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BrainPlay'07: Playing with Your Brain

Brain-Computer Interfaces and Games

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BRAINPLAY 07

Brain-Computer Interfaces and Games Workshop at ACE (Advances in Computer Entertainment) 2007

POSITION PAPERS OF THE
BRAINPLAY 07 WORKSHOP

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Preface

BrainPlay 2007 is the first international workshop on games and brain-computer interfacing. Organizers of BrainPlay 2007 are Anton Nijholt (Human Media Interaction, University of Twente, the Netherlands) and Desney Tan (Microsoft Research, Redmond, USA). The workshop is organized as part of the ACE 2007 conference on Advances in Computer Entertainment Technology in Salzburg, June 2007. We think that it is interesting to have this workshop organized outside the traditional brain-computer interfacing (BCI) community, outside the traditional human-computer interaction (HCI) community, and inside an emerging entertainment computing community.

Advances in cognitive neuroscience and brain imaging technologies provide us with the increasing ability to interface directly with activity in the brain. Researchers have begun to use these technologies to build brain-computer interfaces. In these interfaces, humans intentionally manipulate their brain activity in order to directly control a computer or physical prostheses. The ability to communicate and control devices with thought alone has especially high impact for individuals with reduced capabilities for muscular response. In fact, applications for patients with severe motor disabilities have been the driving force of most brain-computer interface research.

Although removing the need for motor movements in computer interfaces is challenging and rewarding, we believe that the full potential of brain sensing technologies as an input mechanism lies in the extremely rich information it could provide about the state of the user. Having access to this state information is valuable to human-computer interaction (HCI) researchers and opens up at least three distinct areas of research:

- direct control by thought, that is, inducing thoughts to manipulate brain activity that can be mapped onto game interaction commands (e.g., move cursor, click buttons, control devices);
- determining the cognitive tasks in which the user is involved in order to evaluate (game) interfaces or game environments;
- using cognitive or affective state of the user to dynamically adapt the interface to the user (e.g., detect frustration or engagement and provide tailored feedback).

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.

The next step in game development is input obtained from the measurement of brain activity. 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. BCI game research requires the integration of theoretical research on multimodal interaction, intention detection, affective state and visual attention monitoring, and on-line motion control, but it also requires the design of several prototypes of games. These may be games for amusement, but also (serious) games for educational, training and simulation purposes. In this workshop we will investigate both the multimodal aspects and context of brain-computer interfacing, and the design of engaging and entertaining gaming and training environments that allow entertainment and training for BCI users, whether they are healthy or handicapped.

We are happy with the support we obtained from the ACE organization, in particular Regina Bernhaupt and Andreas Boldt. Obviously, we are also thankful to the program committee of BrainPlay'07: Brendan Allison (University of Bremen), Peter Desain (University of Nijmegen), Alan Dix (Lancaster University, Robert Jacob (Tufts University), Tan Le (Emotiv Systems Inc.), Craig Lindley (Gotland University), and Peter Werkhoven (TNO - Soesterberg). Organizational support was obtained from Charlotte Bijron and Hendri Hondorp.

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Contents

Introductory Paper

Contributed Position Papers

Playing with Your Brain: Brain-Computer Interfaces and Games

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ABSTRACT
In this workshop we investigate a possible role of brain-computer interaction in computer games and entertainment computing. The assumption is that brain activity, whether it is consciously controlled and directed by the user or just recorded in order to obtain information about the user's affective state, should be modeled in order to provide appropriate feedback and a context where brain activity information is one of the multi-modal interaction modalities that is provided to the user.

Categories and Subject Descriptors
H5.2. [**Information interfaces and presentation**]: User Interfaces. I.2 [**Artificial Intelligence**]: Cognitive simulation, Philosophical foundations, Games, Analogies.

General Terms
Algorithms, Design, Economics, Human Factors.

Keywords
Games, Brain-Computer Interfacing, Affect, Multimodal Interaction.

1. INTRODUCTION
In this workshop we study the research themes and the state-of-the-art of brain-computer interaction in order to look at applications for games. Brain-computer interfacing has seen much progress in the medical domain, for example for prosthesis control or as biofeedback therapy for the treatment of neurological disorders. Here, however, we look at brain-computer interaction especially as it applies to research in Human-Computer Interaction (HCI) and games. Through this workshop and continuing discussions, we aim to define research approaches and applications that apply to able-bodied users across a variety of real-world usage scenarios. Entertainment and game design is the main application area that is considered here.

Advances in cognitive neuroscience and brain imaging technologies provide us with the increasing ability to interface directly with activity in the brain. Researchers have begun to use these technologies to build brain-computer interfaces, in which patients with severe motor disabilities can communicate and control devices with thought alone. Although removing the need for motor movements in computer interfaces is challenging and rewarding, we believe that the full potential of brain sensing technologies as an input mechanism lies in the extremely rich information it could provide about the state of the user. Having access to this state information is valuable to human-computer interaction (HCI) researchers and opens up at least three distinct areas of research: (1) Controlling computers with thought alone, (2) Evaluating interfaces and systems, and (3) Building adaptive user interfaces.

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2. CONTROLLING COMPUTERS WITH THOUGHT ALONE
Much of the current BCI work aims to improve the lives of patients with severe neuromuscular disorders in which many patients lose control of their physical bodies, including simple functions such as eye-gaze. However, many of these patients retain full control of their higher level cognitive abilities. These disorders cause extreme mental frustration or social isolation caused by having no way to communicate with the external world. Providing these patients with brain-computer interfaces that allow them to control computers directly with their brain signals could dramatically increase their quality of life. The complexity of this control ranges from simple binary decisions, to moving a cursor on the screen, to more ambitious control of mechanical prosthetic devices.

Nearly all current brain-computer interface research has been a logical extension of assistive methods in which one input modality is substituted for another [1]. This makes sense because when these patients lose control of their physical movement, the physiological function they have the most and sometimes only control over is their brain activity.

3. EVALUATING INTERFACES AND SYSTEMS
The cognitive or affective state derived from brain imaging could be used as an evaluation metric for either the user or for computer systems. Since we can measure the intensity of cognitive activity as a user performs certain tasks, we could potentially use brain imaging to assess cognitive aptitude based on how hard someone has to work on a particular set of tasks. With proper task and cognitive models, we might use these results to generalize performance predictions in a much broader range of tasks and scenarios.

In addition to evaluating the human, we can understand how users and computers interact so that we can improve our computing systems. Thus far, we have been relatively successful in learning from performance metrics such as task completion times and error rates. We have also used behavioral and physiological measures to infer cognitive processes, such as mouse movement and eye gaze as a measure of attention. However, there remain many cognitive processes that are hard to measure externally. For example, it is still extremely difficult to ascertain cognitive workloads or particular cognitive strategies used, such as verbal versus spatial memory encoding.

Brain imaging can potentially provide measures that directly quantify the cognitive utility of our interfaces. This could potentially provide powerful measures that either corroborate external measures, or more interestingly, shed light on the interactions that we would have never derived from these measures alone.

4. BUILDING ADAPTIVE USER INTERFACES

If we tighten the iteration between measurement, evaluation, and redesign, we could design interfaces that automatically adapt depending on the cognitive state of the user. Interfaces that adapt themselves to available resources in order to provide pleasant and optimal user experiences are not a new concept. In fact, we have put quite a bit of thought into dynamically adapting interfaces to best utilize such things as display space, available input mechanisms, device processing capabilities, and even user task or context.

We assert that adapting to users' limited cognitive resources is at least as important as adapting to specific computing affordances. One simple way in which interfaces may adapt based on cognitive state is to adjust information flow. For example, using brain imaging, the system knows approximately how the user's attentional and cognitive resources are allocated, and could tailor information presentation to attain the largest communication bandwidth possible. For example, if the user is verbally overloaded, additional information could be transformed and presented in a spatial modality, and vice versa.

Another way interfaces might adapt is to manage interruptions based on the user's cognitive state. For example, if a user is in deep thought, the system could detect this and manage pending interruptions such as e-mail alerts and phone calls accordingly. This is true even if the user is staring blankly at the wall and there are no external cues that allow the system to easily differentiate between deep thought and no thought.

Finally, if we can sense higher level cognitive events like confusion and frustration or satisfaction and realization (the "aha" moment), we could tailor interfaces that provide feedback or guidance on task focus and strategy usage in training scenarios. This could lead to interfaces that drastically increase information understanding and retention.

5. GAMES AND BRAIN ACTIVITY

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. The next step in game development is input obtained from the measurement of brain activity. 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 [5]. Relaxation games have been designed [4] and also games that adapt to the affective state of the user [2,3]]. BCI game research requires the integration of theoretical research on multimodal interaction, intention detection, affective state and visual attention monitoring, and on-line motion control, but it also requires the design of several prototypes of games. These may be games for amusement, but also (serious) games for educational, training and simulation purposes.

6. CHALLENGES OF BCI IN HCI AND GAME RESEARCH

There are many challenges unique to BCI applications in HCI. One example is the inevitable presence of artifacts traditionally deemed to be "noise" in traditional BCI explorations. In our applications, we cannot typically control the environment as tightly as in many medical applications (e.g. we do not typically want to be gaming in a faraday cage) nor are we usually willing to restrict the actions of the user (e.g. tie them down so they don't move). Hence, we have to devise techniques that either sidestep these issues, or better yet, that leverage the additional information we have availabe to us. A particular point of interest is how to fuse information coming from more traditional input modalities (e.g. touch, speech, gesture, etc.) with information obtained from brain activity.

7. Acknowledgements

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Neurofeedback Gaming for Wellbeing

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ABSTRACT
In this paper we discuss our vision on future neurofeedback therapy. We analyze problems of the current situation and debate for a change in focus towards a vision in which neurofeedback therapy will ultimately be as easy as taking an aspirin. Furthermore we argue for a gaming approach as training, for separation between neurofeedback therapy and gaming has become noticeably smaller after recent development in brain manipulated interfaces. We conclude by providing suggestions of how to achieve this vision.

Categories and Subject Descriptors
H5.2 [**Information Interfaces and Presentation (e.g. HCI)**]: User Interfaces - *Input devices and strategies (e.g., mouse, touchscreen),*

General Terms
Theory, Design

Keywords
Neurofeedback therapy, neurofeedback training, gaming, EEG, mental and physical wellbeing, prevention as healthcare

1. INTRODUCTION
Neurofeedback [2], as therapy of the future, may realize the vision of fighting the cause rather than the symptoms. It treats health problems like attention deficit disorders, hyperactivity disorders and sleeping problems, formerly all suppressed with medication. Based on EEG measurements, the user's mind is trained to bridge new connections and to either increase or decrease the use of specific brain functions. And best of all: it is achieved by simply undergoing a number of non-intrusive sessions, which we propose to improve by interconnecting with gaming appliances. However, if it is such a promising concept, why hasn't this therapy been adopted by the general public and health companies yet?

2. REVIEW
The results of research in the field of neurofeedback seem very promising, but various aspects like discrepancy in society focus, general acceptance and practical issues (time and money) form challenges that have yet to be overcome.

In present day society, people only consult a doctor when experiencing physical complaints. In other words: the focus is too much on the physical aspect of health and on curing the symptoms. In contrast, the main focus of neurofeedback is on mental issues, e.g. concentration or sleeping disorders and on fighting the cause of these disorders, rather than the symptoms. The gap between the health focus of society and neurofeedback therapy is noticeable, which may be one of the reasons that neurofeedback is not applied to its full potential yet.

For neurofeedback to be integrated in society, there is a need for neurofeedback to be accepted. However, another problem might be that neurofeedback therapy is based on a 'mind over matter' perspective, implying that not only the physical and mental wellbeing are interconnected [3, 5] but also that the physical wellbeing can actually be a result of the mental one. Although this statement has been proven in various studies [3], people may experience problems with acceptance. Ungrounded conservative opinions have been formed, perhaps as a result of the natural fear of the unknown. Still, although neurofeedback therapy has shown to have a positive influence [6] on numerous disorders, absolute and undeniable proof of absence of possible side-effects has not been supplied yet. Whether this is a potential issue for the therapy not to be accepted, remains open for debate. However, it has been said that if some or another medication could be as broadly and effectively applicable as neurofeedback therapy, it would already be available at every pharmacy in the world. [11]

More practical problems with neurofeedback therapy (compared with for example medication) include its expensive and time consuming aspects. Currently, a regular therapy exists of approximately 40 sessions of 1 hour each, preferably one or two sessions a week. However, this hour includes only 30 minutes of actual contact time, since existing EEG products simply take a lot of time to prepare. A closer look at the method: In most cases, EEG products involve placing an elastic cap on the head, with 19 sensors held in place on the scalp. To optimize scalp contact, dead cells are removed and hair is parted out of the way to place sensors with gel on the scalp. The ElectroCap (figure 1) [1] is the far most used example of this category. Other cases include the use of a 2-channel EEG measurement, involving only 2 sensors and clips on each earlobe. In those cases, the sensors are placed on the scalp directly (without the elastic cap), for the cap mainly functions for defining the location of scalp electrodes.

Figure 1. ElectroCaps [1]

Besides the extensive preparation, these sessions take place at a clinic, therefore waiting time and obviously travelling time should be counted as well. Besides the time aspect, neurofeedback therapy is very expensive and not refunded by health insurances.

The identified issues, varying from practical to emotional, might all slow down the development of neurofeedback therapy and its acceptance by society.

3. AIM

We suggest a change in the focus of neurofeedback in two ways, both the aim as well as the practical realisation. Furthermore we emphasize the importance of intrinsic motivation (gaming) [9] in neurofeedback training.

As applied for health-related training systems, current aims of neurofeedback therapy might include:

- training to improve overall fitness;
- training to alleviate attention and hyperactivity disorders, e.g. for ADHD patients;
- training for specific sports such as rowing, cycling etc.;
- training for relaxation and meditation to cope with mental strain;
- training muscular tonicity recovery for cardiovascular patients;
- training and eating schemes to maintain proper weight or loose overweight.

Aims described above, include therapies applied in the medical area, focusing on people with mental disorders. Using neurofeedback training they are able to improve their quality of life and bring their wellbeing level up to a regular standard. But what if we would apply this therapy before any disorder has occurred? Given the fact that both mental and physical health are interconnected [3], neurofeedback therapy could function as prevention rather than a cure. This insight brings closer the European dream, emphasising quality of life over accumulation of wealth [10].
Imagine the possibilities of using neurofeedback training as tool to improve the quality of our lives; consequences on a macro scale would be immense, ranging from a decrease in diseases to a reduction of health insurance fees. As a matter of fact, this shift of focus from cure to prevention is already taking place in healthcare; a Dutch health insurance company actually stimulates the use of low-cholesterol margarine by partly refunding it [8].

