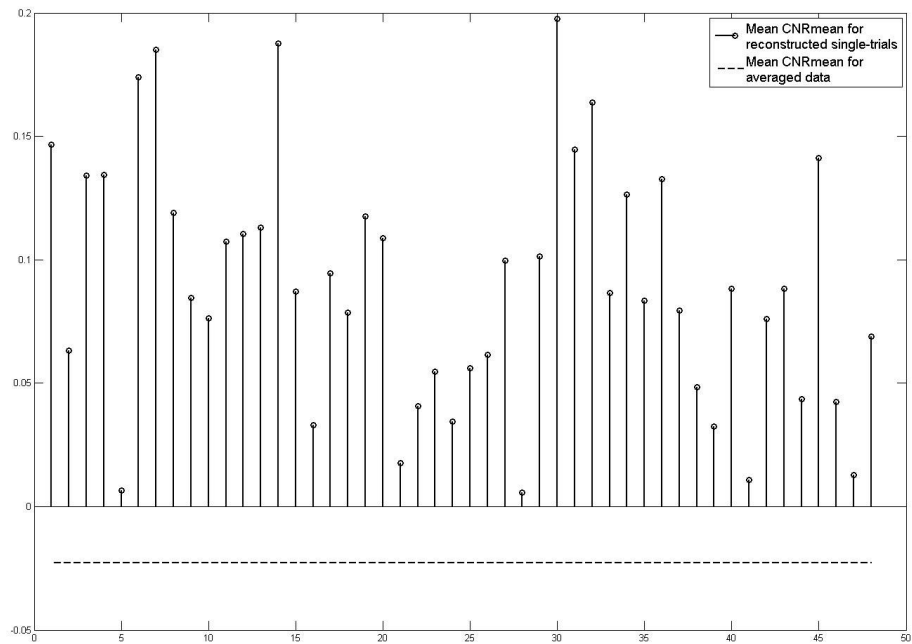


Figure 4. Average CNR_{mean} over all electrodes for ERPs reconstructed using a chosen independent component. The CNR_{mean} measure is given for all 48 trials. The dotted line corresponds to the mean electrode CNR_{mean} for the averaged ERP template. It can be seen that an improvement in the CNR_{mean} measure is obtained for all the reconstructed ERPs.

Adaptive Brain-Body Interfaces

Paul Gnanayutham¹ and Jennifer George²

¹Department of Computing, University of Portsmouth, Buckingham Building, Lion Terrace, Portsmouth,
PO1 3HE, United Kingdom

²SAE Institute, United House, North Road, London, N7 9DP, United Kingdom
{ paul.gnanayutham@port.ac.uk, jennifer.george@sae.edu }

Abstract. This paper describes an adaptive brain-body interface (BBI) that was designed to cater for traumatic brain injured personnel to use the computer screen as a means for communicating, recreating and controlling their environment. The paper describes how the initial interface was developed and optimised for this group of personnel. It also deals with the challenges involved in designing an adaptive interface and the adaptive features incorporated in to the interface.

1 INTRODUCTION

A brain-computer interface (or Brain-Body Interface) is a communication system that does not depend on the brain's normal output pathways such as speech or gestures but by using electrophysiological signals from the brain as defined by Wolpaw. There are various brain-body interfaces that have been developed which uses interfaces with fixed configurations but this research looked for an inclusive interface that can be personalised for individual needs of the users. A computer program that would enable a non-verbal, quadriplegia head injured person to communicate, recreate or control their environment. A non-invasive assistive technology device named Cyberlink™ was chosen as the brain-body interface for this research. Cyberlink™ combines eye-movement (EOG), facial muscle (EMG) and brain wave (EEG) bio-potentials detected at the user's forehead to generate input via the mouse port. A major problem encountered while designing this interface was the inconsistent control of the cursor, which was caused by the 'irrelevant' electrooculographic (EOG), electromyographic (EMG) and electroencephalographic (EEG) signals being picked by the brain body interface. This had to be solved by controlling the cursor navigation on a computer screen. The bio-potentials obtained by the brain-body interfaces had a voltage range of micro volts to mini volts, which meant navigating a cursor through a computer screen was a difficult task and needed a method to push the cursor towards the target. The design solution chosen to solve these two issues were to calculate the directions of travel and push the cursor towards the intended target, use tiles to control the cursor navigation and give the users personalised settings to create individual interfaces [1][2] (Figures 1 - 4). There was also need for minimum training since the interface had to cater for the short-term memory of some users.

This study was carried out in three phases. Phase one of this research which was an exploratory one which indicated that the users had problems navigating certain parts of the screen or

when travelling in certain directions [1]. Sibert and Jacob [3] recommend a target practice with random target with no target being repeated. Jacko and team [4] state allowing individual time to reach a target will cater for any individual with minor visual impairment. One possible approach to accommodate varying individual capabilities would be to have a target practice to show individual preference of a screen location through time to reach the target.

Target practice could have a screen with, for example, twenty four targets (Figure 5). Then the participant would be asked to hit each target at random, as each appeared one at a time, within a prescribed time interval. The time taken to reach each target would be recorded and a program could automatically decide which areas are fastest for each participant. Once the user finishes target practice, the program can come up with a tailor-made profile for that particular individual user (Figure 6). Different numbers of targets could be set for a particular individual interface, for example 2 to 6 depending on ability of the user. Targets could also be programmed to do various tasks such as read text, launch applications or switch devices.

Automated target practice for a personalised interface based on this results could improve an interface but will this automated process work with severely brain injured individuals? Do we need a manual configuration facility to give the carer even better control of the parameters to fine-tune the interface or even over-write the results of the automated process? A program could give the carer options to choose target size, target distance from starting point, tile dimensions, the gap between tiles, number of targets and all time allocations associated with the interface. Default settings could be obtained by using able-bodied participants to optimise parameters. This could be used as a starting profile.

Schlunbaum [5] states that the individual user interface can be an adapted user interface (adapted to the end user at design time), an adaptable user interface (end user themselves may change) or an adaptive user interface (interface that changes its characteristics dynamically at run time which is used in this phase). Schneider-Hufschmidt and his team [6] state that adaptability increases usability. Phase two of this research aimed to add *adaptable* features to the interface to produce a better match between device demands and user capabilities. This had to be achieved with minimal training time, and allow reconfiguration of the interface at any time. An interface would combine pushing the cursor in the intended direction of travel termed 'discrete acceleration' within a new paradigm that could also be personalised for individual capabilities. This would reduce the impact of noise and consequent erratic involuntary

movement of the cursor by presenting users with targets that best matched their capabilities.

Masliah and Milgram [7] recommend a goal (target) directed process as a means of communication, which this study took on board when using a ‘Starting Area’ and target as the end points of navigation. The interface could be a window with targets, tiles, gaps between tiles and a ‘Starting Area’ for the cursor to start from (Figure 1). Then the user navigates to the intended target via tiles. At each tile an algorithm moves the cursor towards the intended target in a tile. The user only moves between the tiles using the gap. An interface was developed so that it can be configured to suit each individual according to his or her ability.

2 ALGORITHM

A screen conforming to Gestalt Laws was designed (Figure 1), where objects with similarity, proximity and symmetry were grouped together. Pickford [9] reports on an experiment carried out by Fechner in 1876, where, out of nine shapes, the rectangle was chosen by a group of five hundred men and women (33%) as their best liked. Schiff [10] states that even infants can perceive rectangular shapes, which further backs the argument for rectangles as a building block for an interface. Hence the rectangle was chosen as the shape for the ‘Starting Area’, tile and the targets.

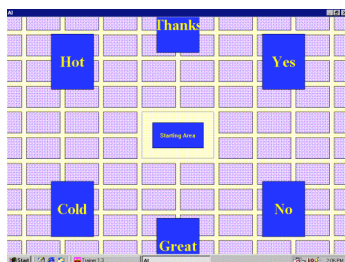


Figure 1 - Targets, tiles and gaps between tiles

Previous investigations show that users have emotional reactions to colours and fonts, this interface gave the option for making changes to suit any user [11]. Laarni’s study also showed that white or yellow text on blue background was more readable, which was taken as the default setting for the interface.

A target test was devised to choose the best parts of the computer screen to suit an individual user. Target enlargement to reduce pointing time was also considered at this stage [12][13]. Cyberlink™ was not a Fitt’s Law device [1], since bio-potentials cannot be used in a controlled manner to navigate a computer screen, it was not adapted. Hence the target sizes were fixed as a default, but there was also a provision for carers to change any of these parameters manually to cater for individual needs. There was also audio feedback [14][15]. The configuration settings took care of all time intervals. There were individual maximum times allocated for every target, which meant the interface automatically recovered to the original position (i.e. starting point in the middle), taking care of error recovery.