Using neurofeedback training as tool to improve life would be a big step in healthcare. It could be argued that healthcare uses neurofeedback to elevate wellbeing to certain standards, while professional athletes use neurofeedback to enhance their already exceptional performances; the so-called field of *peak-performance*. With neurofeedback therapy, athletes are able to teach themselves to consciously enter a state of ‘relaxed focus’, resulting in an optimal performance also known as the winning mood. Now imagine that everyone could consciously evoke this feeling; neurofeedback could be used to not only cure or prevent diseases but to elevate our entire standard of living.

However, before neurofeedback training is accepted, there’s a need to cope with multiple challenges neurofeedback is facing, for example the practical issues described before. Neurofeedback therapy currently involves a lot of time, money and other practical issues which can obstruct the acceptance of neurofeedback therapy. We suggest a world in which neurofeedback training is as easy as taking an aspirin.

To realise this vision, we suggest home-use should be enabled. For this to happen, first of all the involvement of a medical expert should be decreased (e.g. only for guidance in defining the goals and keeping an eye on the progress). Of course, it is still strongly recommended to undergo a medical investigation, to exclude certain causes of possible complaints and to check for counter-indications.

Our second suggestion is that a user should be able to conduct a therapy session independently. This implies the need to be able to easily locate the necessary contact-points and applying the sensors. It can be assumed that most of the households already have a computer which can calculate sensor input and provide feedback. This means that in principle, only an EEG measurement device and a software package needs to be applied, which would greatly reduce costs. As a final demand, the training software should be easy to operate and perhaps even more important: the software should be intrinsically motivating (playful).

Based on observations, the following assumptions are formulated, which could be advisable to keep in mind when designing for playful neurofeedback training sessions:

- A_1: that it is helpful to give the user rewards based on performance;
- A_2: that it is helpful to simulate elements from an assumed context of use;
- A_3: that it is helpful to provide the user with quantitative performance data.

Similarities between gaming and neurofeedback training software are identified, for example: reward schemes with levels, credits, bonuses, etc. (A_1), sound generation and rendering of high-resolution real-time environments (A_2), statistics and graphs etc. (A_3). Given the fact that intrinsic motivation is found in gaming [7] and that it provides positive influences on concentration and motivation, we suggest to focus on gaming when creating neurofeedback training software (e.g. ‘Brainball’ of Hjelm [4] is considered to be an interesting example). Imagine neurofeedback, applied as a treatment, being perceived as fun and enjoyable. In this case a shift from ‘treatment’ to ‘play’ could be both desirable and achievable. It should be kept in mind however, that gamers might not be satisfied with any rewards, contexts and data that are much more naïve and low-tech than their media experience; or in other words: neurofeedback training might have to keep pace with gaming.

4. APPROACH

In this section, issues that are possibly slowing down the development of neurofeedback will be addressed. Suggestions for realising the proposed aims of neurofeedback gaming will be discussed as well, starting with the acceptance.

It is likely that, before society can accept neurofeedback, there is a need for awareness about the system and its functioning. This would imply that before society can exploit the various opportunities of neurofeedback training, such as improving personal capabilities, people need to be made aware of the possibility called neurofeedback training. For this to be reached, we should realize that neurofeedback therapy (as applied at the moment) is the frontier of neurofeedback training. Early adopters like athletes and people with mental disorders presumably have a bigger drive to look further, which resulted into neurofeedback therapy. More might follow and neurofeedback could become more and more accepted when positive media attention keeps on going. Furthermore, part of this acceptance probably has to be achieved by means of scientific proof, especially regarding the governmental and health insurance area. Therefore we debate for large scale research proving the positive influence of neurofeedback therapy and the absence of negative side-effects.

However, increasing acceptance of neurofeedback therapy would only be the first step. We also propose to enable neurofeedback training controllable by the user in home context, which could be achieved by designing products according to specific user requirements. These requirements are based on the aim of shortening and simplifying the training methodology and would therefore include being able to:

- easily locate contact points
- easily apply sensors (including conducting gel) to one's head
- have access to training software and the ability to control it
- receive feedback on electrode impedance and act accordingly
- easily clean the sensors and reuse the system

With these suggestions, time and money issues are addressed. Additionally, it is likely that neurofeedback would become available to a broader public. This might help to accomplish the aims regarding wellbeing (being: focus on prevention and mental health, increase capabilities by consciously training brain signals). We propose to increase accessibility of neurofeedback training in both a physical and social way. The physical accessibility (or easiness of home-use) combined with the social accessibility (or intrinsic motivation of gaming) logically increases enjoyment of the training. This could result in a consumer demand contributing to elevating the standard of living of the general public.

Additionally, specifically focusing on certain target groups may support development in crucial adoption stages. For example children with small attention disorders, who would normally never be treated or trained, can be reached by increased accessibility of neurofeedback.

Also, we consider playfulness to be another important factor of accessibility. When implementing gaming approaches as shown in assumptions A_1 – A_3, neurofeedback training could profit from keeping up with gaming. On the other hand, neurofeedback can be seen as an extension to the already existing tools for gaming; actually the only change in the gaming application would be the input. Instead of movement information sent by a mouse to the software, EEG signals are derived from the brain and used as input. In short: current gaming can be extended with EEG signals as input.

5. CONCLUSION

We identified several possible issues holding back the development and implementation of neurofeedback therapy. New aims of neurofeedback are suggested, including: 1) a focus shift (in healthcare) from cure to prevention, 2) increasing the focus on mental wellbeing in healthcare, 3) elevating the standard of living by enabling users to consciously train brain signals 4) implementing gaming approaches in neurofeedback to increase intrinsic motivation. In general, we propose to make neurofeedback training more accessible by designing single-user products for the home environment and thereby achieving our idea of using neurofeedback to its full potential. Furthermore we argue the use of gaming as motivational tool and to support society adopting neurofeedback training.

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Why Use A BCI If You Are Healthy?

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ABSTRACT

Brain – computer interface (BCI) systems are typically used to provide disabled users with the functionality normally afforded by conventional interfaces. As BCI progress continues, BCIs may become useful for healthy users in specific situations. This paper briefly reviews existing BCI applications for healthy users and discusses several relevant considerations. Many potential applications are presented, followed by brief discussion of likely early adopters of BCI technology.

Categories and Subject Descriptors

J.3 [**Computer Applications**]: Life and Medical Sciences

General Terms

Design, Experimentation, Human Factors, Theory

Keywords

Brain – computer interface, brain – machine interface, BCI, BMI, EEG, gaming, virtual reality, simulation, attention, hybrid, assistive communication.

1. INTRODUCTION

A brain - computer interface (BCI) enables communication without movement. Instead, BCIs infer user intent via direct measures of brain activity. Most BCI research focuses on restoring communication for severely disabled users (e. g., 1, 8, 11). BCIs may also be useful for treating other disabilities, such as stroke, autism, epilepsy, or emotional disorders (3). Although BCI research will likely continue to focus on medical applications, BCIs may also be useful to healthy users for other applications.

BCIs have several serious drawbacks relative to conventional interfaces such as keyboards or mice. Conventional BCIs have a much lower information throughput because they are slower, less accurate, and allow lower bandwidth. They require expensive hardware and an electrode cap. This cap must be plugged in to a computer via a cable that is very sensitive to movement. The cap requires several minutes of preparation by someone else, gel in the user's hair, and another couple minutes of cleanup time. Some BCIs require training, are unreliable in some subjects, and are difficult to use. BCIs are not familiar to most people, and may seem intimidating, exotic, Orwellian, or even nerdy. BCIs require hardware and software that is not well known. It is thus not surprising that BCIs are not currently used by mainstream users in conventional settings, and this will not change in the near future.

Most authors take for granted that BCIs, at best, allow people to send the same information that they could otherwise convey much more quickly and easily via other interfaces. This perspective is wrong. This paper presents some ways that BCIs might be useful to healthy users in specific situations. Important research questions for these alternative BCI applications are also discussed. Emphasis is placed on games and simulations, since most BCIs meant for healthy people use these applications. Further, this paper focuses on BCIs that rely on information acquired from electrodes on the scalp. While other neuroimaging approaches have been used in BCIs, these are not practical for most applications with healthy users, because they require either neurosurgery or expensive, bulky, impractical equipment (1, 15).

2. EXISTING BCIs FOR HEALTHY USERS

While most BCI articles use healthy subjects, their authors' intent is to develop assistive tools for disabled users (1, 3, 8). However, some articles have presented BCI systems that were designed with healthy subjects as end users. These articles often allow people to use BCIs to control games or virtual environments. Middendorf and colleagues presented a BCI that allowed people to bank a full motion aircraft simulator (9). Another SSVEP BCI allowed users to move a map in two dimensions (14). In Bayliss and Ballard (2000), subjects used a conventional driving simulator while a BCI detected the P300 elicited by traffic lights and could use this to trigger brakes (2). Some games or virtual environments allow users to turn or lean left or right with a BCI (7, 11, 12) or control a pong paddle (4). A few companies have sold BCIs intended to enable healthy subjects to play similar simple games, such as ibva.com, cyberlink.com, and smartbraingames.com.

The state of the art BCI game has the following characteristics. It usually allows one degree of freedom, or dimensional graded control. The precision of this graded control varies and is not well studied, but is often no better than two choice direct selection. Most new subjects could use the BCI effectively within about 10 minutes, and performance varies considerably across subjects (see also 6). It can operate in challenging field environments despite extensive background activity and electrical noise, including the noise produced by an aircraft simulator or head mounted display.

3. CONSIDERATIONS FOR BCI APPLICATIONS WITH HEALTHY USERS

3.1 BCIs might supplement other interfaces

In typical BCI games, players may only effect control via electrodes or other direct measures of neural activity. Thus, these *exclusive* BCI games exhibit very low bandwidth, and the appeal of the game rests largely with the fun of using an alternative interface. There has been little consideration of using BCIs in combination with other interfaces, due perhaps to the technical difficulty of developing such *hybrid* BCI games (1, 2) and the assumption that BCI use requires the user's full attention. Recent research has shown this to be incorrect in some circumstances.

Some trained subjects could successfully perform other tasks during BCI use (1). Other groups have shown that learning to use some types of BCIs is similar to learning other procedural skills such as typing, riding a bicycle, or playing the piano. As people practice these activities, they become less distracting. An expert piano player or typist may be able to simultaneously have a casual conversation or listen to a TV, just as a BCI expert may be able to multitask in ways that novices could not (e. g., 1, 3). The "distraction quotient" of BCI use has not been well explored. How can BCIs best be integrated with other interfaces? Which types of BCIs work best with other interfaces, environments, and games? How does distraction change with practice? How do these issues vary across users with different personalities, backgrounds, motivations, abilities, and other characteristics?

These issues might also depend heavily on how the BCI supplements other interfaces. The BCI could provide an additional independent signal, such as an additional key used to fire a weapon, or could modify commands send by the primary interface. For example, in many first person shooter games, the "W" key by itself moves the character forward, and holding down the "SHIFT" button at the same time makes the character run. The BCI could replace either or both of these. Perhaps an image of shows or wings might oscillate on the screen. If the user focuses attention on this image while holding down "W," this could make the user run. Other icons might allow players to move forward while crouching, dodging, or prone, freeing up several other keys.

3.2 Induced disability

One approach to considering BCI applications in healthy users is: When are healthy users like disabled users? That is, under what circumstances are healthy users unable to effectively use conventional interfaces? If someone's hands are busy, and voice communication is unfeasible due to background noise or the need to maintain silence, BCIs might be the best communication tool.

Surgeons, mechanics, soldiers, and pilots are examples of healthy individuals who might sometimes experience this phenomenon of "induced disability." A BCI could allow these people to request tools, convey vital information to colleagues, navigate maps or schematics, or perform other tasks that might otherwise be difficult, distracting, dangerous, or impossible.

Induced disability may also occur if conventional interfaces are unable to provide sufficient bandwidth. Expert computer gamers often use a variety of keys at once, and controls for console games have become increasingly sophisticated, requiring several fingers on both hands for effective control. If gamers or other users could use the BCI to supplement conventional controls, effective bandwidth could be increased. Again, this hinges on further research involving the BCI distraction quotient.

When BCIs can reliably provide additional, supplemental information without impairing the use of mainstream interfaces, even in limited situations with highly trained users, this will be a major benchmark. Consider the first time that an expert gamer, playing a mainstream game that is normally played with a conventional interface only, actually exhibits greater total bandwidth and/or improved performance if he supplements conventional control with a BCI. This news would spread very quickly, and generate tremendous demand for hybrid systems.

3.3 Ease of use (hardware)

The keyboard and mouse seem like very natural, intuitive, convenient interfaces – when expert users happen to have these tools in their laps. If a user just happened to be wearing EEG sensors at other times, she might find a BCI easier to use than other interfaces.

Given the limitations of conventional electrode caps, this situation is quite rare. However, EEG sensor technology is an area of rapid progress (1). New electrodes are becoming available that require little or no preparation or cleanup time, little or no gel, and may not require direct contact with the scalp. These sensors might be easily integrated with other devices such as headphones, gamer microphones, earbuds, helmets, or head mounted displays, as well as clothing such as hats, caps, hair berets, or glasses. Improved electronics and signal processing are further catalyzing smaller, better, cheaper sensors and amplifiers. Technologies such as bluetooth and ubiquitous wireless internet facilitate wireless BCIs. If BCIs become so wearable as to become effectively transparent, they might be even more convenient and accessible than cell phones, watches, remote controls, or car dashboard interfaces.

Laziness is the bastard child of invention. Laziness may produce a sort of induced disability, and can be very motivating. Although televisions are still equipped with viable interfaces, people prefer more portable alternative interfaces that provide no advantage except remote control. Some people retype words or sentences rather than engage a mouse to cut and paste. These users might instead select, drag, or click via a BCI, eliminating the need to temporarily disengage from the keyboard. Humanity might finally escape the inconvenience of leaning forward to grab a remote control or cell phone, let alone press buttons.

3.4 Ease of use (software)

Some people assume that BCIs operate through a mindreading metaphor – users think of a certain letter or word, and it appears on the screen. This is not possible. However, some BCIs may be more literal than others. In most BCIs, like most conventional interfaces, the activities performed have nothing to do with the desired output. Paying attention to specific flashes or moving fingers across a keyboard may allow someone to convey a message, but these activities are very different from natural communication. On the other hand, Pfurtscheller and colleagues describe an immersive environment called the CAVE system, which allows users to walk forward by imagining foot movements, or turn left or right by imagining left or right hand movements. This BCI is still somewhat interpretive, but relies on a more obvious mapping between cognition and output than most BCIs. People who used this BCI reported that it was more natural and usable than less immersive BCIs they had tried (11). Further research should address which mental activities seem most natural, easy, and pleasant for different users in different situations. Users might choose which activities map onto which commands, further improving usability.