Irregularities in user input rule out jumping directly to the nearest predicted target. Instead, a step-by-step approach is taken that leaves the user in control at each point. There is not only an automated process to personalise interfaces, but also

provides manual choices to change any parameter of the interface to better match the needs of a brain-injured individual.

The run-time profile interface thus has further features that allow the cursor’s path to be controlled by settings for a specific user (Figures 2 - 4). These settings include:

- Time spent on the ‘Starting Area’ to relax the user before navigating towards a target;
- Time spent on each tile to control the bio-potential to allow navigation to take place;
- Size of tile to suit each user, smaller tiles will control the cursor better, but will take longer to reach the target;
- Gap between tiles to suit each user, the bigger the gap, the more work for the user and time to reach a target, depending on the ability of the user.

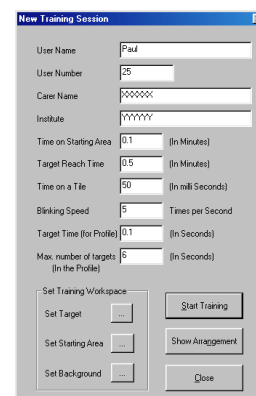


Figure 2 – Personalising the interface

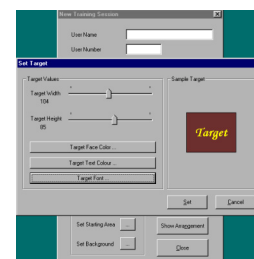


Figure 3 – Configuring targets

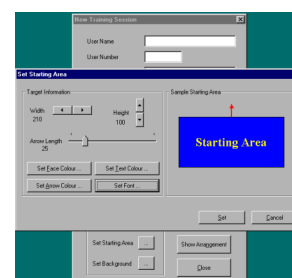


Figure 4 – Configuring starting area

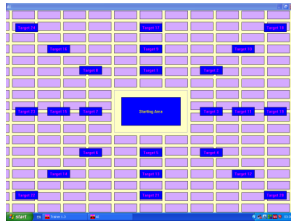


Figure 5 – Targets

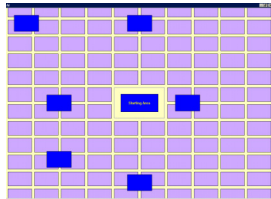


Figure 6 – Personalising the interface

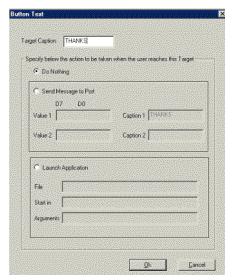


Figure 7 – Window for configuring individual targets

3 OPTIMISATION

Optimisation was carried out in this phase of the research. Kelton [16][17] states that if a search is made for a configuration of inputs that maximises some key output performance, you need to decide very carefully which configurations you will run (and which ones you will not) and also choose your scenario carefully. As a preliminary response to this recommendation, four target practices with different dimensions for tiles and gap between tiles were presented to the participants (Table 1). The dimensions for targets and 'Starting Area' were fixed for the experiment since they played no part in navigation of a cursor from 'Starting Area' to the target. This was an experiment with no prior training for the users. The result from this phase was to be used as a starting point for the interface settings to be used in phase three with disabled participants.

Profile	Tile (pixels)		
	Width	Height	Gap
1. All low	80	30	10
2. Medium, small gap	90	50	10
3. Medium, large gap	90	50	20
4. All high	130	70	20

Table 1 – Profiles used for optimising interfaces

Ten able bodied participants were used to conduct summative experiments with the four profiles shown in Table 1, in order to optimise the interface. There was a time limit of one month to conduct optimisation with the ten able-bodied participants, which limited the number of profiles to four and the number of

participants to ten. Feedback from the development group had indicated that small and large tiles were difficult to navigate in comparison to medium tiles, hence the choice of four profiles shown in Table 1. The development group also indicated that large gap between tiles did not allow the user to control navigation between tiles, hence two small and two medium size gaps between tiles were used for the experiment. The study started with summative evaluations to obtain individual preferences for the four profiles. Then the users completed further summative evaluation using the four profiles to hit targets within a given time interval (24 x 4 trials per participant) and the success rate was recorded. The data were used to obtain the best profile as the default for the experiments to be carried out with the severely brain-injured participants in the next phase of this research. Results obtained were analysed, and conclusions drawn for the next phase of the research.

The target test (trainer program) automatically collected the data shown below:

- Number of targets reached;
- Time taken to reach the targets;
- Dimensions of targets, tiles and gap between targets;
- Fonts and chosen colours.

The results of ranked profile preferences by individuals, eighty percent of the participants preferred Profile 2 with medium tiles and small gap between tiles.

	Successes	Trials	%Success
1. All low	70	240	29.2%
2. Medium, small gap	110	240	45.8%
3. Medium, large gap	45	240	18.8%
4. All high	44	240	18.3%

Table 2 – Summative Evaluation for: Success Rates

The dimensions and times recorded during summative evaluation showed (Table 2) that the interface with medium tiles and small gap between tiles (Profile 2) gave a better performance than interfaces with small/large tiles and medium/large gap between tiles, as shown in Table 2, when the success rates are compared. Hence Profile 2 was chosen as a good default setting for evaluation with disabled participants. Although Profile 2 is to be the starting point for the next phase of this study, the provision to overwrite any automated process and configure interfaces manually gives the opportunity for carers to personalise using Evidence-Based Personalisation [18] and to create interfaces to include all brain-injured individuals (except the users with visual impairment, comatose or affected by adverse medication). No further exploration of the design space was required, nor was there time for exhaustive systematic optimisation. The approach was an engineering, rather than scientific method.

4 EXPERIMENT AND RESULTS

The experiment to be carried out here is to answer the question, can a disabled participant give consistent answers using personalised tiling and discrete acceleration? Participants had to wait in the 'starting area' for a user dependent pre-configured delay and then reach the appropriate target within a

user dependent pre-configured time, to achieve success (Figure 1). Table 3, shows details of participants of this third and final phase of research. The best settings investigated in phase two (Profile 2) were used as the starting point for this phase. Manual re-configurations had to be made for some individuals, over-writing the automated process due to the severity of the brain injury (participants 46 and 49) and usage of evidence based personalisation [18].

Data from each disabled participant was collected once or twice a week (Wednesday and/or Fridays), depending on the availability and health of the participants. Data collection sessions lasted twenty minutes to one hour, with one or more breaks as needed for each participant. The BBI was also left by the researcher at the Holy Cross Hospital for three weeks in a month, and for one week every month at Castel Froma for independent usage by the carers and medical staff [19].

The research question raised in phase three was, can a disabled participant give consistent answers using the personalised interface with discrete acceleration. The number of targets was from two to six depending on the severity of the disability. The data recorded were: percentage of targets reached to indicate correct answers, behaviour of participant, any reconfiguration of interface, changes in medication, duration of visit, and other input devices used. There was also one participant who had been able to use a foot switch. This gave an opportunity to double check the answers given by the user interface. The configuration information and the personal interface for each participants is shown in Figures 8 – 17.

The head of Participant 46 had to be held by a brace, which prevented any electromyographic signals being used for communications, Participant 49 had a twitch, which resulted in unreliable electromyographic signals being picked up the BBI. This meant these two participants had to rely exclusively on electroencephalographic signals to move the cursor along the screen, effectively limiting them to two targets. The automated profiles for Participant 46 had to be manually re-configured to bring the targets close to the 'Starting Area' and the height of the target also had to be increased, since she produced only a small amount of electroencephalographic signals. The targets had to be moved further back manually for Participant 49, since his twitch produced unwanted electromyographic signals which had to be ignored while using only his electroencephalographic signals for communications. Participants 45, 47 and 48, were able to use some electrooculargraphic signals in addition to electroencephalographic signals, hence they were able to use four to six targets in their individual profiles.

Encouraging feedback was received from the locked-in syndrome participant, who used his thumb to indicate approval. All five suitable Participants (45, 46, 47, 48 and 49) were able to communicate using the Cyberlink™. They could use the Cyberlink according to their own ability, using their personalised interface to communicate. The communication took the form of asking participants various questions connected with their day to day tasks, e.g., Do you want the CD player on? Do you want the curtains closed? Would you like a bath? Are you tired? How many targets do you see in the screen? These profiles below demonstrate how each participant had his or her individual interface with personalised times to suit their abilities, which made the interface inclusive of the five participants with different abilities.

Part. No	Institute	Gender/ Age	Clinical Diagnosis	Additional Information
45	Holy Cross	M38	Locked-in syndrome	Non-verbal
46	Holy Cross	F61	Severe cerebral haemorrhage, brain stem injury	Non-verbal
47	Holy Cross	M45	RTA, Diffuse axonal brain damage	Non-verbal. Can use a foot switch but it takes a lot of effort from the participant
48	Holy Cross	M60	Brain stem injury	Non-verbal
49	Castel Froma	M32	Traumatic Brain Injury	Non-verbal, can respond by thumb occasionally

Table 3 – Details of the participants used in phase three

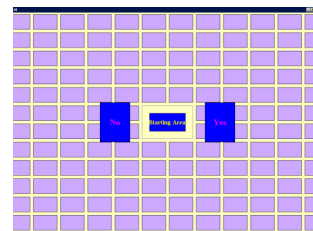


Figure 8 – Profile of Participant 46

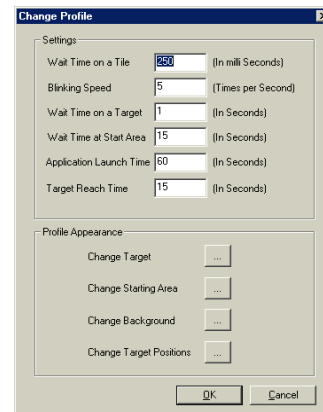


Figure 9 – Profile settings of Participant 46

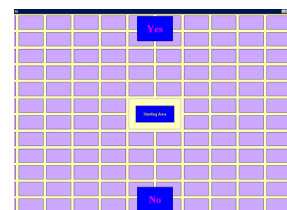


Figure 10 – Profile of Participant 49

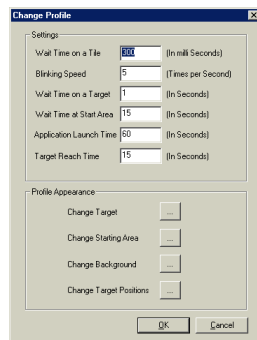


Figure 11 – Profile settings of Participant 49

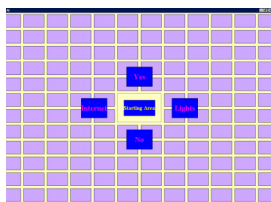


Figure 12 – Profile of Participant 47

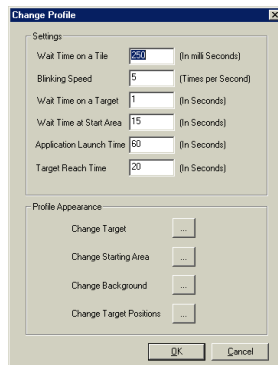


Figure 13 – Profile settings of Participant 47

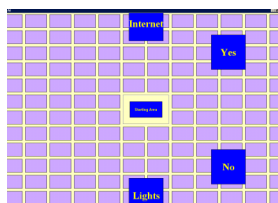


Figure 14 – Profile of Participant 48

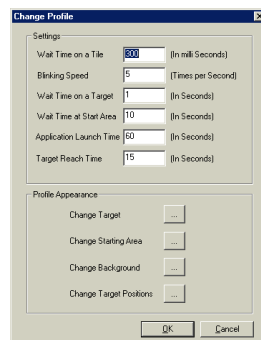


Figure 15 – Profile settings of Participant 48



Figure 16 - Profile of Participant 45

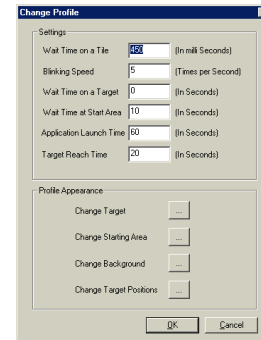


Figure 17 – Profile settings of Participant 45

The success rate was measured only with disabled participants. Participants 47 was able to use a foot switch. This was valuable at times for double-checking answers given. The success rate averaged around 75% for all these participants. As Table 4, shows, three participants (45, 47 and 48) could launch applications such as switch devices. We have thus achieved a wider range of Participants. 45, 47 and 48 had television and music systems in their room and showed interest in doing more with the interface than other participants. These three participants used the interface to control these devices and also launch applications such as the Internet browser. Participant 47 had days where he wanted to be left alone, which reduced his success rate. However, on a good day he used the interface to communicate, switch devices and launch applications. The ability of these three participants to do more than communicate demonstrated the superiority of a personalised interface that can expand or shrink the number of targets to match an individual's capability. Several participants had problems with their eyesight and were greatly encouraged by audio feedback that enhanced their experience. The text to sound facility incorporated in the target of the interface also lets users hear any phrase they wanted to use, not just YES or NO.

Participant	Used text to audio	Launched applications	Switched devices
46, 49	Yes	No	No
45, 47, 48	Yes	Yes	Yes

Table 4 – Evaluation Results

The provision of personalisation greatly improved the interface by giving a facility to configure the interface to suit each participant as shown in Figures 8 to 17. This interface also gives the user the possibility of another target test and reconfiguration at any time, which reduces error frequency. Further flexibility in the interface is provided by adaptable dimensions (manual configurations), fonts and colours, which can cater for colour blindness and other visual impairments. The

speech therapists (three from Holy Cross Hospital and one from Castel Froma) and the Matrons in both institutes were able to carry out independent usage of the BBI for daily routine communications. Communications with participants were carried out at least three times a week in Holy Cross Hospital by support staff in addition to the visits by the researcher. Apparatus was left for independent usage three weeks a month at Holy Cross hospital. Independent usage was carried out at Castel Froma three times a month minimum, but the Apparatus was left there only one week per month

7 CONCLUSIONS & FUTURE WORK

All five brain-injured participants chosen for this the research were able to use the interface to varying degrees to communicate and control applications. This demonstrated the inclusivity of interface, leaving out only participants who had serious visual impairment, were in comatose or adverse effect of daily medicine intake. The rate of success averaged around 75% for all participants. Participants 46 and 49 were able to use the interface to communicate using a two target Yes or No interface, due to the severity of their brain injury. Participants 45, 47 and 48 had television and music systems in their rooms and showed interest in doing more with the interface than the other participants. They were able to switch devices on and off and also launch the Internet using their interface. The success rate for Participants 45 and 48 averaged around 75%, but Participant 47 had days where he wanted to be left alone, which reduced his success rate. The ability of these three participants to do more than communicate demonstrates the superiority of a personalised interface that can expand or shrink the number of targets to match an individual's capability.

This research shows that the combined discrete acceleration and personalised tiling allows faster and more extensive interaction. Discrete acceleration has been shown to improve performance. A flexible interface can be configured to suit each person, with targets positioned by either using the target test program or manually placing them where participants wish. As a result, we have been able to extend effective interaction for some users to tasks beyond simple communication.

The carers were able to use it as part of their communication with the disabled individuals. A portable BBI which can be used in the field outside the laboratory environment to carry out independent usage for daily routine communications was one of the main achievements of this research. At present the researchers are working on visually impaired to communicate using the interface developed in this research.

REFERENCES

- [1] Gnanayutham, P., Bloor, C., Cockton, G., (2005), Discrete Acceleration and Personalised Tiling as Brain-Body Interface Paradigms for Neurorehabilitation, CHI 2005, April 2005, ACM Press, Portland, Oregon, 261 - 270.
- [2] Gnanayutham, P., Bloor, C., Cockton, G., (2003), AI to enhance a brain computer interface, Stephanidis, C., (Ed.), 1397 - 1401, June 2003, Lawrence Erlbaum Associates, HCI International 2003, Crete.
- [3] Sibert, L. E., Jacob, R. J. K., (2000), Evaluation of Eye Gaze Interaction, CHI 2000, April 2000, Amsterdam, 281 - 288.
- [4] Jacko, J. A., Dixon, M. A., Rosa Jr., R. H., Scott, I. U., Pappas, C. J., (1999), Visual Profiles: A Critical Component of Universal Access, 330 - 337, May 1999, CHI 99, Pittsburgh, USA.
- [5] Schlungbaum, E., (1997), Individual User Interfaces and Model-based User Interface Software Tools, 229 - 232, IUI 97, Orlando.
- [6] Schneider-Hufschmidt, M., Kuhme, T., Malinowski, U., (Eds.), (1993), Adaptive User Interfaces: Principles and Practice, Elsevier Science Publishers, Netherlands, 1 - 9, 149 - 165, 331 - 336.
- [7] Masliah, M. R., Milgram, P., (2000), Measuring the Allocation of Control in a 6 Degree-of-freedom Docking Experiment, CHI 2000, April 2000, Amsterdam, 25 - 32.
- [8] Ware, C., (2000), Information Visualization, Morgan Kaufman Publishers, USA, 203 - 213.
- [9] Pickford, R. W., (1972), Psychology and Visual Aesthetics, Hutchinson Educational, London, 17 - 30.
- [10] Schiff, W., (1980), Perception: An Applied Approach, Houghton Mifflin, 202 - 228.
- [11] Laarni, J., (2003), Effects of color, font type and font style on user preferences, Stephanidis, C., (Ed.), Adjunct Proceedings of HCI International 2003, June 2003, Crete University Press, Crete, 31 - 32.
- [12] Zhai, S., Conversy, S., Beaudouin-Lafon, M., Guiard, Y., (2003), Human On-Line Response to Target Expansion, CHI 2003, Florida, USA, 177-184.
- [13] Ren, X., Moriya, S., (1997), The Best among six Strategies for Selecting a Minute Target and the Determination of the Minute Maximum Size of the Targets on a Pen-Based Computer, 85 - 92, Howard, S., Hammond, J., Lindgaard, G., (Eds.), Chapman & Hall, Interact'97, Sydney, July 1997.
- [14] Brewster, S., (2003), Nonspeech Auditory Output, *The Human-Computer Interaction Handbook*, Jacko, J.A., Sears, A., (Eds.), Lawrence Erlbaum Associates, 220 - 239.
- [15] Gnanayutham, P., Bloor, C., Cockton, G., (2003), AI to enhance a brain computer interface, Stephanidis, C., (Ed.), 1397 - 1401, June 2003, Lawrence Erlbaum Associates, HCI International 2003, Crete.
- [16] Kelton, W. D., (1997), Statistical Analysis of Simulation Output, Andradottir, S., Healy, K J., Withers, D. H., Nelson, B L., (Eds.), 1997 Winter Simulation Conference, Atlanta, Georgia, USA, 23 - 30.
- [17] Kelton, W. D., (1999), Designing Simulation Experiments, Farrington, P.A., Nemhard, H.B., Sturrock, D. T., Evans, G. W., (Eds.), Proceedings of the 1999 Winter Simulation Conference, Phoenix, Arizona, USA, 33 - 38.
- [18] Nutley, S., Walter, I., Davies, H., (2003), From Knowing to Doing: A framework for understanding the evidence into practice agenda, *National College for School Leadership 2003*, 1 - 7.
- [19] Vallender, L., Communications via email, 12th April 2007.