3.5 Otherwise unavailable information

All software has been heavily influenced by available interfaces. Operating systems would look very different if eye trackers and voice commands were the dominant interfaces. Just as keyboards and mice are inherently better suited to certain tasks, different BCIs may provide information that is effectively unavailable via other means. Three possibilities are considered here.

Several articles have explored EEG activity that occurs when a subject believes that he or she just made a mistake. The error – related negativity (ERN), which may be recognized within about 200 milliseconds after recognizing a mistake, has been used for realtime error correction with BCI systems (10). Other recent work has shown that the P300 and related activity might also be used to detect errors (5). Reliable realtime detection of the presence or absence of perceived error could have many benefits. For example, if a user types a word that spellchecking software does not recognize, that word might be underlined in red. This forces the user to either correct the word or inform the spellchecker that no mistake was made. The presence or absence of error activity might facilitate this process. If a user realizes he just mistyped a word, he would be automatically presented with a list of alternate words. On the other hand, if no error was detected, the software might ignore or remember the word. In either case, the need to communicate via the keyboard or mouse is reduced.

BCI systems might detect emotion or arousal and thereby modify the way information is sent and/or presented. BCIs might automatically send a different message if the user is happy, bored, or upset, and could modify the display or other parameters based on the user's state. Some companies, such as Emotiv, NeuroSky, and Smart Studio, have already developed games that use sensors on the head to detect emotion and react accordingly. These systems likely utilize information from EMG and EOG activity, which is probably more informative than EEG alone. BCI systems that sense emotion will likely utilize both EEG and other signals.

EEG activity may reflect attention in different ways, leading to different possibilities for attention – based applications. The P300 has been used in many BCI systems because users can voluntarily change its amplitude by choosing to be interested in a specific event. Similarly, the P300 may index attention to other recent events. If a gamer is informed of an attack elsewhere on the map, he may wish to "jump" to that location to respond. A BCI might automatically detect this, replacing the spacebar in many realtime strategy games (thus leaving this very large and central key available for other commands). The P300, SSVEP, and other signals may reflect regional attention. Software that could determine which areas of the screen or auditory space are of most interest to users could then follow links, magnify or jump to regions of interest, or modify how information is presented in the future. Again, eye movements or other activity might supplement EEGs to improve precision, speed, or other factors.

Many other applications and EEG signals are possible, but some of them challenge the definition of a BCI. Detection of emotion, arousal, or attention could be very useful in neuromarketing, an application that has recently attained considerable attention. However, in this situation, the user is not intentionally sending a message or command via EEG activity. Similar systems could also be useful in diagnosing a wide variety of disorders or responses to medications, but would not be BCIs for the same reason. EEG activity has also been used to treat many disorders, infer deception, index the detection of recognizable images, estimate fatigue or workload, and perform other tasks, but these BCI – like applications also do not allow communication (1).

3.6 Improved training or performance

At least two research groups are currently exploring the possibility that the process of learning BCI use could improve training or performance with some motor tasks. Since some BCIs rely on imagined movement, and training teaches subjects to produce specific patterns of neural activity over sensorimotor areas, BCI training might have positive side effects. This possibility has not been well explored, and negative side effects should be considered as well. A related question is whether subjects' athletic and motor background and skills might help identify the right BCI parameters.

3.7 Confidentiality

A BCI may be the most private communication channel possible. Since conventional interfaces require movement, other people can eavesdrop simply by observing these movements. This is a problem in some competitive gaming environments, especially if two opposing players are seated next to each other using the same console. Many console gamers are familiar with the experience of choosing an offensive play in a football game, only to look over and notice the opponent glancing at his controller to select a corresponding defensive play. The covert communication offered by BCIs could be of value in other situations that require secrecy.

3.8 Faster signal detection

EEG activity necessary for movement is typically apparent several hundred milliseconds before the movement begins, and may even precede awareness of the decision to move (e. g., 12). Some BCIs that rely on invasive electrodes have allowed people or animals to initiate movement more quickly than they could through conventional pathways. Current BCIs could only provide a rudimentary estimate of movement intent, but the ability to send even one signal 50 milliseconds more quickly could provide a tremendous advantage in competitive gaming and other situations. Further research should provide earlier movement prediction with greater precision and accuracy, explore how to integrate predicted with actual movements, and evaluate training and side effects.

3.9 Novelty

Some people may want to use a BCI simply because it seems novel, futuristic, different, or exciting. This consideration, unlike most others, loses steam over time. That is, BCIs will likely continue to become more flexible, easier to use, or better integrated with existing interfaces as research continues.

However, if BCIs continue to improve, public perception will follow a pattern similar to that seen after the invention of cell phones. BCIs will first be exotic, then novel, then widespread, then unexceptional, and finally boring.

4. HEALTHY TARGET MARKETS

Most healthy BCI users today fall in to one of four categories: BCI research scientists, friends, research subjects, and people who happen to like our booths at public expositions. In addition, a few people order BCIs from commercial firms online, forming a fifth category that is unique in that no BCI expert was needed to prepare either the software or hardware for each individual user. This fifth user category will of course be crucial if BCIs are to develop a significantly wider distribution.

If BCIs could provide useful functionality without significant setup time or hassle, who would first want to use them? Gamers seem likely early adopters for several reasons. Many gamers wear headgear, are strongly attracted to new and futuristic technologies, enjoy technical challenges such as those that may come with an early BCI, have time available for training, and have a proven track record of spending money on peripherals. Gamers are extremely competitive and might work hard for the marginal benefit provided by an early BCI. The rapid rise in both PC and console games, combined with increasing support for peripherals and pressure for a novel competitive advantage, may result in considerable funding for BCI game development. Personnel in specific military or government roles may soon follow. These sectors may initially be more cautious, as they often prefer to see technology validated elsewhere. Highly professional and specialized users such as surgeons, welders, machinists, or aircraft mechanics, who are typically intelligent and already spend substantial time and money on equipment and interfaces, are also likely second – generation adopters.

More mainstream applications, such as error correction hybridized with a word processor, are more distant. These approaches hinge on significant prior validation with other groups, new software development efforts, and much more convenient EEG sensors. Public perception is also important. While it is difficult to imagine that BCIs might someday be boring, this is a better outcome than them being considered unreliable, useless, unfashionable, dangerous, intrusive, or oppressive. Inaccurate reporting and related technologies like lie detection or might create a bad reputation for BCIs. This should be minimized by proper dissemination of results and positive appearances at conferences, expositions, or media events. Websites such as bci-info.org also serve to educate the public and reduce miscommunication.

5. CONCLUSION

BCI research has focused primarily on providing disabled users with the same functionality as mainstream interfaces. Hence, there has been little consideration of how they might be useful to healthy users. BCIs will not soon replace conventional interfaces in most situations, but may be more useful to healthy users in specific situations due to several considerations. The integration of BCIs with other interfaces raises many questions best addressed with parametric research involving different users, interfaces, mental activities, goals, output devices, and training parameters.

6. ACKNOWLEDGMENTS

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Advanced Human-Computer Interaction with the Berlin Brain-Computer Interface

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ABSTRACT
Brain-Computer Interfaces (BCIs) are systems capable of decoding neural activity in real time, thereby allowing a computer application to be directly controlled by the brain. Since the characteristics of such direct brain-to-computer interaction are limited in several aspects, one major challenge in BCI research is intelligent front-end design. Here we present the mental text entry application 'Hex-o-Spell' which incorporates principles of Human-Computer Interaction research into BCI feedback design. The system utilises the high visual display bandwidth to help compensate for the extremely limited control bandwidth which operates with only two mental states, where the timing of the state changes encodes most of the information. The display is visually appealing, and control is robust. The effectiveness and robustness of the interface was demonstrated at the CeBIT 2006 (world's largest IT fair) where two subjects operated the mental text entry system at a speed of up to 7.6 char/min.

1. INTRODUCTION
Brain-computer interfaces (BCIs) translate brain signals into control commands. The measured brain signals reflect, to some extent, the intentions of a subject. The control commands may be used for a computer application or a neuroprosthesis. There is a variety of BCI systems being developed that use signals recorded from the scalp, the surface of the cortex, or from inside the brain. It has been shown that invasive BCI systems enable monkeys, and recently also humans, to operate a robotic arm ([11, 6]). Furthermore it was demonstrated that noninvasive BCI systems enable healthy subjects as well as patients to control an internet browser or simple word processing software ([14, 22, 7]).

Since a principle motivation of the development of BCIs is to provide paralyzed patients with independent communication tools, BCI-driven spelling devices are an important topic in BCI research. The Tübingen BCI group developed a system that could be operated by patients suffering from amyotrophic lateral sclerosis ([1]). Binary decisions of the BCI were used to select letters in a procedure where the alphabet was iteratively split into halves. The achieved spelling rate was about 0.5 char/min. With a similar front-end but a different BCI approach, a spelling application of the Graz group could be operated by one patient suffering from severe cerebral palsy at about 1 char/min ([17]). In [18] a spelling application is proposed that is based on a three-class BCI. While one class can be used to scroll through the alphabet which is presented on two 'assembly lines' left and right of the cursor, the other two classes are used to select the character from either the left or the right line. Since scrolling is uni-directional, missing the desired character necessitates scrolling through the whole alphabet for another chance. Two out of three BCI-trained users are able to operate the device at spelling speed 2.35 resp. 1.62 char/min (average for 5 words).

Furthermore there are BCI spelling devices that are based on the detection of potentials that are evoked by external stimuli rather than endogeneously altered mental states. Most prominent is the approach proposed by Donchin et al. ([10]) using the P300 component. Here all characters are presented in a 6×6 matrix. The symbol on which the user focuses her/his concentration can be be predicted from the brain potentials that are evoked by random flashing of rows and columns. The role of directing the gaze to the desired letter is so far not investigated. Further developments (e.g., [12, 13]) suggest that high spelling rates can be achieved using this approach. In the online experiments that have been reported so far, many repetitions of the stimuli have

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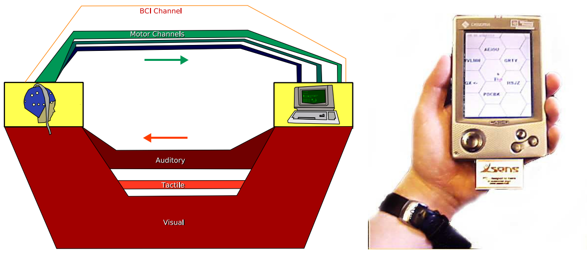

Figure 1: (a) Left: Asymmetry of BCI communication. (b) Right: Text entry system *Hex* for mobile devices.

been used in order to increase the signal-to-noise ratio for P300 detection. Accordingly the spelling speed could not exceed about 6 char/min even at 100% classification accuracy. Nevertheless offline analyses show that in principle fewer averages could be used, such that up to 15 char/min could be possible. Still, this has to be shown in practice.

Although the proof-of-concept of BCI systems was given decades ago (e.g. [9]), several major challenges are still to be faced. One of those challenges is to develop BCI applications which take the specific characteristics of BCI communication into account. Apart from being prone to error and having a rather uncontrolled variability in timing, its bandwidth is heavily unbalanced: BCI users can perceive a high rate of information transfer from the display, but have a low-bandwidth communication in their control actions, cf. Fig. 1 (a).

The Berlin Brain-Computer Interface (BBCI) is an EEG-based BCI system which operates on the spatio-spectral changes during different kinds of motor imagery. It uses machine learning techniques to adapt to the specific brain signatures of each user, thereby achieving high quality feedback already in the first session ([3]). The mental text entry system *Hex-o-Spell* which is presented here adapts modern, dynamic text entry methods into a suitable form for brain-computer control.

The idea for Hex-o-Spell was taken from the Hex system ([21, 20], see Fig. 1 (b)), which was designed for use on mobile devices augmented with accelerometers, where tilt control was used to maneuver through a hexagonal tesselation. The system adapted the response dynamics in order to make control behaviour for likely actions easier than unlikely ones, without altering the ideal path for any given word trajectory. This was intended to maintain a level of stability in the patterns required to generate letter sequences, such that the user could "bootstrap" from closed-loop to open-loop control. The adjustment was based upon a continuously-updating language model which inferred the next character given the previous text sequence. Hex-o-spell was adapted from this original system, replacing the two-dimensional tilt control with a rotation/forward switching input (see Section 2.1) and introducing layout rearrangement in place of the adaptive dynamics. In BCIs, where there is enormous asymmetry in the bandwith of the channels in the control loops (see Fig. 1 (a)), high-quality language models are essential to extract every drop of salient information from the user, using the large display bandwidth to make the user aware of the effect of their actions in combination with the language model. Although these introduce continual changes which may be difficult to predict (from the point of view of the user), the consequent reliance on continuous feedback may be tolerable given the extremely limited bit rates. Users have to move so slowly that they have plenty of time to search the space for changes.

2. METHODS

The decoding of mental states from brain activity as used in the Berlin Brain-Computer Interface system is described in another contribution in this volume, see [16], and in earlier publications ([3, 5]). In short, the BBCI detects the user-specific spatio-spectral changes of the EEG during motor imagination of, e.g., the left or the right hand or the feet. Applications are controlled by a continuous control signal. Typically this is the graded classifier output which discriminates two motor imagery classes. It has been demonstrated that the machine learning approach which is realized in the BBCI allows to achieve high quality feedback already in the very first session without subject training ([3, 5, 2]). Bit rates (measured during one dimensional cursor control) range between 6 and 40 bits per minute. The intention-to-control delay is difficult to quantify. The reaction time from stimulus presentation to significant BCI control is between 750 and 1750 ms with a large intra-subject trial-to-trial variability (compared to 300 to 450 ms in a 2 alternative forced choice task with finger movement responses to visual stimuli).

Note that there is a non-negligible percentage of the population for which BCI control does not work well enough to control applications. Since this phenomenon is reported from all BCI laboratories it seems not to be a problem of data analysis but rather inherent in the neurophysiological properties of the scalp EEG in some subjects. An investigation of this issue will require a large experimental approach which is definitely one of the burning issues in BCI research.

2.1 Character Selection Procedure in Hex-o-Spell

The challenge in designing a mental text entry system is to map a small number of BCI control states (typically two) to the high number of symbols (26 letters plus punctuation marks) while accounting for the low signal to noise ratio in the control signal. The more fluid interaction in the BBCI system was made possible by introducing an approach which combined probabilistic data and dynamic systems theory based on our earlier work ([21]) on mobile interfaces.