Towards natural human computer interaction in BCI

Ian Daly¹ (Student) and Slawomir J Nasuto¹ and Kevin Warwick¹

Abstract. BCI systems require correct classification of signals interpreted from the brain for useful operation. To this end this paper investigates a method proposed in [1] to correctly classify a series of images presented to a group of subjects in [2]. We show that it is possible to use the proposed methods to correctly recognise the original stimuli presented to a subject from analysis of their EEG. Additionally we use a verification set to show that the trained classification method can be applied to a different set of data.

We go on to investigate the issue of invariance in EEG signals. That is, the brain representation of similar stimuli is recognisable across different subjects.

Finally we consider the usefulness of the methods investigated towards an improved BCI system and discuss how it could potentially lead to great improvements in the ease of use for the end user by offering an alternative, more intuitive control based mode of operation.

1 INTRODUCTION

Brain computer interfaces (BCI's) are able to provide alternative methods of communication. This can allow individuals with severe motor disabilities additional channels for communication with their family and friends and control of their environment [3].

The majority of BCI systems work via the reading and interpretation of cortically evoked electro-potentials across the scalp via an Electro-encephalogram (EEG) or Magneto-encephalography (MEG) system. The subsequent classification and interpretation of this data is an area of much current research as it offers the key to improved performance of BCI systems and improved quality of life for individuals who require such systems.

Traditionally BCI research has focused on signals that are quickly identifiable by simple and fast classification methodologies. This is to get the systems working reliably for end users quickly. However this approach hasn't always resulted in intuitive systems. For example much research has gone into classifying motor movement signals [3] and quickly classifiable events generated by indirect means such as the P300 [2]. While these control methodologies work reliably and can be performed quickly on relatively cheap technology they are not an ideal and intuitive means for humans and computers to interface. It's not necessarily intuitive for the end user to have to attempt to move their foot to spell a word for example.

This is a serious drawback from the human computer interaction perspective. Unintuitive control signal perception tests which are unrelated to the intended outcome make the

interaction cumbersome and may result in subject's fatigue, loss of concentration and an increase in error rates. Such tasks may effectively act to distract the subject from their goal.

To this end this paper details an investigation into the methods proposed originally in a series of papers [1], [4], [5] and [6]. These methods attempt to recognise the original stimuli presented to a subject from EEG recordings made while the subject was exposed to a range of different stimuli.

This potentially opens up the possibility for creating BCI systems whose mode of operation is more direct and task-relevant, and hence more natural and intuitive for the end users. This could provide a less tiring system which can be operated in a more focused manner and hence with improved levels of overall performance, concentration and motivation for the end user who can now concentrate solely on their desired goal. Subsequently human computer interaction within BCI could be able to more directly meet the needs of the end users.

The authors of the papers investigated here report high recognition rates achieved via their methods. However no apparent attempt is made to verify these results against a third data set. The recognition methods used can be thought of as a type of classification method. Prototype waveforms are matched using a trained and optimised filtering technique to trials from a training set via a Euclidean distance calculation. However unlike standard classification methods no attempt is made to verify the classification by applying the classification results to a verification data set. It is well known in classifier research that typically high classification rates achieved on the training data do not guarantee especially good results on new data sets.

Therefore we attempt to properly evaluate and extend these methods to show whether they can be used to successfully classify the original stimuli presented to subjects during an experiment intended to evoke P300 events for use in a BCI system. Furthermore we attempt to apply the results of our classification to a verification data set.

The data we use comes courtesy of the work of Ulrich Hoffman et. al. [2] and was originally used to train and verify classification methods for identifying P300 events. The P300 events were evoked by the subjects' exposure to a series of six different images. Their intention was to use the most successful classification methods for identifying P300's in a BCI system to assist with communications and control for disabled individuals.

Here we attempt to apply the methods outlined in [1], [4], [5] and [6] to identify which image the subjects from [2] were looking at in each trial.

Additionally [5] and [6] indicate a level of invariance across sessions and subjects. That is, trained classifiers from one subject or session are shown to be able to correctly recognise trials from a different session or subject. Verifying this is important to BCI work as it indicates whether a trained classifier can be used again to classify trials at different times or from different subjects.

¹ Department of Cybernetics, School of Systems Engineering, The University of Reading, RG6 6AY, UK

2 METHODS

Data analysis outlined in [1], [4], [5] and [6] share common fundamental steps with a few problem specific modifications. We based the approach on that outlined in [5] as this paper describes results obtained from visual stimuli, hence the stimuli type was the closest to the one used in our studies.

Table 1. Steps performed by our method.

1. Separate the trials corresponding to each stimulus for an individual session into Prototype, Training and Verification sets.
2. Normalise each of the trials.
3. Subtract out the pre-stimulus baseline.
4. Mirror and smooth the data using a Gaussian function (exploratory).
5. Fourier transform the trials.
6. Optimally filter the trials with a 4th order Butterworth filter.
7. Estimate the inverse of the Fourier transform.

2.1 Recording

The data used was recorded from 8 subjects observing a series of 6 randomly presented images as detailed in [2]. The subjects were asked to count the occurrences of a particular image with the intention of evoking a P300 event which could then be classified.

Both uni-polar and bi-polar montages were used for the analysis. The average of the two mastoid channels was used as the reference for the uni-polar electrodes.

The following uni-polar electrodes were used.

FP1, AF3, F7, F3, FC1, FC5, T3, C3, CP1, CP5, T5, P3, PZ, PO3, O1, OZ, O2, PO4, P4, T6, CP6, CP2, C4, T4, FC6, FC2, F4, F8, AF4, FP2, FZ, CZ.

The following bi-polar electrodes were used.

CZ-C4, CZ-P4, CZ-PZ, CZ-P3, CZ-C3, F4-FP2, F4-F8, C4-F8, C4-T8, C4-P8, P4-P8, P3-P7, C3-P7, C3-T7.

2.2 Data separation

Our data set for a single session is made up of four runs, for each of which a different stimulus was chosen to be the target intended to evoke a P300 event. For the purpose of our study we treat these four runs as a single data set.

From this data set we identify individual trials. The inter-stimulus interval used in the experiment was 400ms; there was also a 400ms pre-stimulus length of recording made for each session. Thus each trial is identified as a 400ms window of observations occurring sometime after the first 400ms of recording and identified explicitly by the meta-data provided with the recordings from [2].

We subsequently separate these trials into 6 sets, one set for each stimulus. We then further separate these 6 sets into 3 subsets, labelled as Prototype, Training and Verification sets with equal (or as close to as the size of our set allows) numbers of trials in each.

The original experiments within a session were performed in different runs over a number of days. In order to account for the potential time dependence of the stimulus waveforms we constructed the stimulus prototypes from waveforms extracted from each run.

The training and verification sets were constructed in an analogous way.

This expands on the work in [1], [4], [5] and [6]. In that work only classifier training was performed and reported with no verification data set used.

2.3 Pre-processing

For each individual trial in each one of these subsets we perform the following pre-processing steps.