Here we take the example that the text entry system is controlled by the two mental states *imagined right hand movement* and *imagined right foot movement*. The initial configuration is shown in the leftmost plot of Fig. 2. Six hexagonal fields surround a circle. In each of them five letters or other symbols (including '<' for backspace) are arranged. For the selection of a symbol there is an arrow in the center of the circle. By imagining a right hand movement the arrow turns clockwise. An imagined foot movement stops the rotation and the arrow starts extending. If this foot imagination persists, the arrow touches the hexagon and thereby selects it. Then all other hexagons are cleared and the five symbols of the selected hexagon are moved to individual hexagons as shown in the rightmost screenshot of Fig. 2. The arrow is reset to its minimal length while maintaining its original direction. Now the same procedure (rotation if desired and extension of the arrow) is repeated to select one symbol. Note that there are only 5 symbols for choice in the second step, cf. rightmost screenshot of Fig. 2. Choosing the empty hexagon makes the application return to the first step without selection. This transition allows a sort of limited undo. Misspelt characters can be erased by selecting the backspace symbol '¡'.

There are several parameters that can be adapted to the specific capacities of the user, like the turning and the growing speed of the arrow.

2.2 Comments on the Design of Hex-o-Spell

Hex-O-Spell is unusual in that it uses that the user applies binary control to produce discrete output, but does so through a continuous control process. Control is effected by imagining motor movements; but these are based upon the feedback from the interface, which has a continuously changing state. This state is the result of the integration the output of the classifier identifying the imagined movements, which is integrated and then thresholded to into a decision between rotation/forward motion with fixed speeds. Fig. 3 shows the structure of this control loop.

Hex-o-Spell could also be modified to work as a T9-style system, with only a single transition for each character rather than a pair. Given that PPM models can compress English to approximately 2 bits per character and choosing one from six transitions gives ~ 2.585 bits, this should be quite practical. [8] describes a functioning entry system using only four transitions followed by a decoding step. Despite of its increment of information transfer rate, it has to be explored whether BCI users are interested in this form of predictive text entry. There are anecdotal reports of patients who preferred a slower spelling system than using a system which suggested word completions based on a probabilistic model.

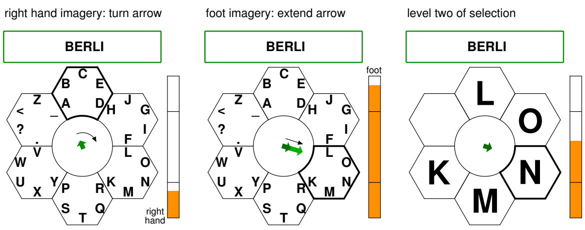

Figure 2: The mental text entry system 'Hex-o-Spell'. The two states classified by the BBCI system (bar on the right in each screenshot) control the turning and growing of the grey arrow respectively (see also text). Letters can thus be chosen in a two step procedure. If the classifier output is undecided (orange bar between the thresholds), the arrow maintains its direction and its length dimishes continuously to minimum.

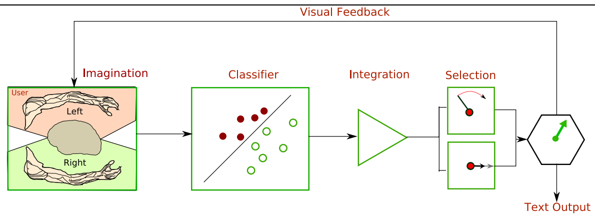

Figure 3: The structure of the control loop in Hex-O-Spell, indicating the transformation of a discrete user intention into a continuous variable which is fed back to the user, while simultaneously generating discrete symbols.

Hex-o-Spell is effectively a *timing*-based interface. The time at which the transition from the rotation state to the forward state occurs determines the letter which is selected. The rate of communication is bounded by how accurately the user can make these transitions, given the noise properties, delays and unfamiliarity of interaction present in an EEG interface. The time to traverse 60° should be calibrated against the reaction time of the user and the system; if the traversal time is much shorter than the reaction time, selection will become impossible. The language model, which adapts the layout, acts to minimize the time required for a selection, trading-off the minimization of the time required to rotate to the appropriate position for selection against the time required to scan the new layout and find the new locations of symbols. The "calmness" of this adaptation strategy means that the user is not always in a tightly-coupled loop with the system; rather than being a flying-like control task, the interaction is broken into smaller chunks which the user can proceed through at their own pace. This is one advantage over systems such as Dasher [19], which although extremely efficient control is possible with continuous, relatively noise-free input devices such as mice or eye trackers, but is less suited to the discrete, pulse-like control present in a BCI.

3. RESULTS

On two days in the course of the CeBIT fair 2006 in Hannover, Germany, live demonstrations were given with two subjects simultaneously using the BBCI system. These demonstrations turned out to be BBCI robustness tests *par excellence*. All over the fair pavilion, noise sources of different kinds (electric, acoustic,...) were potentially jeopardizing the performance. A low air humidity made the EEG electrode gel dry out and last, but not least, the subjects were under psychological pressure to perform well, for instance in front of several running TV cameras or in the presence of the German minister of research. The preparation of the experiments started at 9:15 a.m. and the live performance at 11 a.m. The two subjects were either playing 'Brain-Pong' against each other or writing sentences with Hex-o-Spell. Except for short breaks and a longer lunch break, the subjects continued until 5 p.m. without degradation of performance over time which is a demonstration of great stability. The typing speed was between 2.3 and 5 char/min for one subject and between 4.6 and 7.6 char/min for the other subject. This speed was measured for error-free, completed phrases, i.e. all typing errors that have been committed had to be corrected by using backspace. The total number of characters spelled in error-free phrases was up to 560 per subject per day.

For a BCI driven text entry system not operating on evoked potentials this is a world class spelling speed, especially taking into account the environment and the fact that the subjects did not train the usage of the BBCI text entry interface: the subjects used Hex-O-Spell only twice before.

4. DISCUSSION

Compared to spelling applications that have so far been coupled to BCIs ([18, 23, 1]) Hex-o-Spell is by far most sophisticated in terms of HCI principles. Conjoint with the powerful BBCI this mental text entry system allowed to achieve world class spelling performance. Hopefully this demonstration initiates the advancement of BCI applications from its rather simple state to more intelligent designed front-ends.

One of the aims of Hex-o-Spell is to make the best use of the language model to reduce the effort required to enter text, without inducing enormous cognitive load or extensive training time. There are four common approaches to introducing language models into text entry systems: post hoc interpretation (e.g. as used in T9); adaptive target resizing (as in Dasher [19]); dynamics adjustment (as in the original Hex); and layout re-ordering (used in Hex-o-Spell). Target resizing is simple to understand, but the visual display fluctuates rapidly and significant space is required to display the resized alternatives. The reinterpretation approach allows for more powerful language modeling (because subsequent letters can affect estimates of previous ones), but the lack of predictability of output can be confusing for users. Adaptive dynamics can be used to produce an efficient and visually stable display, but is less suitable for the one dimensional control inputs present in the BCI interface. The rearrangment strategy does require visual search at every new letter input, but the minimal reorganization algorithm used in Hex-o-Spell significantly reduces the impact of this. Compared to other potential entry styles, such as Dasher or grid selection mechanisms, Hex-o-Spell is also very visually compact; the hexagonal display can potentially be used as a small overlay on top of a text being edited, giving the user an overview of the context in which they are editing.

The prospective value of BCI research for rehabilitation is well known. In light of the work presented here we would advocate a further point. BCI provides stimulation to HCI researchers as an extreme example of the sort of interaction which is becoming more common: interaction with 'unconventional' computers in mobile phones, or with devices embedded in the environment. These have a number of shared attributes: high-dimensional, noisy inputs, which describe intrinsically low-dimensional content; data with content at multiple time-scales; and a significant uncontrolled variability. The mismatch in the bandwidth between the display and control channels (as explained in the introduction) and the slow, frustrating error correction motivate a more 'negotiated' style of interaction, where commitments are withheld until appropriate levels of evidence have been accumulated (i.e. the entropy of the beliefs inferred from the behavior of the joint human-computer system should change smoothly, limited by the maximum input bandwidth). The dynamics of a cursor, given such noisy inputs, should be stabilized by controllers which infer potential actions, as well as the structure of the variability in the sensed data. Hex-o-Spell demonstrates the potential of such intelligent stabilising dynamics in a noisy, but richly-sensed medium. The results suggest that the approach is a fruitful one, and one which creates the potential for incorporating sophisticated models without *ad hoc* modifications.

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Psychophysiological Inference and Physiological Computer Games

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ABSTRACT
This paper is concerned with the use of real-time psychophysiological monitoring to control the interaction between the player and the computer game. In the context of the current paper, psychophysiology is used to represent the cognitive/motivational/emotional state of the player. The paper explores fundamental concepts and assumptions underpinning the design of a physiological computer game, including: (1) the use of psycho-physiological inference, (2) the representation of the state of the player, and (3) the biocybernetic control loop.

Categories and Subject Descriptors
H1.2 [**User/Machine Systems**]: Human Factors. H5.2 [**Information Interfaces and Presentation**]: User Interfaces. I.2 [**Artificial Intelligence**]: Games.

General Terms
Algorithms, Measurement, Human Factors.

Keywords
Games, Affective Computing, Psychophysiology.

1. INTRODUCTION
Physiological Computing [1] represents a category of affective computing [2] that incorporates real-time software adaptation to the psychophysiological activity of the user. The goal of this approach is to devise a computer system that responds in a rational and strategic fashion to real-time changes in user emotion (e.g. frustration), cognition (e.g. attention) and motivation as represented by psychophysiology. At present, human-computer interaction is both explicit (via keyboard or mouse) and asymmetrical (i.e. the computer can convey a wealth of information regarding its status to the user whereas the user is able to convey very little to the computer about his or her status) [3]. The central innovation of the physiological computing approach is to enable implicit and symmetrical human-computer communication by granting the software access to a representation of the user's psychological status.

Research into physiological computing has been directed towards a number of technological domains, such as: cockpit automation [4, 5], computer-based learning [6], and robotics [7]. The application of this approach to computer games remains relatively overlooked with a small number of exceptions [8, 9]. The incorporation of psychophysiology into gaming software has the potential to tailor the gaming experience to the cognitive, motivational and emotional responses of the player in real-time. This is important innovation as gaming software is designed to reliably create a positive state of psychological challenge. In addition, game designers place great emphasis on players' emotional engagement with the computer game [10] in order to expand player demographics, and to achieve higher levels of immersion within the game 'world'. Physiological computing offers the opportunity for real-time adaptation of gaming parameters to promote positive experience and to avoid undesirable responses such as frustration or boredom.

The physiological computing approach has the potential to revolutionize the game industry, in terms of hardware and software design, as well as rewriting the modes of information flow within the human-computer interaction. However, the potential of physiological computer games will only be fully realised by paying close attention to the scientific foundations of this technology, and a clear appreciation of how closed-loop systems function within this context.

2. PSYCHOPHYSIOLOGICAL INFERENCE
In principle, there are several possible methods to represent the psychological state of the user to a computerized monitor. Automatic detection of facial expression may be achieved at a reasonable level of accuracy via machine vision algorithms for core emotional expression [11]. Similarly, detection of vocal affect offers another option for data collection, particularly for those systems that rely on speech as the primary mode of user input [12]. A straightforward approach is to monitor the behavioural response from the user by measuring physical force when manipulating input devices to index frustration[13]. Psychophysiological indices offer several advantages over these methods [14]. Psychophysiological changes are continuous whereas vocal and behavioural expressions are discrete and episodic. Psychophysiological measures are covert and implicit whereas facial expression relies to an extent on the display rules governing emotional expression in the public domain. Psychophysiology can be also used to operationalise psychological variables beyond the emotional domain, such as cognition (attention, cortical activation) and motivation (mental effort). Finally, psychophysiological activity represents the only available data source when the user interacts with the computer without any explicit communication (emotional display or speech) or the operation of an input device. The primary disadvantages of psychophysiology is that data capture with current technology is often intrusive, although there is a limitation of non-ambulatory apparatus, which is currently the standard in this field [15, 16].

The complexity of psychophysiological inference [17, 18] is a fundamental issue for the development of physiological computing. These systems rely upon a tacit assumption that the psychophysiological measure (or array of measures) is an accurate one-to-one representation of a relevant psychological dimension, e.g. mental effort, task engagement, frustration. This assumption of isomorphism is often problematic as the relationship between physiology and psychology is complex and may be described as [17, 18] :

- Many-to-one (i.e. two or more physiological variables may be associated with the relevant psychological element)
- One-to-many (i.e. a physiological variable may be sensitive to one or more psychological elements)
- Many-to-many (i.e. several physiological variables may be associated with several psychological elements)

In the many-to-one case, an investment of mental effort in response to a demanding task may be only be fully represented by changes in cortical activity from the frontal lobes [19], increased systolic blood pressure [20] and changes in heart rate variability [21]. This pattern of linkage is reversed in the one-to-many relationship; for example, systolic blood pressure may increase when a person is excited, frustrated or stressed [22]. In the many-to-many case, a mixture of increased mental effort and stress may combine to exert a multiple, overlapping paths of influence over both systolic blood pressure and heart rate variability.

The implications of this analysis for the development of physiological computing should be clear. At a basic level, any system that operationalises a psychological element using a psychophysiological inference that falls into the one-to-many or many-to-many categories may not respond as anticipated by the user or the designer. This is mainly because the linkage between physiology and psychology is not 'clean,' and the variable is responding to other psychological elements besides the desired one. For example, imagine a game designed to reduce player anger or frustration that uses systolic blood pressure to infer frustration levels, and reduces the demands of the game as a response. Frustration or anger does increase blood pressure [23], but increased systolic blood pressure also characterizes a state of positive challenge [24], e.g. a one-to-many relationship. Therefore, the system may inadvertently reduce game demand when the player is in a state of positive challenge, which would frustrate the player, leading to increased blood pressure, which prompts a second downward adjustment of demand from the software and so on. The fidelity of the psychophysiological inference is vital for a physiological game to respond in an appropriate fashion.

The selection of 'strong' psychophysiological candidates for a physiological computing system requires that candidate variables have demonstrated a degree of validity. At a basic level, the careful selection of psychophysiological variables based on a thorough review of the existing literature will ensure a requisite degree *content validity*, i.e. that a precedent exists (either theoretically or experimentally) for the variables to measure what the designer intends to measure. However, the designer may also wish to test the quality of the psychophysiological inference experimentally to establish a degree of *concurrent validity*, i.e. how well does the psychophysiological measure predicts an psychological outcome based upon another set of variables? Several approaches have been adopted to establish the concurrent validity of psychophysiological measures by inducing emotional states in the laboratory, these include: face-pulling [25], exposure to emotional media [26, 27] and exposure to demanding or frustrating tasks [28, 29]. In most cases, concurrent validity is demonstrated by correlating psychophysiological data with self-report data or using discriminant analyses to distinguish different patterns of psychophysiological activity. The systematic approach associated with concurrent validity is contrasted with the concept of face *validity*, which captures a looser, 'quick-and-dirty' approach where the quality of the psychophysiological inference is assessed based on intuition or direct experience.