Firstly we take the pre-stimulus baseline, that is the first 400ms of recording prior to stimulus onset at the beginning of our session and normalise to the range -1 to 1. We then normalise the individual trials into the same range and subtract the baseline from each normalised trial.

In order to increase the signal to noise ratio the training and verification waves were averaged over five trials giving eight averaged waveforms in each training and verification subset for each stimulus.

We then took every trial in our Prototype subsets and average them all together to form a single Prototype wave form.

As an additional step here we investigated a technique introduced in [4] to use a mirroring technique in conjunction with a Gaussian function to smooth the trials for the subsequent use of Fast Fourier transforms.

2.4 Analysis

The training is performed by calculating a Euclidean distance between a prototype corresponding to a given stimulus and the input wave form at a given pass-band frequency and electrode location. The exhaustive search of pass-band frequencies and electrode locations is used to find the best parameters for the classifier.

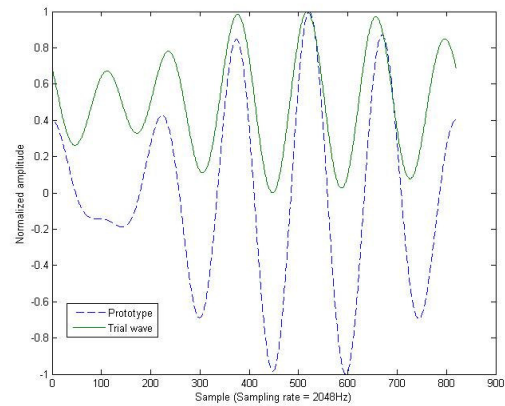


Fig 1. Typical prototype and test waveforms for stimulus 3 at a low pass value of 12Hz and width of 2Hz after a Fourier transform, filtering with an optimised filter and an inverse Fourier transform.

To illustrate further we take a given prototype for a given stimuli and a wave form from each of the training subsets for each stimuli. Thus for example if we were trying to classify stimuli number one (a picture of a television), we would take the prototype waveform for stimuli one and one waveform from the training subset for each stimuli, so one waveform for stimuli one, one waveform for stimuli two etc.

We then performed a fast Fourier transform on both the chosen prototype and each of the chosen training waveforms. We pick the optimal band-pass parameters for a fourth order Butterworth filter and filter both the prototype and each of our training waveforms with these same parameters. We then perform an inverse fast Fourier transform to put all our waveforms back into the time domain.

A typical prototype waveform is shown next to a typical test waveform in Figure 1 and the steps used in this method are summarised in Table 1.

2.5 Mirroring and Gaussian smoothing

Our analysis method involves filtering in the frequency domain to obtain the best match between our Prototypes and the Training trials for the same stimuli. Therefore our methods include both a Fourier transform and an inverse Fourier transform. To achieve faster computation times at this stage we here investigate a method proposed in [4] and used in [4], [5] and [6] but not in [1]. We therefore investigate the effects on the classification results both with and without including this step in our pre-processing.

The technique is as follows. For each waveform (a Prototype, Training or Verification waveform) we took the complete sequence of observations in the waveform and placed them at the centre of a sequence 2,048 observations thus scaling the data to a size of 2^n to allow faster processing of our Fourier transforms in the analysis section.

We then mirrored the first half of our shorter centred sequence onto the first half of the longer sequence before the start of our shorter sequence and the end half of our shorter sequence onto the end of the longer sequence after the end of our shorter sequence. We then positioned a Gaussian function in the centre of our entire longer sequence and set its standard deviation equal to half the length of our shorter sequence.

Finally for every observation in either the beginning or end of our longer sequence outside of our shorter sequence we multiplied the value of the observation by the ratio of the value of our Gaussian function at this point to the value of the Gaussian function at either the beginning or end of our shorter sequence respectively.

This is illustrated in Figure 2.

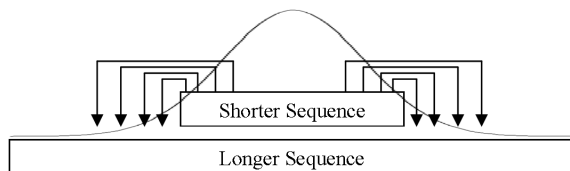


Fig 2. Mirroring and Gaussian smoothing process schematic.

2.6 Recognition surfaces

As we don't know the optimal band-pass parameters we perform the above analysis for each waveform from our group of eight waveforms in the training subsets. When we sum the results together for our groups of eight waveforms it's possible to produce for each electrode a recognition rate surface (correct matches on the training set against the low pass and width of our band-pass filter).

By finding the peak in this surface we can identify the optimal classifier parameters for a given electrode. If these optimal parameters provide good performance when used to classify trials from the verification set then we can say a good rate of verification has been achieved.

The classifier training can therefore be thought of as a kind of dimensionality reduction. We take a set of parameters for a given subject and session, EEG channel, band-pass parameters etc. and reduce them down to a single point (the peak in the recognition surface). The parameters at this point are said to be trained and we use them to classify data in our verification data. Thus only the peaks in the recognition surfaces are considered for analysis.

By way of illustration, if we have a peak in our recognition rate surface for the training data with a low pass frequency of 5Hz and a band-pass width of 3Hz at electrode C3 we should get a high rate of classification when attempting to match the waveforms in the verification set to the prototype using these parameters. We therefore select the same electrode and filter using these parameters on the verification set before calculating using the Euclidean distance calculations to find the recognition rate. If we get a similarly high rate of recognition with these parameters in the verification data set we can say we have a correctly verified classification method.

3 RESULTS

We present the classification rates achieved from different subjects and sessions and look at the verification of these classification methods by applying the trained classifiers to our verification data sets. We will investigate how classifiers trained on one subject perform classifying data from another subject to test inter-person invariance. Analogously the temporal invariance is investigated by testing how classifiers trained on one session perform on data from another session.

3.1 Training vs. Verification surfaces

We constructed recognition rate surfaces for the training and verification sets. These allowed a visual inspection and comparison between the locations of the optimal parameters for best recognition (the highest peaks in the recognition rate surfaces) in the two different sets.

For a given session, for a given subject, recognition rate surfaces are compared for each channel and for each stimulus. A large correlation was found between the training and verification surfaces for some stimuli and for several electrode locations. The results of these correlations are not presented here due to space constraints.

Table 2 lists the best recognition rates achieved with the training data and the corresponding rate of recognition when these trained parameters are applied to the verification data set.

Table 2. Optimal filter parameters obtained on the training data against the recognition rate achieved when applying these parameters to the verification data. Uni-polar electrodes only.

Sub ject	Training				Verification
	Optimal filter			Recon. Rate (%)	Recon rate (%)
	Lower cut off (Hz)	Upper cut off (Hz)	Best EEG sensor		
S1	11	18	AF3	100	75
S2	39	43	FP1	100	87.5
S3	21	30	F4	100	100
S4	12	14	FC1	87.5	75
S6	17	22	CP1	87.5	62.5
S7	16	20	P8	100	50
S8	8	10	FP1	100	100
S9	9	11	P7	100	100

Table 3. Recognition rate achieved using the following optimal parameters from subject 6 on the training data. EEG channel = PO4, band-pass lower cut off = 9Hz and band-pass upper cut off = 12Hz, against recognition rate achieved by applying these parameters to the verification data.

Prototype source (subject / session)	Trials source (subject / session)	Training	Verification
		Recon. Rate (%)	Recon. Rate (%)
6 / 1	6 / 2	100	87.5
6 / 1	6 / 3	100	100
6 / 1	6 / 4	100	62.5
6 / 1	7 / 1	100	75
6 / 1	8 / 1	100	100

Table 4. Confusion matrices. Target stimuli against the results of each classifier. Results are averaged across subjects, sessions and waveform presentations and are hence out of 256. Uni-polar electrode montage.

Training data								Verification data							
		Target stimuli								Target stimuli					
		TV	Phone	Lamp	Door	Window	Radio			TV	Phone	Lamp	Door	Window	Radio
Classifier result	TV	205	16	0	12	11	12	Classifier result	TV	63	50	4	52	42	45
	Phone	13	206	0	8	15	14		Phone	54	58	5	47	42	50
	Lamp	2	1	251	0	1	1		Lamp	10	10	212	6	12	6
	Door	11	17	1	204	13	10		Door	48	49	6	53	39	61
	Window	6	14	3	9	212	12		Window	50	49	9	44	52	52
	Radio	15	11	1	9	13	207		Radio	46	39	7	49	56	59

These results are for session four, for stimuli number three for each subject.

Table 4 shows confusion matrices which illustrate the performance of this method. Notice that in the training data a large number of correct recognitions are made. However these high rates of training data recognition only translate into a high rate of classification within the verification set for the lamp stimulus.

To assess the statistical significance of these results we considered the null hypothesis that the results were obtained by random chance. This is modelled by a binomial distribution with $p=0.5$. The results for the correct classification of the lamp from the verification set was 212 correct matches out of 256 and had a statistical significance of $p < 1\%$ from our null hypothesis distribution. Therefore we can say this is a statistically significant result.

By way of contrast we also assessed the probability of 63 correct classifications (as occurs for the TV stimulus in our verification set). The probability of this occurrence from our null hypothesis binomial distribution shows that this result is not statistically significant.

It's important to note that in general the results showed some level of correlation between training and verification for each stimuli. However the only statistically significant peaks were produced by stimuli three and it is these results that are presented here. This is discussed further later.

3.2 Mirroring and Gaussian smoothing

As the original work we are investigating uses the technique of mirroring and Gaussian smoothing in [4], [5] and [6] but not

in [1]. We investigated the effects on the classification and verification processes both with and without using this technique.

When Gaussian smoothing was used the general effect was to lower the size of the peaks in our recognition rate surface. That is when using the Gaussian smoothing technique when training our classifier we were unable to achieve as high a rates of recognition as we could without using it. Therefore while all the analysis was done both with and without the use of the Gaussian smoothing technique we here present only the results obtained from not using it.

3.3 Invariance between subjects and sessions

One of the key claims of the [1], [4], [5] and [6] is that there exists a level of invariance between the representation of a stimulus across multiple sessions or subjects. That is; a prototype for a given stimulus could be used to correctly classify that stimulus in multiple trials across different subjects or over time.

Assessing the validity of this claim is very important for any potential applications of this technique to a BCI system. If the same trained classifier can recognise stimuli from different subjects or across different days then the need to retrain the classifier is reduced to a practical amount for the end users needs.

The similarity of the peaks in the recognition surfaces for the training and verification sets already show a certain level of invariance between different trials within one session. However for our purposes it's necessary for us to show that this invariance extends across sessions and across subjects.

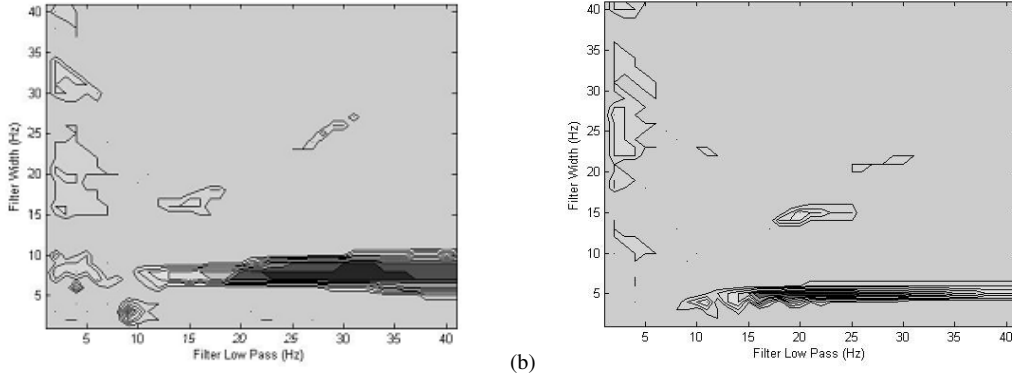


Fig 3. Recognition rate surfaces for unipolar electrode montage, channel FP1 (a) and bipolar electrode montage, channels C4 – T6 (b) The darker the surface the higher the rate of recognition at these filter parameters.

To assess the invariance levels we take a trained prototype from one subject / session and apply its parameters to verify trials from a different subject / session. For example to show that there exists a level of invariance between the representations of the stimuli of a picture of a lamp within the EEG of subjects one and two we take the trained prototype for this stimuli from subject one and attempt to use it to classify the trials from subject two.

We created a recognition rate surface for the prototype from one subject / session applied to the verification data from a different subject / session and compared it to the recognition rate surface for the training data.

Table 3 shows examples of the optimal parameters from the training being applied to classify data from a different subject / session.

We noticed a strong intersession correlation between the classification and verification surfaces. We also noticed a strong inter-subject correlation in the recognition surface peaks between the classification and verification sets. This suggests a level of invariance in the brains response to stimulus across a short period of time and across different subjects.

3.4 Montages

The analysis was performed using both uni-polar and bi-polar montage systems.

The effects of the use of these different montages are negligible. Generally equally good recognition rates appear to have been achieved from both the uni-polar and the bipolar montages. The only significant difference is in the shape of the recognition surfaces produced. The recognition surfaces produced with the uni-polar montage are in general fatter than the surfaces produce by the bipolar montage.

Two such example surfaces are compared in figure 3 (a) and (b).

4 DISCUSSION

Our results are able to verify the classification methods investigated for individual stimuli during individual sessions.

That is, for a given session with a given subject we have shown that a peak in the recognition rate surface of the training set for certain specific stimuli has a correlation with the peak in the recognition surface of the verification set for that same stimuli.

It's important to note that we obtained very different recognition surfaces for different stimuli. For stimuli number three the recognition surfaces were of a very distinct shape with one or occasionally two clearly defined peaks that were closely matched in the classification and verification surfaces.

While the optimal classification parameters from the training set led to in general high recognition rates on the verification set the recognition rate surfaces for other stimuli were less distinct. This is most clearly indicated by our confusion matrix for our verification set in Table 4. We achieve high rates of correct classification with stimulus 3 but much lower rates with the other stimuli.

This implies that while it is clearly possible to classify original stimuli from EEG recordings as shown by the trials for stimuli three, certain stimuli do produce more distinct and easily classifiable signals than others. Why this should be is unclear at this stage and may be a course of further investigation.

In the original methods, [1], [4], [5] and [6], the recognition rate surfaces for each stimuli were summed together to get a higher more distinct signal peak. The parameters at this single peak could then be used to recognise any stimuli using the appropriate prototype. We were unable to verify this summation technique due to the unclear results produced by some of the stimuli. However if different original stimuli were presented to the subject that each produced clear recognition surfaces it may be possible to use this technique to achieve better results.

The methods used in our data source [2] count the occurrences of a P300 event triggered by the subject counting the occurrences of a particular image. This means that for some of the trials we are using there will be a P300 event within the EEG. We therefore must consider here the possibility of such events causing a distortion on our results.

Due to the averaging of trials described in section 2.2 the effects of a P300 event within an individual trial are thought to be negated. This is further supported by our experimental results which don't show any distortion that could be attributed to a P300 event.

4.1 Invariance

The results achieved from using the prototype from one session to classify trials from a different session or even from a different subject are very encouraging. We can very clearly see a level of invariance here across sessions and subjects. That is, a prototype trained on one session for one subject can be used as the basis for producing verified classification results for a different subject or a different session for that same subject.

We can therefore say that there exists a level of invariance across subjects in the representation of stimuli within the EEG. Because all the sessions for a subject are recorded within a relatively short period of time (for every subject the time between the first session and the last session was less than two weeks), we cannot confidently claim the results to show invariance over time. However as there exists a level of invariance over subjects then a level of invariance over time is thought to be likely.

4.2 Applicability to BCI

The usefulness of these results within a BCI system is an important point of consideration. The possibility of correctly classifying the original stimuli presented to subjects from their EEG alone offers a lot of potential to end users of BCI systems.

There exists considerable research to suggest that the representation of actual events within the brain and the imagination of the same events are closely correlated [3]. For example the brain representation of movement and the imagination of the same movement are very similar. It is this principle that forms the basis of much research in motor control based BCI's [7]. The end user imagines moving some part of their body and this is interpreted as a movement by the classifier. As both able bodied and disabled individuals are able to imagine movement this allows disabled individuals the ability to use a BCI system by imagining motor movement.

It follows that the brain representation of stimuli and the imagination of the same stimuli by the individual are likely to have a close correlation for a wide range of different types of stimuli. Furthermore if it is, as we show here, possible to recognise original stimuli in the form of images from the EEG then it should be possible to recognise the imagination of the same stimuli from the EEG.

This leads us to the potential of more natural forms of human computer interaction within a BCI system. Instead of controlling a system indirectly via an external device or directly but by none intuitive means that can often actually distract from the task they are attempting to perform, such as moving a toe to spell a word. The possibility is suggested that much more natural and direct control could be achieved by recognising stimuli or imagined stimuli such as command words from the EEG.

This suggests the possibility for a form of human computer interaction within BCI that allows much more direct, less tiring and potentially faster control for the user. As an example consider a speller which works from the users imagining of command words. It's easy to see how this methodology could provide a higher level of natural, task relevant control to the user.

The encouraging results in the invariance experiments furthermore suggest that this method could be applied over time

and over different subjects resulting in more intuitive natural ways for humans and computers to interact that can be applied in the real world.