In the interests of optimising the quality of psychophysiological inference, which is the cornerstone of the physiological computing system, it is important to opt for concurrent validity over face validity. However, this approach introduces a number of methodological complexities. As psychophysiological variables seek to represent private psychological events, subjective self-reports represent an important psychological outcome with which to 'benchmark' the psychophysiological response. This link between physiology and self-report is often problematic as the latter are totally reliant on conscious perception, prone to bias due to personality or memory distortion [30], and therefore, their correspondence with psychophysiological activity is often erratic [31]. For example, in a study conducted in our laboratory, the maximum amount of variance associated with a subjective index of task engagement captured by an array of psychophysiological variables never exceeded 53% across the whole group [28]. If physiological computing systems are to be developed on the basis of concurrent validity, the sensitivity of psychophysiology should be tied to alternative outcomes in addition to subjective self-report, such as: implicit observable behaviours (facial expression, verbal gestures), performance quality (rate of progress through goals, frequency of errors) and measures of motivation (e.g. goal setting, desire to continue playing the game). It is proposed that the simultaneous consideration of multiple outcomes provides the strongest evidence for concurrent validity.

It is reasonable that a designer or scientist should view the criteria of face validity as a poor relation to content and criterion validity. However, consider the different varieties of validity from the perspective of the player engaged with a physiological computer game. If the player experiences an adverse subjective state, such as frustration, he or she expects the software to respond accordingly, by making the task easier or offering help. In other words, the player assesses the system response *purely* based on subjective self-assessment, which represents a form of face validity. Human factors research into the use of psychophysiology to control adaptive automation has included both approaches. The work conducted by NASA [4] used a generic measure of cortical activation via EEG to capture task engagement. In another study, a psychophysiological algorithm was generated individually for each participant in order to produce a personalised, operationalisation of subjective mental effort [32]. The latter study provided no evidence for the superiority of personalised approach (which emphasized face validity) over the generic approach (which emphasized content validity). From a usability perspective, the personalised approach offers the advantage of tailoring the psychophysiological inference to the individual– however in doing so, runs the risk of 'blunting' the sensitivity of psychophysiological variables, which respond to both conscious and unconscious activity at the psychological level. Designers of physiological computer games should consider both forms of validity when assessing the psychophysiological inference used by their systems.

Physiological computer games require strong psychophysiological inference to produce accurate and timely interventions. This is particularly important as the system must measure and diagnose in real-time. The linkage between physiological variables and psychological elements must be sensitive, discriminative and based on existing research. The quality of the psychophysiological inference should be tested with respect to both concurrent validity (in the interests of basic research) and face validity (in the interests of system usability). At the present time, there is little research contrasting generic psychophysiological algorithms with those generated specifically for the individual. Dynamic computer algorithms such as neural networks and evolutionary algorithms may offer a solution that satisfies both criteria of concurrent and face validity [33, 34].

3. REPRESENTATION OF THE PLAYER

If the psychophysiological inference fulfills the criteria of validity, the designer may consider how they wish to represent the psychological status of the player to the system. This is an important aspect of system design that determines the range of adaptive strategies available to physiological computer game as well as the "intelligence" exhibited by the system.

Physiological computing systems all contain an element that may be termed an adaptive controller. This element represents the decision-making process underlying software adaptation. In its simplest form, these decision-making rules may be expressed as simple Boolean statements; for example, IF frustration is detected THEN reduce game demand. The adaptive controller encompasses not only the decision-making rules, but also the psychophysiological inference that is implicit in the quantification of those trigger points used to activate the rules. In our study [32], for example, the adaptive controller took the form of a linear equation to represent the state of the player, e.g. *subjective effort* = x_1 ** respiration rate* – x_2 ** eye blink frequency + intercept*, as well as the quantification of trigger points, e.g. *IF subjective effort > y THEN adapt system.* The adaptive controller uses raw psychophysiological input to represent the psychological state of the player to its decision-making rules.

Previous research into physiological computing has represented the psychological state of the user as a one-dimensional continuum, e.g. frustration [8], anxiety [9], subjective effort [32], task engagement [35]. This is an appropriate starting point for research but reliance on a one-dimensional scale restricts the range of options available to of the adaptive controller, which may only characterize the psychological state of the player as low, medium or high on a given dimension. For some systems, where the gaming context is simple and required adaptive range is limited, this may not be a problem. However, the entertainment value of many computer games is based upon an interaction with a complex probabilistic 'world' with many contingencies. These complex game worlds demand an elaborated representation of the player in order to: (1) provide the adaptive controller with a higher fidelity of diagnostic information, and (2) to enable the controller to extend its repertoire of adaptive responses, which, if designed correctly, should have the net effect of enhancing the "intelligence" of the system as a whole.

One straightforward way of moving beyond a one-dimensional representation is model the psychological state of the player in a two-dimensional space. For example, emotion may be decomposed into two dimensions of activation (alert vs. tired) and valence (happy vs. sad) [36]. Within a gaming context, we may wish to consider motivational as well as emotional variables in order to characterize different degrees of challenge. Matthews and colleagues at Dundee University developed a subjective tool called the Dundee Stress State Questionnaire (DSSQ) to assess three meta-factors linked to cognition, motivation and emotion [37]. Two of the DSSQ factors, Task Engagement and Distress, could be used to create a representation of the player interacting with a computer game. Task Engagement was defined as an "effortful striving towards task goals", which increased during a demanding cognitive task and declined when participants performed a sustained and monotonous vigilance task [37]. The Distress meta-factor was characterised by "an overload of processing capacity" which increased when participants experienced a loss of control over performance quality [37]. The combination of engagement and distress allows us to consider the current state of the player as a point in the two-dimensional space shown below.

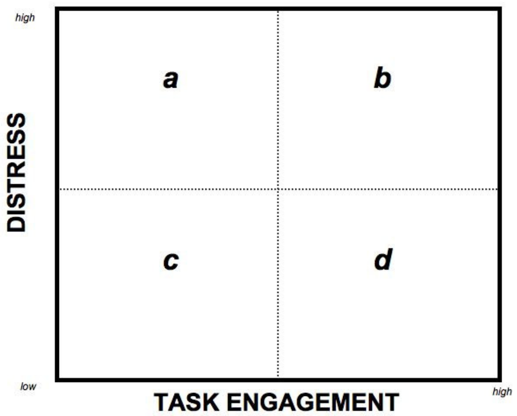

Figure 1. Two-dimensional representation of psychological state of the player.

Figure 1 partitions the psychological state of the player in four quadrants or 'zones'. Zone **a** represents an undesirable state of high distress in combination with low task engagement. In this case, the player is overloaded from a cognitive perspective as well as being disengaged from the task. It might be expected that a player in zone a is on the point of 'giving up' on the game. When engagement and distress are both high (zone **b**), the player occupies a "stretch" zone where they remain highly engaged, but also feel overwhelmed by the task. The player may tolerate this state for a short period, particularly during learning phases of the game. In zone **c**, the player is fundamentally bored as indicated by low levels of distress and engagement. Once again, a player in this zone may choose to switch the game off this state persists for a sustained period. When a player is comfortable with the level of demand yet remains motivated by game play, they fall into zone **d** (low distress and high task engagement). This state may subside into boredom (zone c) if the game lapses into monotony or give way to a learning phase (zone b) if gaming demand increases appropriately. We have attempted to operationalise both dimensions of task engagement and distress using psychophysiological methods during a sustained and demanding task, with some degree of success [28].

The benefit of a two-dimensional player representation should be apparent in the sophistication and timeliness of the response from the adaptive controller. The two-dimensional representation (Figure 1) allows the adaptive controller to make a distinction between two states of low engagement for example, both of which require completely different kinds of adaptive response, e.g. in zone a, task demand ought to be reduced, whereas the opposite response is appropriate in zone c. A complex representation of the player provides the adaptive controller with greater freedom and specificity when selecting an appropriate response.

This approach may be extended by combining the "problem space" of the game with the representation of the player during the formulation of an adaptive response. It is anticipated that representation of the gaming context may greatly enhance the specificity of the adaptive response. An existing model of mental workload [38] may be used for explanatory purposes, which represents the problem space along two dimensions of: (1) distance from the goal, and (2) time remaining to complete the goal. The adaptive response from a physiological computer game may be formulated on the basis of the psychological state of the player (Figure 1) in combination with a representation of the player's position within the problem space of the game, e.g. a second level of two-dimensional space formed by combining distance from the game goal and time remaining to the player.

It is anticipated that early examples of physiological computer games will rely on one-dimensional representations of the player and highly constrained adaptive responses. The full potential of this technology will only be realized when designers incorporate complex representations of the players into their systems – because this complexity is a prerequisite for sophisticated, timely and "intelligent" responses from the game software.

4. THE BIOCYBERNETIC LOOP

The biocybernetic control loop [35] describes the closed loop system that receives psychophysiological data from the player, transforms that data into a computerized response, which then shapes the future psychophysiological response from the player. This is a classic control theory model [39] which may operate on a positive (approach a desirable standard) or negative (avoid an undesirable standard) basis. Control theory models have also been used to study motivation and the process of goal regulation [40], which provides a bridging metaphor between computational and psychological domains.

The biocybernetic control loop at the heart of a physiological computer game is often conceptualized as a negative control loop. Previous research into biocybernetic control demonstrated that negative control loops ensure higher levels of stability [41], which allows the user to avoid undesirable extremes of boredom (zone c in Figure 1) or distress (zone a in Figure 1). This type of biocybernetic control shapes the gaming experience by avoiding those zones associated with sudden transition and instability. However, is a desirable development from the perspective of the player? A positive control loop tends towards instability as player-software loop strives towards a higher standard of desirable performance (zone b in Figure 1). The physiological computer game may wish to incorporate both positive and negative loops into the adaptive controller. During the early stage of game play, a novice player may require 'protection' from overload zones, such as a and b in Figure 1, which is inherent within the negative control loop. However, the 'expert' player may prefer the option of a positive control loop that 'stretches' their skill capacity and directs game play towards high and inherently unstable domains of performance.

The biocybernetic adoption of control theory emphasizes systems which respond to psychophysiology to produce an adaptive response in real-time. In other words, the adaptive response represents a real-time reaction to the present. One problem of this approach is that undesirable psychological states must occur before the biocybernetic control is able to respond. Therefore, it is proposed that biocybernetic systems accumulate psychophysiological data to be used in a predictive sense, i.e. to anticipate and avoid undesirable states. This type of approach calls upon dynamic data modeling such as time series analysis. The goal of this predictive modeling is to enable the biocybernetic loop to respond to the future rather than remaining in the present

Imagine the case of the experienced player who has spent many hours with a physiological computer game. As a novice, the player was aware of how the game software seemed to interact with subjective thoughts and feelings. As the player gained more experience, the adaptive controller was forced to adjust trigger points for interventions and switch between positive and negative modes of control. In other words, the system had to 'grow' with the player to sustain the sensitivity of the biocybernetic loop. As the physiological computer game underwent this adaptation, the player notices that the system response has changed, and may adapt his or her behaviour accordingly. A sustained experience of physiological computing locks the player and the system into a co-evolutionary spiral [42], as the system adapts to the player and vice versa. Players are often highly motivated to understand the rules underlying game play in order to develop their skills, and it is imagined that most physiological computer games will eventually function as a source of biofeedback from the players' perspective. The logical outcome of speculation is that the value of physiological computer game software will be determined by its co-evolutionary potential (i.e. the capacity of the software to adapt in unpredictable ways over time), which determines both the quality and quantity of game time.

The interaction between the player and a physiological game should be considered as a closed-loop system. The behaviour of the control loop will shape the playing experience and the flexibility of the software will determine the co-evolutionary potential of the interaction.

5. CONCLUSIONS

Physiological computer games offer great scientific and economic potential. However, the development of physiological games must be based on a solid empirical and theoretical foundation. If the process of psychophysiological inference is ignored, players will be faced with gaming software that responds in an erratic or highly constrained fashion. The fidelity and range of the adaptive response is determined by complexity of the representation of the player. The adaptive potential of biocybernetic loop determines the quality of the human-computer interaction in the long-term.

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New Applications for Non-invasive Brain-Computer Interfaces and the Need for Engaging Training Environments

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ABSTRACT
Brain-computer interfaces (BCIs) are able to measure the activity of the human brain and detect and discriminate specific brain patterns. The main application of BCIs has been and is to control assistive devices and provide communication for people who have lost voluntary control of their muscle activity. Recent progress in BCI research, however, has broadened the field of possible applications. Intelligent devices that can compensate for the unreliability of and lack of information content in the BCI signal may become useful for less disabled people as well. Also, neurological rehabilitation and neurofeedback therapies are new emerging BCI applications, where the focus is not on communication and control, but primarily on facilitating effective physiological regulation and cortical reorganization of brain structures. Regardless of the application, learning to voluntarily modulate brain patterns is an integral part of endogenous BCIs. Present-day BCIs seldom provide accurate feedback within an interesting and graphically appealing training environment. Specially designed computer games that provide both a motivational environment and appropriate feedback which facilitates effective learning may be necessary to motivate the users for the long training periods necessary in BCI rehabilitation and neurofeedback therapy applications.

Categories and Subject Descriptors
J.3 [**Computer Applications**]: Life and Medical Sciences

General Terms
Design, Human Factors

Keywords
Brain-computer interface, BCI, BMI, EEG, brain signals, brain activity, neuro-feedback, neurological rehabilitation

1. INTRODUCTION
Ever since the first recordings of human brain waves were made at the 20's of the last century, it was speculated that this technology could be used to decipher thoughts or control external devices. Although deciphering thoughts in general is not possible, using brain waves to produce control signals is nowadays not science fiction anymore but has become reality due to the progress made in various scientific fields such as neuroscience, computational hardware, and signal processing in the last decades. This technology that establishes a direct interface between the human brain and a machine or computer is called a brain-computer interface (BCI).

Usually the BCI is defined as an additional output channel from the brain that does not require voluntary muscular control [10]. Sometimes this strict requirement is weakened by allowing eye movements. It is, however, important to note that these BCIs requiring gaze shifting solely utilize brain signals and not oculographic or myographic activity produced by the movement of the eyes. The absence of the requirement for any physical movement (excluding some SSVEP based systems) is the main difference between BCIs and other human-computer interaction systems. One of the most important reasons that this is significant is that the main application of current BCI systems is to provide assistive devices for people suffering from a medical condition called locked-in syndrome, and who, therefore, are not able to produce voluntary movements anymore.

A BCI cannot decipher thoughts in general. It can only detect and classify specific patterns of activity in the ongoing brain signals that are associated with specific intentions, tasks or events. These tasks or events can be either exogenous or endogenous. Correspondingly, one may differentiate between exogenous and endogenous BCIs [3]. Exogenous systems utilize the neuropsychological reaction of the brain to an external stimulus resulting in activity patterns such as visual evoked potentials or auditory evoked potentials. In contrast, endogenous systems do not require an external stimulus. The users have to learn the skill of producing specific patterns at will. This is usually done by neurofeedback training so users learn to voluntarily modulate specific brain patterns. The length of the training is naturally subject-dependent, but it also depends on the experimental strategy and the training environment. The strategy chosen determines how the BCI users learn and what they must do to produce the required activity patterns. There are basically two different strategies for endogenous systems: Operant conditioning and performance of specific mental tasks. BCI systems that rely on operant conditioning use training with feedback and positive reinforcement [3, 10]. The user must rely on the feedback to learn to produce the intended brain activity. In contrast, the mental tasks used for some BCIs are well defined and known to produce brain patterns that can be quite reliably produced and discriminated. The most common mental task is motor imagery, which is the imagination of movements of body parts such as hand or foot movement imagery. The users are supposed to perform such imagery tasks without actually performing the related movement and by doing so produce activity patterns in corresponding cortical areas. These patterns are called event-related desynchronization (ERD) and event-related synchronization (ERS) [6].

2. NEW BCI APPLICATIONS

2.1 BCI for communication and control

A BCI is primarily used to control assistive devices for people with severe motor impairments. Typical applications are spelling devices (mental typewriters), environmental control, and very limited control of computer programs such as an internet browser. More sophisticated applications are concerned with movement reconstruction of limbs by functional electrical stimulation (FES) or prosthetic devices controlled by BCIs.

Since BCI systems do not allow rapid communication, intelligent devices should offload as much work as possible and also compensate for the unreliability and low information content of the BCI output. Controlling a wheelchair or a robotic arm could be slow, frustrating, or dangerous if it solely relied on BCI output. An intelligent wheelchair which can automatically avoid collisions and dangerous situations or a robot arm that can autonomously conduct specific movement scenarios and detect and resolve safety issues are much more suitable for being controlled by an unreliable control signal like that provided by a BCI.

Moreover, BCI applications should present the user with high-level, goal oriented choices instead of burdening the user with unnecessary details of the processes needed to complete a task [9]. For instance, instead of directly maneuvering a robot arm in 3-D space to pour water from a bottle in a glass (which would be a difficult task, if it were controlled only by BCI signals), the robot arm is instructed by one specific command to perform the pouring scenario. It then automatically detects the position of the bottle and the glass, grabs the bottle, moves the bottle to the glass while avoiding any possible collisions, pours the water into the glass while automatically detecting the amount of water needed to fill the glass, and finally puts the bottle back in its original position. These steps are conducted autonomously without any further interference from the user. That is, only one BCI command has to be issued to execute many different processes.

Such intelligent semi-autonomous BCI applications are currently being developed by the Institute of Automation (IAT) at the University of Bremen and also by a few other research labs worldwide. It is important to ensure that goal–oriented BCIs do not overly constrain the user's choices. If a user can only direct a wheelchair to travel between rooms, or instruct a robot arm to pour water from a bottle, he or she would be unable to maneuver within a room, or pour a drink from a different container. This concern might be addressed by providing users with an alternate menu that does allow medium–level commands, and by frequent communication with patients and caretakers to ensure that the BCI meets each user's needs and desires.

2.2 BCI for neuro-physiological regulation and rehabiliation

Although communication and control for disabled people is the main application of BCIs, recent advances have broadened the range of possible applications to encompass computer games as well as neurological rehabilitation and neurofeedback therapy (neuro-physiological regulation). In fact, a BCI system can be considered to be the most advanced neurofeedback system available. Traditional neurofeedback systems are simple in terms of the number of acquired signal channels and employed signal processing. Modern BCIs, on the other hand, often record a large number of channels and apply very sophisticated signal processing methods in order to capture the ongoing brain activity as accurately as possible. While a BCI applied for computer games may mainly be used as an additional control or communication channel along with normal human-computer interaction methods, applications for neurological rehabilitation and neurofeedback therapies use BCIs in a slightly different way. As a device for neuro-physiological regulation and rehabilitation, a BCI is mainly concerned with the self regulation of brain patterns as well as the cortical reorganization and compensatory cerebral activation of intact brain areas. High information transfer rates and accurate control, which are important performance measures for standard BCI applications (communication and control applications), are only secondary for these new BCI applications.

The range of possible applications of neuro-physiological regulation is broad. In fact, it can be expected that where normal neurofeedback is useful, BCI based neurofeedback therapies are even more effective. Possible neurological disorders that might be effectively treated are attention deficit hyperactivity disorder (ADHD), memory disorders, epilepsy, and stroke [6].

This branch of BCI research is rather new, and thus published results are still rare. One notable exception is Birbaumer's research about epilepsy which was already done almost 20 years ago. He showed that patients with intractable epilepsy can learn to control brain patterns called slow cortical potentials by neurofeedback training which in turn helped to significantly reduce the number of seizures [1]. Interestingly, his work started out as neurofeedback experiment and lead eventually to the development of the BCI called thought-translation device – a BCI based on slow cortical potentials.

Today the situation is reversed: There are very sophisticated BCIs for communication and control which might be applied very successfully in neuro-physiological regulation applications. As already mentioned, this research has just begun. Again the Tuebingen BCI group is pioneering this research. Birbaumer and Cohen at the National Institute of Neurological Diseases and Stroke (NINDS) together with the Tuebingen group have developed a BCI system for stroke rehabilitation [1]. This system employs the dynamics of sensorimotor oscillations (ERD/ERS) to control a motorized hand orthosis. The focus is on chronic stroke with no remaining finger mobility, because this form is resistant to standard treatment and shows no spontaneous recovery. Patients suffering with stroke onset of more than one year ago and no residual hand movement are first trained by a magnetoence-phalography (MEG) based BCI. The magnetic brain activity recorded by the MEG is used because it provides better signal-to-noise ratio and spatial resolution than the EEG. After the patients are able to control the hand orthosis for hand opening and closing by having learned to voluntarily modulate their sensorimotor activity, the patients are switched to an EEG based system, which is more mobile and considerably less expensive. The first results obtained from one patient are promising, but the results from a considerably larger clinical study which is currently carried out are necessary to assess the value of this new form of stroke rehabilitation.

A similar study is also planned by our group at the University of Bremen. However, our main focus is on chronic stroke rehabilitation where residual finger/hand or arm mobility is still available. Our goal is to demonstrate that BCI based neuro-physiological regulation can be an effective addition to the standard stroke rehabilitation therapy. The experimental procedure we are going to apply is similar to the one of the Tuebingen group. The patients will be instructed to control a wearable robot (exoskeleton) which is controlled by an EEG based BCI employing ERD/ERS. Other BCI output devices, such as a virtual hand/arm and functional electrical muscle stimulation, will also be explored.

Functional neuroimaging [2] and also EEG studies [6] have shown that activation of sensorimotor areas may be induced by three tasks: 1) motor imagery, 2) observation of movement, and 3) passive training of movement. BCI rehabilitation combines all three tasks. Motor imagery controls the movement supporting device (robot or FES), which performs the actual movement. This in turn leads to the observation of this movement by the patient. In this way it is believed that the activation of brain structures can be intensified, and the neural plasticity after stroke can be enhanced.

3. BCI TRAINING ENVIRONMENTS

Successful BCI operation with endogenous BCIs typically requires users to develop and maintain the ability to deliberately modulate and control specific brain patterns such as ERD/ERS. This ability is a new skill that has to be learned [10]. Training is an integral component of most BCI applications, especially BCI rehabilitation, where not communication and control but training neuro-physiological regulation itself is the core part of the application. BCI training is usually done by feedback training, where the classifier output of the BCI is translated into a performance representation showing how successful the subject was in modulating the brain patterns. The feedback representation can have various forms; most often visual feedback is used, but auditory and tactile feedback have been suggested as well. The training protocol and the feedback representation have to be carefully designed to support learning. How this is actually done is beyond the scope of this paper, for details see [4-6]. It should be noted, however, that the training protocol should support important aspects of learning such as attention, concentration, and motivation. Motivation is of particular importance for BCI rehabilitation, because the number of training sessions required to achieve the desired reorganization of the specific brain structures may be considerably larger than for BCI control applications.

In order to increase the motivation of BCI users, computer games allowing input from a BCI have been designed [4, 7]. These games are usually arcade like games such as Pong (table tennis), which are simple and offer only a slightly more motivational environment than non-game like BCI feedback protocols. Pineda et al [8] have demonstrated that BCI training with computer games presenting rich visual feedback (3-D first-person shooter) is possible as well. A conclusive comparative study demonstrating that rich visual feedback does indeed support BCI training better than simple feedback is not available yet. It can be assumed, however, that computer games that provide an environment that is more realistic and interactive are also more motivational engaging. A first-person shooter game, however, is certainly not an ideal environment for most people. A BCI driven computer game should to be designed to be interesting and graphically appealing to engage the user, but it should, on the other hand, also apply neuro-psychological principles to provide accurate feedback information to support the learning process. Moreover, the training environment should be flexible enough to be adjustable for the individual user. This is necessary because feedback that is suitable for one user might be distracting for another user [5, 6]. The training environment should ideally be simple but not boring, provide immediate neurofeedback and clear performance measures, involve deep but effortless involvement (low mental load), and ensure that other stimuli (external or internal) does not interfere with the neurofeedback. Obviously, designing motivational BCI training environments is not an easy task. It is a research question in itself and requires expert knowledge from diverse fields such as computer game design, art, and neuro-psychology.

4. CONCLUSION

The main application of BCIs has been and still is to provide a means of communication and control for the most severely disabled people. Since a BCI is their only option for communication, this part of BCI research is extremely important. On the other hand, the population of people who are locked-in is rather small. This, together with the limited performance of first generation BCIs, might explain the rather tepid reaction to BCI research to date. However, the recent advances in the field have demonstrated the growing feasibility of BCI technology for a diverse range of applications which might be useful for less disabled people as well. As a result, the field of BCI research has attracted increased interest and attention by American and European funding agencies and major companies like Microsoft, Sony, Honda, and Hitachi. It can be expected that this increased interest in this emerging technology will lead to further rapid progress in the near future. New applications for communication and control will employ intelligent devices that can increase what users may accomplish with the limited control available with modern BCIs. Hopefully, the interest of the gaming industry in BCIs will stimulate the field and produce new engaging training environments for future clinical BCI applications like BCI stroke rehabilitation and BCI neurofeedback therapies.

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How many people can control a brain-computer interface (BCI)?

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ABSTRACT

Ninety-nine healthy people participated in a brain-computer interface (BCI) field study conducted at an exposition held in Graz, Austria. Each subject spent 20 to 30 minutes on a two-session BCI investigation. The first session consisted of 40 trials conducted without feedback. Then a subject-specific classifier was set up to provide the subject with feedback, and the second session – 40 trials in which the subject had to control a horizontal bar on a computer screen – was conducted. Subjects were instructed to imagine a right-hand movement or a foot movement after a cue stimulus depending on the direction of an arrow. Bipolar electrodes were mounted over the right-hand representation area and over the foot representation area. Classification results achieved with (i) an adaptive autoregressive (AAR) model (39 subjects) and (ii) band power estimation (60 subjects) are presented. Roughly 93% of the subjects were able to achieve classification accuracy above 60% after two sessions of training.

Keywords

Brain computer interface (BCI), electroencephalogram (EEG), motor imagery, event-related desynchronization (ERD), rehabilitation

1. INTRODUCTION

An electroencephalogram-based brain-computer interface (EEG-based BCI) creates a new communication channel between the human brain and the computer [1, 2, 3]. This channel may provide patients who suffer from severe motor impairments (e.g. late-stage Amyotrophic Lateral Sclerosis (ALS), severe cerebral palsy, head trauma and spinal injuries) with an alternative form of communication, where the interaction between brain and computer is realized in real time.

Currently, more than 100 labs are working on communication channels between the brain and the computer [4], exploring possible BCI input signals that include evoked potentials [5], slow cortical potentials (SCPs) [6] and oscillatory components [3, 7, 8]. Most studies have been conducted with small subject populations (one to 13), and data have mainly been used to develop systems that are highly optimized to the subjects participating in the studies. Subjects' ability to control a BCI vary greatly, however, and some subjects have been excluded from further investigation due to their inability to control the BCI in early training [4].

One of the most successful BCI strategies relies on the subjects' ability to learn to alter the mu and central beta components of the EEG at will. This method has resulted in accuracies of 80 to 100% for one-dimensional cursor-control tasks. Wolpaw and McFarland have shown that healthy subjects and spinal-cord-injury patients usually need several months to develop high-accuracy cursor control (i.e., > 90%) using mu and beta frequency components [2, 7]. Birbaumer's group also reports that healthy patients require a training period of several months to achieve accuracies of 65 to 80% using slow cortical potentials in a one-dimensional cursor-control task [9]. Some ALS patients have been trained for more than a year [6]. Each of these methods requires training over weeks or months.

Another approach relying on similar components, requires the computer system to "learn" to detect distinct EEG patterns related to the imagination of movement based on EEG recordings over the respective sensorimotor areas. When utilizing two bipolar recordings and either band power or adaptive autoregressive parameters, a single EEG trial classification accuracy of 80 to 97% can be achieved after approximately six to 10 20-minute sessions [3, 10, 11].

To improve the usefulness of BCI methods researchers must address issues of user-acceptance and training methodology. Reduction in the total number of electrodes necessary to operate a BCI and the length of training time should significantly improve the rate of user acceptance and the general usefulness of BCI methods. We set out to investigate these issues with a large group outside the laboratory. Of interest was how many people at a public exhibition would be able to operate an EEG-based brain-computer interface after only 20 to 30 minutes of training with only two bipolar EEG derivations. In the same large data set, we compared the performance of a BCI using adaptive autoregressive parameter estimation to band power estimation. It must be emphasized, however, that the short training period precludes the subject from finding the best mental strategy to control the BCI system. Hence, in this case, it is the system that adapts to the subjects' EEG patterns and not the other way around.

2. EXPERIMENTAL PARADIGM

A total of 99 people (mean age = 38±22.4 years) participated in the experiment. The subjects were free of medication and central nervous system abnormalities and had no prior experience with EEG-based communication systems. The experiments were performed over two months.

The BCI requires EEG trials recorded during two different types of motor imagery. Based on experiences from previous investigations with healthy volunteers, the subjects were asked to concentrate on right-hand versus both-feet movement, which was expected to yield distinct EEG patterns over the sensorimotor regions. The timing of one trial is shown in Figure 1.