It is important to note that although there is evidence to suggest that trained classifiers on one subject / session can be applied to a different subject / session there also is a level of variability in the best EEG sensor. That is, the EEG sensor with the highest recognition rate for one subject may not have the highest recognition rate on a different subject. The amount of effect this will have on the applicability of this technique to a BCI system is a subject for further investigation.

Therefore the applicability of this technique in a BCI requires further evidence to quantify. However this study indicates that this is an area of research worth investigating further.

5 CONCLUSIONS

The results obtained during the course of this investigation are promising. It is possible to use the EEG recording made while subjects are exposed to a range of different stimuli to recognise the original stimuli presented to the subject. We show that high classification results can be achieved for certain stimuli by using a prototype (or template) of the stimuli and a trained, optimised filter. We go on to verify that this trained classification method can be used to achieve high rates of recognition in a third data set.

We also show that there exists a level of invariance across different subjects and different sessions for the same subject. Prototype data from one subject or session can be used to achieve high classification results with a different subject or session.

These results indicate a new approach to more intuitive and natural forms of, either goal based or control based, human computer interfacing.

5 ACKNOWLEDGMENTS

The authors would like to thank Dr Ian Bland for his considerable technical assistance and support during the course of this work. They would also like to thank Ulrich Hoffman et. al.[2] for the availability of the data sets used in this work and the referees for their comments which helped improve this paper.

REFERENCES

1. PATRICK SUPPES, Z.-L.L., BING HAN, *Brain wave recognition of words*. PNAS, 1997. **94**(1): p. 14965-14969.
2. Ulrich Hoffmann, J.-M.V., Touradj Ebrahimi, Karin Diserens, *An efficient P300-based brain-computer interface for disabled subjects*. Journal of Neuroscience methods, 2007.
3. Wolpaw, J.R., *Brain-computer interfaces as new brain output pathways*. The Journal of Physiology, 2007. **579**(3): p. 613-619.
4. PATRICK SUPPES, B.H., ZHONG-LIN LU, *Brain-wave recognition of sentences*. PNAS, 1998. **95**(1): p. 15861-15866.
5. Patrick Suppes, B.H., Julie Epelboim, and Zhong-Lin Lu, *Invariance between subjects of brain wave representations of language*. PNAS, 1999. **96**(22): p. 12953-12958.
6. Patrick Suppes, B.H., Julie Epelboim, and Zhong-Lin Lu, *Invariance of brain-wave representations of simple visual images and their names*. PNAS, 1999. **96**(25): p. 14658-14663.
7. PFURTSCHELLER Gert, N.C., *Motor imagery and direct brain-computer communication*. Proceedings of the IEEE, 2001. **89**(7): p. 1123-1134.

BrainGain: BCI for HCI and Games

Anton Nijholt¹, Jan B.F. van Erp², Dirk Heylen¹

Abstract. In this position paper we describe part of the Dutch BrainGain research project on Brain Computer Interfacing (BCI) and our planned research in this project. We focus on BCI research for healthy users. In the BrainGain project our task is to look at Human Factors aspects of BCI applications, to look at multimodal interactions that include BCI interactions, and to design games, game environments and game interfaces that allow BCI interactions. Recently we see game companies taking an interest in BCI, among others leading to some games where movements of the ‘healthy’ user help to intensify brain patterns that control a virtual environment. One line of research we hope to exploit is the use of BCI in exertion interfaces.

1 INTRODUCTION

BCI (Brain-Computer Interfacing) has become a research topic in computer science and, in particular, human-computer interaction. In 2007 a large scale BCI project was approved in the Netherlands. This BrainGain project (<http://www.nici.ru.nl/braingain/>) started in September 2007 and is funded by the Dutch government with 14 million Euro. Part of this funding is assigned to BCI research for the ‘healthy user’. That is, research that does not necessarily aim at results and applications for users with special needs. In the project description it is mentioned that:

- The psychiatric and neurological professionals in the consortium also want to investigate the use of modern methods of analysis of brain signals for specifically developed therapies. These developments could also be applied to the needs of healthy users, in terms of health, performance, or quality of life. For example, the costs of stress to the society are high, and learning to relax, concentrate or meditate could provide a useful application of BCI for healthy users.

And there is an economical perspective too:

- In order to also create an economical impulse, the consortium will develop a broad range of applications, which will allow healthy users to also benefit from the newly developed technologies. Possible applications include entertainment, such as computer games driven by brain signals. Or, in more professional surroundings, to present information on a computer screen only when visual attention is detected, such as might be useful for air traffic controllers or customs officials checking scanned luggage.

From [1]: “Also, the elderly in general and the 100 million baby boomers in specific –in control of the largest concentration

of funds than any other demographic group– will demand longer life, personalised health care, intelligence and memory support, and improvement of their senses and mobility.” Future interfaces will allow us to communicate at an emotional and intentional level. Sensors and actuators will be integrated everywhere in our environment. They will capture verbal, nonverbal, physiological, and brain information and this information will be processed and interpreted in order to support the users in their daily activities.

Obviously, also in professional environments captured information can help the environment to support a user in performing his tasks. BCI can play a role in solving the threat of sensory and cognitive overload for, for example, pilots and crisis team members, but also for everyday life activities such as driving, controlling devices and gaming. Especially in the latter applications the hardware must be designed for use in everyday life, i.e. unobtrusive, lightweight and wearable, preferably wireless, and with low power consumption. Often there is not a single task to be performed, as is mostly the case for severely disabled persons. Moreover there is information to be captured and fused from various input modalities and brain activity displayed in various brain regions with not always distinguishable functions.

2 BCI FOR HEALTHY USERS: TOPICS

In the part of the BrainGain project that is devoted to BCI for healthy users we have chosen the following topics to research [1]:

- **Attention Monitoring and Adaptation:** To stay highly alert for extended periods of time is critical for flight controllers, truck drivers and security personnel scanning luggage or checking many video monitors. To detect visual alertness is an important prerequisite to warrant user performance. Experiments have shown that ongoing brain activity (in particular posterior alpha activity) is a better detector of visual alertness than behavioural measures. These new findings could be used to create a BCI that determines the user’s visual alertness and for example adjust the visual load in the interface or even advise the user to take a break. Such systems can be installed at airport traffic controllers, security inspectors etc. The combination with other physiological measures used in HCI is an important multi-dimensional challenge.
- **Classifying Images:** The brain outperforms software tools when it comes to classifying images or the semantic understanding of images. In many areas, enormous amounts of images are available but very hard to access because they are not labelled. Automatic analysis of image contents is very difficult and despite the huge efforts put into machine algorithms, limited progress is made, while the brain does these kinds of tasks very easily. Using a BCI may give us access to these very powerful brain mechanisms to interpret

¹ University of Twente, Human Media Interaction, PO Box 217, 7500 AE Enschede, the Netherlands, {anijholt,heylen}@cs.utwente.nl

² TNO Human Factors, Soesterberg, The Netherlands, Jan.vanerp@tno.nl

images. E.g., specific event related potentials may occur when a primed object is present in an image, even when many images are shown in rapid serial presentation. By using this effect, observers may be able to reliably classify images at very high speeds.

- **Motion Control for Virtual or Remote Worlds:** The general question here is “to what extent can brain signals be used for navigation in (relatively) fast in-the-loop applications for gaming, simulation, and remote control applications”. In these areas, using our locomotion system as input device (e.g., walking on a treadmill) is cumbersome, complicated and expensive. Usually, motion control is accomplished by keyboard or joystick, sometimes in combination with a head tracker to allow for a natural way of looking around. The drawback of these motion control devices is that they are unnatural, possibly disturbing the user’s feeling of presence, and that they occupy the hands. The latter is undesirable when the hands are required to interact with the remote or virtual world. In this research hands-free (self-) motion control interfaces based on brain signals will be investigated.
- **Multimodal Measures of the User Experience:** In this research we investigate the following topics. (1) Brainsignals and user experience: In the case of intelligent, adaptive interfaces the system tries to adapt itself to the way the user experiences the interaction. The brain signals contain information about this experience. In a series of controlled experiments it will be determined what brainsignals can tell us about the user experience. (2) Correlations between brainsignals and other information from the body: Measures of biosignals such as heart rate, respiration, perspiration, body temperature and muscle tension can point to factors of the user experience as well. In experiments brainsignals will be traced together with other physiological measures and information from voice, face and head. (3) Expressivity and reliability: For each modality and each combination of modalities it has to be determined what they can express and how reliably they express this. Combination of modalities reduces noise and can dissolve ambiguities. It is important to have a good indication of the reliability of the various measures. (4) Interface: The inferences about the cognitive and affective state of the user that can be made on the basis of the information from the various measures will be used in the development of adaptive interfaces for games.
- **Employing BCI in game environments:** Currently there is a development from traditional videogames using keyboard, mouse or joystick, to games that use all kinds of sensors and algorithms that know about speech characteristics, about facial expressions, gestures, location and identity of the gamer and even physiological processes that can be used to adapt or control the game [2]. The next step in game development is input obtained from the measurement of brain activity [3,4]. User-controlled brain activity has been used in games that involve moving a cursor on the screen or guiding the movements of an avatar in a virtual environment by imagining these movements. Relaxation games have been designed and also games that adapt to the affective state of the user. For the design of game and training environments we need the integration of theoretical research on multimodal interaction, intention detection,

affective state and visual attention monitoring, and on-line motion control. It also requires the design of several prototypes of games. Some of these games will be elaborated into events for the general audience (as dissemination projects). Next to games for amusement we will explore (serious) games for educational, training and simulation purposes. Selection and design of BCI methods feasible for commercial computer games is still difficult. Here price, ease of fitting, required data rate, etc. put strict constraints on the technology. However, the computer game industry is ready to embrace these applications and can even drive some of the developments.

It should be mentioned that the development of (serious) brain games fits in many initiatives in the Netherlands to develop company-based game technology, such as the Benelux Game Initiative (BGIN) in which Dutch game development companies are the founding fathers and the GATE research project (started in 2006) in which many Dutch game development companies are involved. The entertainment games market in the Netherlands was estimated (AGS) 200MEuro in 2005 and is growing, with impact on education, care, sports and digital lifestyle. For serious gaming the market was estimated to be over 350MEuro, with areas of interest that include care, safety and defense. Initiatives to stimulate economic activity in these areas are taken by governmental organizations (Ministry of Economic Affairs, and others).

3 BCI FOR GAMES

3.1 BCI for Games: Commercial Explorations

Presently, the majority of BCI users are patients that do not have control, or full control, of their muscles and that have to learn to control a prosthetic device, a communication device, or a mobility device (e.g., a wheelchair) by thought. Nevertheless, there are various reasons to look at the use of BCI technology in the context of exertion interfaces [5] for healthy users. Exertion interfaces are interfaces that deliberately require physical effort. These interfaces can play a role in sports, health (fitness), and entertainment. Often they are accompanied with a large screen where opponents are displayed and where computer vision and other sensors are used to capture the bodily activity of players. There are good reasons to investigate the role of BCI for such interfaces. BCI allows:

- Finding out about the user’s mental state and trying to adapt the interface and the interaction modalities to this mental state. Obviously, there are other modalities that can be considered too, for example, physiological information or information obtained from nonverbal cues (pose, facial expression, prosody). In exertion interfaces monitoring this information can help to adapt the required or desired exertion efforts to the user’s physical and mental state [2]. Existing exertion interfaces only have limited knowledge about the user. For example, in a mediated football game [5] the interface knows about who kicked the ball that hits a wall, where the wall is hit, and how hard the wall is hit. More direct information about the player is, however, not available. Adding knowledge about brain activity to

knowledge obtained from other measured input modalities helps to adapt the interface to the user.

- Making exertion interfaces more interesting and engaging by adding a new modality to the already available and more ‘traditional’ input modalities for exertion interfaces. Again, existing exertion interfaces have not only poor knowledge about their users; they also make poor use of modalities that are available for the user to control the exertion interface. Obviously, it should be mentioned, that depending on the interaction that is required, there is not always a need to take into account all possible input modalities for an exertion interface. Nevertheless, BCI provides an extra input modality. That is, BCI allows the adding of an extra input modality to the ones that have already been made available for a long time. This input modality consists of voluntarily and consciously produced or externally evoked brain activity that can be recognized and translated into commands to the interface.

Measuring brain activity for gamers can be used so that the game environment (1) knows what a subject experiences and can adapt game and interface in order to keep the gamer ‘in the flow’ of the game, and (2) allows the gamer to add brain control commands to the already available control commands for the game. The general assumption is that the added value of BCI commands or the adaptation of the game to a mental state of a gamer that can be measured from brain activity, may lead to a commercial ‘killer application’. For example, a game that can be played by enormous numbers of gamers, but a top level in the game can only be reached when the gamer is able to master a certain BCI command that adds to the already available multimodal commands of the game or that can be used to modify a more traditional game control command. The willingness of gamers to spend large amounts of time to games they are interested in makes it possible to integrate BCI learning requirements in a natural way in game situations. Another issue that need to be dealt with when we want to move forward in attracting the game audience to BCI is the hardware that has to be used, in particular the use of EEG caps. This ‘hardware’ is improving. Some game companies provide rather fancy caps (Figure 1) that rather than being considered obtrusive provide more status to the gamer. It is expected that wireless technology will allow a gamer to move around freely in an environment, rather than being connected through cables to a computer.



Figure 1. Left: A traditional EEG cap. Right: A helmet used in commercial applications.



Figure 2. Lifting a heavy stone in a Stonehenge game designed by Emotive Systems.

3.2 BCI for Games: Motor Imagery Applications

As is well-known, an interesting class of brain activity for game playing is related to motor imagery. That is, the user imagines a certain movement. For example imagining a left foot movement can be distinguished from imaging a right foot movement. This kind of mental simulation of movement can be measured and distinguished. Not only for feet, but also for arms or hand, the tip of the tongue, et cetera. Intending to move, imagine a movement, planning a movement, they all activate similar cortical areas.

This explains the success that BCI has for patients who are not able to use hands or feet, or patients who suffer the locked in syndrome (ALS) and are not able to move or to speak. In various applications it has been shown that they can learn to move a cursor on a screen, to navigate in a virtual world and to control a wheelchair. Much of the current BCI research concentrates on improving such medical applications and also at looking at other ways to improve the quality of life of those patients.

However, although not really of interest for ALS patients and other disabled patients, these imagined movements activate the brain areas that are also activated by the execution of the same movements. Hence, for healthy users it becomes possible to activate brain patterns by consciously produced movements and have these brain patterns measured and translated into commands for a computer, in order to navigate in a virtual world, to move or lift (heavy) virtual objects (Figure 2 [6]) or to control a robotic device. Moreover, it allows us to design games, game environments, and exertion interfaces that are also controlled by body movements but where the capturing of the body movement is not done by sensors or cameras, but by measuring associated brain activity.

3.3 BCI for Games: The Braingain Project

Investigating the possibilities of BCI for HCI and game applications, including exertion interfaces, is one of our tasks in the Dutch national BrainGain project. Apart from fundamental research on distinguishing various types of brain activity when the user (or gamer) is involved in various tasks, using different modalities to perform this task, we will also introduce BCI versions of games and exertion interfaces we have introduced previously [7]. One example is the ‘Jump and Run’ exertion interface where the gamer controls the movements of an avatar,

who moves at high speed in a virtual world and has to avoid obstacles (Figure 3). A camera observes the movements of the human player and our aim is to play a similar game (similar, i.e., not necessarily requiring imagined movements resembling the physical movements in the original game) by measuring brain activity associated with imaginary and/or real movements in such a way that no cameras are needed anymore: “Look Ma, No Cameras!”



Figure 3. The ‘Jump and Run’ exertion interface

Acknowledgements

This work has been supported by funding from the Dutch National SmartMix project Braingain on BCI, funded by the Ministry of Economic Affairs and the GATE project, funded by the Netherlands Organization for Scientific Research (NWO) and the Netherlands ICT Research and Innovation Authority (ICT Regie).

REFERENCES

- [1] J. van Erp, A. Nijholt, D. Heylen, and O. Jensen. BCI for Healthy Users. Project proposal description for the BrainGain project. December 2006.
- [2] K. Gilleade, A. Dix & J. Allanson. Affective Videogames and Modes of Affective Gaming: Assist Me, Challenge Me, Emote Me. In: Proc. DIGRA'2005, 2005.
- [3] A. Nijholt and D. Tan (Eds.). Brain-Computer Interfaces and Games. Proceedings Workshop at ACE (Advances in Computer Entertainment), 12 June 2007.
- [4] A. Nijholt, D. Tan, G. Pfurtscheller, C. Brunner, J. del R. Millan, B. Allison, B. Graimann, F. Popescu, B. Blankertz, and K.-R. Müller. Brain-Computer Interfacing for Intelligent Systems. IEEE Intelligent Systems, 2008, to appear.
- [5] F. Mueller and S. Agamanolis. Exertion interfaces. In: Proceedings CHI '07: CHI '07 Extended Abstracts on Human factors in computing systems. ACM, New York, NY, USA, 2857-2860 (2007).
- [6] Emotive Systems: www.emotiv.com
- [7] A. Nijholt, D. Reidsma, Z. Ruttkay, H. van Welbergen, and P. Bos. Non-verbal and Bodily Interaction in Ambient Entertainment. In: Proc. Fundamentals of Verbal and Non-verbal Communication and the Biometrical Issue, A. Esposito et al. (eds.), IOS Press, Amsterdam, 343-348.