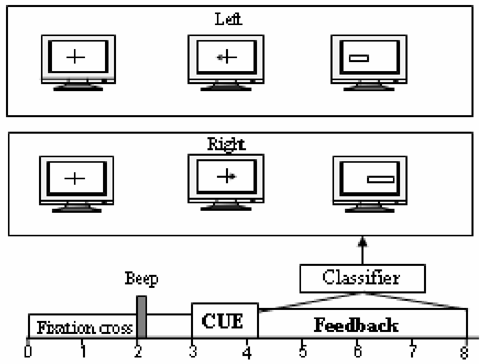

Figure 1. Timing of the experimental paradigm for right hand and feet movement imagery.

The subjects sat in a comfortable armchair 150 cm in front of a computer screen and were instructed not to move and to keep both arms and feet relaxed. The experiments started with the display of a fixation cross in the center of a screen. After two seconds, a warning stimulus was given in the form of a "beep." After three seconds, an arrow (cue stimulus) pointing to the left or right was shown for 1.25 seconds. The subjects were instructed to imagine a right-hand movement or a both-feet movement until the end of the trial, depending on the direction of the arrow. In sessions with feedback, the EEG patterns were detected and classified online throughout the session.

The arrow disappeared, between second 4.25 and second 8 and the classification result was used to give a continuously updated feedback stimulus in form of a horizontal bar that appeared in the center of the screen. If the person imagined a both-feet movement, the bar -- varying in length -- extended to the left, as shown in Figure top row. If the subject imagined a right-hand movement, the bar extended to the right, as shown in Figure bottom row (correct classification assumed). During this time period the subjects' task was to extend the bar toward the left or right edge of the screen. One trial lasted eight seconds and the time between two trials was randomized in a range of 0.5 to 2.5 seconds to avoid adaptation. All 99 subjects performed one session without feedback, and most of them (94) also performed one session with feedback. Each session consisted of 40 trials with randomized cue direction (20 arrows pointing to the left and 20 to the right). The whole experiment lasted about 20 to 30 minutes including electrode application, breaks between sessions and all settings for the experiment.

3. METHODS

The EEG was recorded with gold electrodes from two bipolar channels over the right-hand and foot representation areas (2.5cm anterior and 2.5cm posterior to electrode positions C3 and Cz of the international 10/20 electrode system). The EEG signals were amplified and band pass filtered between 0.5 and 30 Hz and sampled at 128 Hz. For the analysis of the EEG patterns, (i) an adaptive autoregressive (AAR) model (first month) and (ii) band power estimation (second month) were applied.

An adaptive autoregressive (AAR) model describes the time-varying characteristics of the EEG. With only a small number of AAR parameters (in this case six), the spectral EEG-signal properties can be monitored, and the parameters can be used to classify the EEG patterns. AAR parameters were estimated with the recursive-least-squares (RLS) algorithm [11, 12].

For band-power estimation, the average power in the alpha and beta band at each electrode position was estimated by (i) digitally band-pass filtering the data in standard frequency ranges of 10-12 Hz (alpha) and 16-20 Hz (beta), (ii) squaring each sample and (iii) averaging over several consecutive samples [3]. A total of 128 samples were averaged, yielding an estimation of the band power for a one-second interval.

In both cases linear discriminant analysis (LDA) was used for the classification of the parameters [13]. An LDA weights each input parameter according to its importance. The classification result, the sum of weighted parameters, indicates the class to which the input belongs by the sign of the result. The confidence that can be placed in the class assignment is given by the magnitude of the result.

4. PROCESSING ENVIRONMENT

The experiments were carried out using a newly developed BCI system running in real time under Windows with a two-channel EEG amplifier [11]. After amplification (g.BSamp) the signals were passed to a laptop computer for data acquisition, processing, visualization and storage. A stimulation unit (g.STIMunit) controls experimental paradigms while a real-time processing system (g.RTsys) performs the data acquisition, real-time parameter extraction and classification of the EEG.

The system provides algorithms for off-line analysis and allows integrating the same algorithms for real-time processing. A key feature is the rapid prototyping environment that enables fast and easy implementation of different processing algorithms and classification methods for optimizing the BCI performance. The system enables us to achieve reliable results in an early stage of design both for development of the BCI itself as well as for the adaptation of the system to the specific needs of subjects/patients. The environment allows the integration of user-specific hardware and processing modules and gives access to MATLAB® and SIMULINK® - Toolboxes (MathWorks, Inc., Natick, USA) to accelerate the BCI research.

The tight coupling between the online experiments and off-line analysis of the acquired data is one of the major advantages of the new BCI system, particularly for building the classifier. There were two types of recording sessions: in one type, data were collected to establish a subject-specific weight vector, and in the other type the subject-specific weight vector was used to classify the EEG online while the subject imagined the requested kind of movement.

In session one, the paradigm, described in Figure 1 but without feedback, was presented to obtain the subject-specific weight vector. The acquired data were then used off-line to (i) estimate AAR model parameters or to (ii) estimate the band power. To obtain a more general view of the classification ability, a 10 times 10 fold cross validation of a linear discriminant was also performed. This validation mixes the data set randomly and divides it into 10 equally sized disjunctive partitions. Each partition is then used once for testing, whereas the other partitions are used for training. The resulting 10 different error rates are averaged yielding an overall error. To further improve the estimate the procedure is repeated 10 times and again all error rates are averaged.

The (i) AAR- or (ii) band-power coefficients of the classification time points with the lowest classification error were used to set up the subject-specific weight vectors with the LDA for the following sessions with feedback. This off-line procedure, beginning from reading the recorded data from hard disk until the availability of the new weight vector, requires approximately two minutes. Therefore, the next session can be started after only a short break.

In session two the outputs of the algorithms were calculated and classified with the weight vector in real time to show the feedback online in form of a bar on the screen. The bar, varying in length, pointed to the left if the output of the linear classification was positive and to the right if it was negative. The size of the bar was determined by the absolute value of the classification result, which represents a measure of how reliable the side was determined.

5. RESULTS

It is interesting that in about 20% of the sessions (about 20% of subjects) the two brain states were distinguished with an accuracy of greater than 80% after only 20 to 30 minutes of training, as shown in Table 1. Further, 70% of the sessions were classified with an accuracy of 60 to 80%, and only in 6.7% was a marginal discrimination between brain states possible (see Table 1 for details).

Table 1. Percentage of sessions which were classified with a certain accuracy for recursive least squares (RLS) algorithm and band power (BP) estimation. N specifies the number of sessions. RLS+BP shows the results for both algorithms.

Classification Accuracy in %	RLS Percentage of Sessions (N=76)	BP Percentage of Sessions (N=117)	RLS+BP Percentage of Sessions (N=193)
90-100	6.6	6.0	6.2
80-89	10.5	14.5	13.0
70-79	30.3	33.3	32.1
60-69	40.8	42.7	42.0
50-59	11.8	3.5	6.7
	100	100	100

The BCI system uses two types of experimental sessions: (i) training sessions where data are collected to set up a subject-specific classifier (with or without feedback) and (ii) sessions where the classifier is used to classify a subject's EEG online while motor imagery is requested (with feedback). Table 2 divides the classification results into sessions without feedback (S1) and sessions with feedback (S2) for RLS and BP. An interesting result is that nonfeedback sessions have a higher accuracy than feedback sessions. S1 of RLS and BP have almost the same performance, but results for S2 differ. Feedback sessions with BP show better results.

Table 2. Percentage of sessions that were in a specific region of accuracy (Acc. %) dived into sessions without feedback (S1) and with feedback (S2) for recursive least squares (RLS) algorithm and band power (BP) estimation. N specifies the number of sessions.

Acc. %	RLS		BP	
	% of S1 (N=39)	% of S2 (N=37)	% of S1 (N=60)	% of S2 (N=57)
90-100	10.3	4.1	8.3	7.3
80-89	10.3	8.9	14.6	13.5
70-79	38.5	22.8	39.6	26.2
60-69	35.8	44.9	35.4	45.7
50-59	5.1	19.3	2.1	7.3
	100	100	100	100

6. CONCLUSION

The results presented show that a large population can perform a BCI operation, and that a high accuracy of above 90 % can be achieved. We know from other investigations that even subjects who have no BCI control in the first few sessions can learn the operation by neuro-/biofeedback training [6, 14, 15].

Feedback plays an essential role in BCI skill development as indicated by several investigations [6, 8, 11, 15]. Feedback can be expected to improve the classification accuracy simply by maintaining the subjects' interest and attention. However, feedback can also degrade performance due to insufficient attention to the imagination or frustration caused by incorrect feedback. Especially during their first attempts at BCI operation, subjects sometimes get overwhelmed by the new experience of controlling a technical device with their thoughts. It is possible that this explains why the nonfeedback sessions gave better results than the feedback sessions. However, the 99 subjects of this study established almost the same results for feedback and nonfeedback sessions, although it was a new experience for them and the experiments were performed in a field experiment at an exposition.

Splitting the results in RLS and BP algorithms shows that both yield to almost the same performance. BP results are slightly superior to RLS results, however. The reason is the robust design of the band-power estimation that suppresses the influence of artifacts. The advantage of using AAR parameters is that no subject-specific frequency range selection, which further improves the classification results [14], is necessary. However, the estimation of the AAR parameters is sensitive to artifacts. Hence, classification results can be biased, i.e. the horizontal feedback bar is more likely to extend in one direction than in the other direction. To overcome this problem more training data must be used to set up the classifier.

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Position Paper for BRAINPLAY ’07: Playing with Your Brain Workshop:
Progressive System Architecture for Building Emotionally Adaptive Games

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ABSTRACT
This position paper describes the work done and future research focus of Helsinki Institute for Information Technology (HIIT) in Fun of Gaming (FUGA) project related to emotionally adaptive gaming. Whereas, the workshop is specifically targeted on BCI gaming application, in our approach we utilize EEG only as one psychophysiological signal source. Besides our architecture, which differs a bit from previously seen, we concentrate also on two other aspects in our work; including the signal calibration in to the game procedure, and what kind of social aspects emerge in emotionally adaptive gaming.

Categories and Subject Descriptors:
H.5.1 [Information interfaces and presentation]: Multimedia Information Systems,

General Terms:
Algorithms, Design, Verification.

Keywords:
Experimental gaming, emotionally adaptive, psychophysiological feedback,

1.Background
Our work is based on two separate backgrounds. First of all we base our understanding of human emotions related to gaming on FUGA[1] (Fun of Gaming)-project, which is a EU Framework Program financed STREP research project on NEST (New and Emerging Science and Technology) call measuring the impossible. The goal of the project is to build measurement scales of game enjoyment. Different partners are utilizing different methods in the project, which are then cross-validated with specifically developed stimulus games. FUGA methods are fMRI, physchophysiological responses including EEG, EKG, EDA, EMG and respiration analysis, implicit association and eye-tracking. Our task in the FUGA project is to utilize the lessons learned during these various and extensive measurements, and then demonstrate the findings by developing “emotionally adaptive game”. The following picture describes the valence and arousal axis, which is used for mapping the psychophysiological signals to emotions.

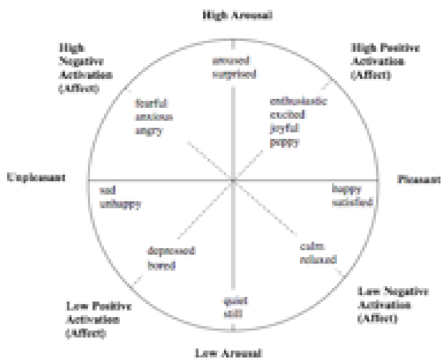

Figure 1: Emotion map with valence and arousal axis

The second background for our work is the research implemented in our research group related to experimental multi-user games. For last four years we have been developing various gaming scenarios, which utilize especially net and mobile interfaces. We[2] have been experimenting with location-based technologies, utilizing camera as a game-interface and build tools for social interaction around gaming. Hence, as an implementation and research team we combine our personal skills (programming, business analysis, games production and design) with the resources offered by the host EU project and our host institute.

In the next three chapters we are going to introduce the system architecture we are currently working with, the calibration issue, which has been one of our central focus areas, and finally the social aspects that we want to experiment with emotionally adaptive games. And the finally we are going to discuss about our

[1] http://project.hkkk.fi/fuga

[2] http://pong.hiit.fi/dcc

current status and how our work fits to general progress in the domain.

2.Progressive System Architecture for Emotionally Adaptive Games

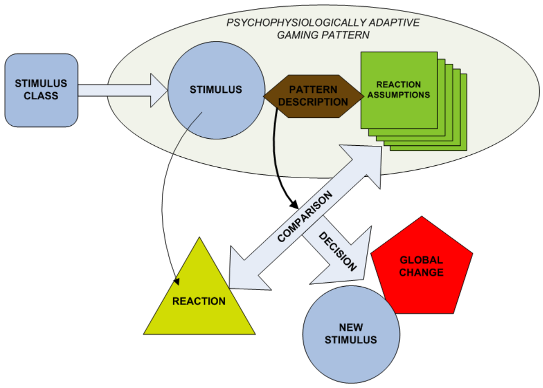

Figure 2. Progressive architecture for emotionally adaptive games

The illustration above describes the basics of our system architecture. In next few paragraphs we will elaborate further this illustration and also explain how this model applies for cases where engine learns. The idea with this architecture is to expect reaction from the user to the stimuli, instead of continuously adapting to users emotions. We are not proposing that our approach would be universally better (in comparison to architecture proposed by Becker et al (2005) for example), but it suits for progressive gaming, were the game tries to impact on users emotion. This makes it also suitable for social gaming (whereas stimuli can be combination of computer generated stimuli and other human created stimuli).

Stimulus can be practically any kind of game event or a logical collection of game events. In Tetris it could be change in the speed of the game, or appearance of one single new item. In a first-person shooter a good example of stimulus is an appearance of an enemy or a sudden explosion which open doors to a new game stage. In practice, it is important that ***stimulae***, which are considered by the engine, are clearly defined and enough powerful and meaningful in the game to produce identifiable ***reaction.*** Only game events that have defined ***stimulus***, ***pattern description*** and ***reaction assumptions*** are considered by the engine. All ***stimulae*** belong to one or many ***stimulus class. Stimulus classes*** are mainly used as a learning tool when calibrating individual patterns. All ***stimulae*** in the same ***stimulus class*** can be expected to have similar group of ***reaction assumptions***. However, each pattern has separate ***pattern description***, which defines how the game should respond to these different potential ***reaction assumptions.***

After ***stimulus*** is initiated the engine begins to analyze in real-time psychophysiological signals in order to identify and isolate a ***reaction***. Engine makes ***comparison*** between the data and the ***reaction assumptions*** and once it reaches a conclusion it initiates the ***decisions*** process. The ***decision*** considers the ***comparison*** result and ***pattern description*** and produces either/and a ***global change*** in the game world or a ***new stimulus. New stimulus*** means that loop continues again. ***Global change*** can mean anything from increasing points to a change in color schemas. The difference between ***new stimulus*** and ***global change*** is that the ***global change*** does not make the engine to expect ***reaction*** from the user.

It is important to note few details that are not shown in this illustration. First of all, the ***comparison*** result is not necessarily just a direct match to a ***reaction assumption***. It can be also a combination of ***reaction assumptions*** and a quantitative indicator for the clarity of the comparison match or for the strength of reaction. Then, in practice it is possible and very probable even that there are several parallel stimulus-reaction pairs in analyzes, in advanced cases these pairs can be also non-linearly dependent on each other. Finally, the illustration does not show how this model helps engine to calibrate based on the users psychophysiological profile. This is explained in the next chapter.

3.Calibration

In our early experiments and experienced gained from exploring others previous work (like for example Relax-to-Win[3], where user can easily impact on the calibration and affect the game result), one big problem of psychophysiological signal adaptation is the calibration of the signals. While it is important and some cases practical to utilize advanced algorithm-based solutions to tackle the calibration issues just like Mandryk and Atkins (2006) describe, we try to build also alternative approach where we use historical data from all users and previous data from this particular users to calibrate the system. Furthermore, we believe that calibration should be designed as part of the game, not an external activity, which would take place prior to gaming.

Our game engine stores psychophysiological profile of each user. Profile describes how sensitive each user is to different stimulus classes, and how user psychophysiological signals behave (e.g. base level, variation strength, peaks etc..). Profile is created in two ways: systematic calibration sessions, and continuous learning of the engine, hence the stimulus-reaction identifiers are not stable, the game engine learns more about the potential reaction and can suggest new reaction assumptions or make the decision process more accurate.

When we have an accurate calibration of the signals it is possible to identify the reaction from many different reaction assumptions, whereas with poor calibration making identification between two reaction assumptions can be hard. Hence good calibration gives more options for the game design.

4.Social Interaction in Emotionally Adaptive Games

Multiplayer gaming has been a hot topic in the industry for some years now. Massive multiplayer games like World of Warcraft are commercially very successful products and they have fostered new kinds of social interactions. Producing visual body language, which is directly derived from the phychophysiological signals is very potential domain, which some actors have been

[3] Relax-to-Win was an EDA based game that was developed in Media Lab Europe. Nowadays this work is continued by Philips http://www.design.philips.com/About/Design/article-14560.html.

experimenting with. Furthermore, many multiplayer games can utilize similar gaming patterns as single player game. However, in these cases choosing the emotional adaptation is bit harder, if the adaptation affects to the directly to individual users avatar attributes the solution are usually fairly trivial, whereas if the adaptation is affecting the general game world attributes then we must calculate somehow a aggregate profile from users emotional status. These are all interesting questions that will be considered while we are building our engine and calibration schema. However, the main interest for us is in social interaction that takes place in the physical location and face-to-face between people.

Visualizing responses is a powerful way to make people aware of their current emotional status, and also make other people aware what is the status of this particular user, and learn how he reacts to different stimuli. Utilizing this notion we have for example experimented with games where one player is gaming and others try to influence the game result by interrupting the game. In the end, there can emerge a new physical and social game genre where many gaming ideas and patters can be taken from existing board gaming culture.

5.Current Status

So far we have implemented the first prototype of a game engine, which is integrated to the psychophysiological data collection equipment called Varioport. Our first proof-of-concept game implementation was emotionally adaptive Tetris, and we are currently working with the next games.

Varioport is a relatively mobile device, so we can consider also other kinds of gaming context than just pure desktop PC. FUGA project started May 2006 and it will be running until April 2009. Other partners in the project have finalized the theoretical background work package and are starting first measurements. We can already utilize the existing knowledge of our partners in iterating the engine, but we expecting to receive initial findings about the measurements of the game enjoyment late 2007 or early 2008.

6.Discussion

It would be more accurate to talk about physophysiological adaptive game than emotionally adaptive game. Some of the signal information is not directly related to emotions, but this signal information can still appear useful in our measurements and utilized in the game. Finally, we believe that the algorithms for such a game should be learning, and there the approach introduced by Becker et al (2005), where they have used Bayesian networks for data analysis, is something we will analyze. In a long run we are expecting that common database with the stimulus and signal profiles will be very valuable asset. This is the way that new games and game patterns can be built without concentrating on massive calibration.

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A tetraplegic patient controls a wheelchair in virtual reality

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ABSTRACT

In this study it could be demonstrated that brain waves can be used by a tetraplegic to control movements of his wheelchair in virtual reality (VR). In this case study a spinal cord injured (SCI) subject was able to induce centrally localized beta oscillations in the electroencephalogram (EEG) by imagination of movements of his paralyzed feet. These oscillations were used for a self-paced (asynchronous) Brain-Computer Interface (BCI) control based on a single bipolar EEG recording. The subject was placed inside a virtual street populated with avatars and was able to move the wheelchair from one position in a virtual street to another other at free will. The task was to "go" from avatar to avatar towards the end of the street, but to stop at each avatar and talk to them. In average the participant was able to successfully perform the experiment with a performance of 90%, single runs up to 100%. After the experiment he reported that he had the sense of being in the street and going to the people, similar to a task in a real street

Keywords

Brain-Computer Interface (BCI), electroencephalogram (EEG), motor imagery, navigation, virtual reality (VR), virtual environment (VE), tetraplegic, spinal cord injury (SCI).

1. INTRODUCTION

Virtual reality (VR) provides an excellent training and testing environment for rehearsal of scenarios or events that are otherwise too dangerous or costly – or even currently impossible in physical reality. The technological progress in the last decade has made VR systems attractive for various research fields and applications ranging from aviation and military applications, simulation and training programs (where real-life training is too expensive or difficult to monitor and control), psychotherapy, and medical surgery. In particular, the area of medical rehabilitation exploits the possibilities and advances made available by VR systems, specifically the rehabilitation of motor functions [7] including stroke rehabilitation (upper and lower extremity training) [9], spatial and perceptual motor training, orthopedic rehabilitation [6], balance training and wheelchair mobility [23]. Such uses rely on the power of a VE to deliver 'presence' - that is the propensity of human participants to respond to events within them as if they are real [21]. A major finding in this field is that people with disabilities can perform motor learning in VR which can then be transferred to reality. In some cases it is even possible to generalize to other untrained tasks including improved efficiency of virtual training and learning [7,22].

Virtual Environments (VE) have already been used as a feedback media for Brain-Computer Interface (BCI) experiments. BCI technology deals with the development of a direct communication channel between the human brain and machines which does not require any motor activity [19,24]. This is possible through the real-time analysis of the electroencephalogram (EEG). Voluntary mental activity (e.g. a sequence of thoughts) modifies bioelectrical brain activity and consequently the EEG. A BCI is able to detect such changes and generate operative control signals. Particularly for people suffering from severe physical disabilities or are in a "locked-in" state a BCI offers a possible communication channel [2]. Recently, the BCI has been used to control events within a VE, either by looking on flashing objects [1,12] or by modulation of specific mental strategies (e.g. motor imagery) [15,18]. Thereby, the EEG was analyzed in predefined time intervals and the participants could decide between two states (either go right/left or forward/stop), but only whenever they were triggered by the system. Transferring the BCI from laboratory conditions towards real world applications needs the identification of brain patterns asynchronously without any timing constraints: the computer is not longer in control of timing and speed but the user.

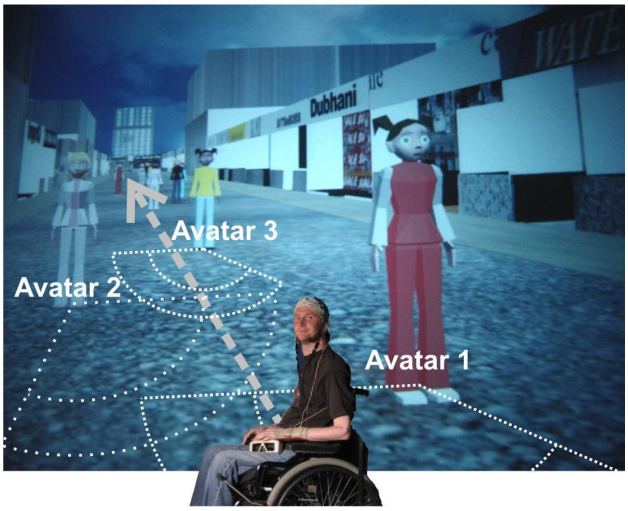

Figure 1: Picture of the virtual street populated with 15 avatars and the patient in his wheelchair. The task of the patient was to go to the end of the street (outlined with a dashed line). The avatars were standing in two rows and each avatar had its invisible communication sphere (draw as dotted line here). The patient had to stop within this sphere, not to close and not to far away from the avatar.

In this case study we want to demonstrate that is possible for a tetraplegic subject to intentionally control his wheelchair within virtual reality by self-paced motor imagery using an EEG-based BCI. The participant is placed inside a virtual street populated with avatars and the task is to "move" from avatar to avatar towards the end of a street by imagination of movements of his paralyzed feet. The reason for the VR-setup is that the visual-rich virtual street with the avatars ensured that the experiment is diversified and engaging but contains enough distraction as it would be in a real street. The defined experiment has a simple goal with clear tasks, nevertheless no instructions or cues from the BCI are necessary. A minimized setup of one bipolar EEG recording should be enough for this asynchronous control under real-world-like VR-conditions. Our second goal is to investigate the interaction between the person who is wheelchair-bound and the VE. In VR he has the freedom to move at will and to access an experience that may be long forgotten (or which he has never had).

2. METHODS

2.1 The patient

The patient enrolled in the study is a 33-year old male, who sustained a traumatic spinal cord injury (SCI) in 1998. He has a complete motor and sensory lesion below C5 and an incomplete lesion below C4. During an intensive training period of approximately 4 months he has learned to control the cue-based Graz-BCI. The training was carried out with different types of motor imageries. Finally he was able to generate centrally localized bursts of beta oscillations around 17Hz in the EEG by imagination of foot movements [16,17].

2.2 The EEG recording

Only one single EEG channel was recorded bipolarly 2.5 cm anterior and posterior to the electrode position Cz (foot representation area) of the international 10/20 system [10]. One single logarithmic band power (BP) feature was estimated from the ongoing EEG by digitally band-pass filtering the recording (Butterworth IIR filter of order 5, between 15 and 19 z), squaring, averaging (moving average) the samples over the past second and computing the logarithm from this time series (see Figure 2). A simple threshold (TH) was used to distinguish between foot movement imagination (intentional control, IC) and rest (non-control state, NC). Whenever the band power exceeded the threshold a foot MI was detected.

2.3 The Virtual Street

The tetraplegic participant was placed with his wheelchair in the middle of a multi-projection based stereo and head-tracked VR system commonly known as a "Cave" [3]. The particular VR system used was a ReaCTor (SEOS Ltd.¸ West Sussex, UK) which surrounds the user with three back-projected active stereo screens (3 walls) and a front projected screen on the floor. Left- and right-eye images are alternately displayed at 45 Hz each, and synchronized with CrystalEye™ stereo glasses. The application was implemented in DIVE [4] and the communication between the BCI and the VR occurred every 40 ms via the Virtual Reality Peripheral Network (VRPN) communication protocol [5]. The VE was a virtual street populated with 15 virtual characters (avatars), which were lined up along the street (see Figure 1, [15]).

2.4 The Experiment

The task of the participant was to go from avatar to avatar towards the end of the virtual street (65 length units) by movement imagination of his paralyzed feet. Only during the time when the TH was exceeded (IC, foot MI detected) the subject moved forward (walking speed 1.25 units/second, see Figure 2). Every time he was short before passing an avatar, he had to stop very close to it. Each avatar was surrounded by an invisible communication sphere (0.5 – 2.5 units) and the subject had to stop within this sphere (see Figure 1). The size of the sphere was adequate to the distance for a conversation in the real world and corresponded to a stopping time slot of approximately 1.6 s. The avatar started talking to the subject, if he was standing still for one second within this. After finishing a randomly chosen short statement (like: "Hi", "My name is Maggie", "It was good to meet you"…) the avatar walked away. Communication was only possible within the sphere; if the subject stopped too early or stopped too close to the avatar nothing happened. After a while, on his own free will, the subject could imagine another foot movement and started moving again towards the next avatar, till the end of the street was reached. The distance traversed depended only on the duration of the foot motor imagery, longer foot MI resulted in a larger distance than short bursts of MI. The avatars were placed on the same positions in all experiments and the participant started from the same point.

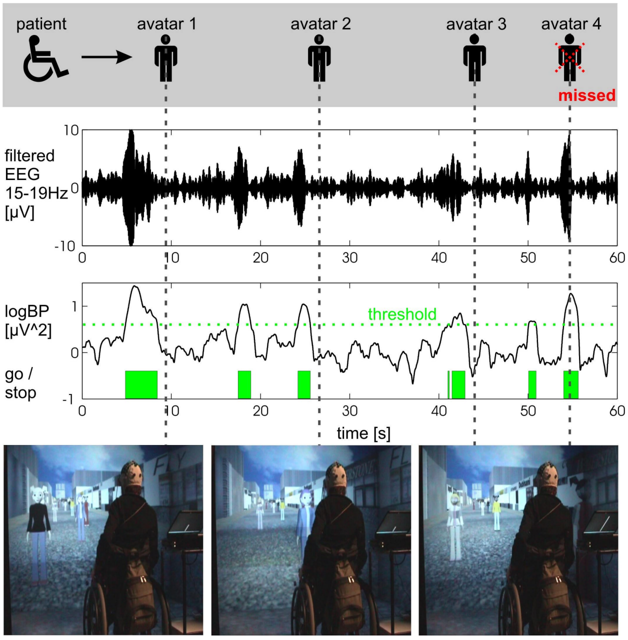

Figure 2: Location of the first 4 avatars in relation to time axes (upper panel), filtered EEG signal (15-19Hz) time course of band power with threshold and go/stop signal used for VE control (middle panels). Examples of the patient view close to the avatar (lower panel). In this run avatar 4 was missed.

3. RESULTS

3.1 Performance measures

One two days the subject performed ten runs and was able to stop at 90% of the 150 avatars and talked to them. In four runs he achieved a perfect performance of 100 %. The distance between the avatar and the patient during talking was 1.81 ± 0.49 units, whereby the communication range (allowed gap between avatar and patient) was 0.5 to 2.5 units. In 11 of the 15 missed avatars (of all runs) the subject stopped within the communication range, but the stopping time was too short (between 0.08 to 0.88 s mean ± SD = 0.47 s ± 0.27 s).

In Figure 3 spatial-temporal tracking data of the first four avatars of three runs are presented. In some runs the subject started earlier with foot MI and walked straight to the avatar, whereby in other runs stops between the avatars occurred. Detailed information of all runs is given elsewhere [13,14]. The duration of one run (each run lasted approximately 355 ± 60 s) depended only on the performance of the subject. In the Graz-BCI the EEG is classified sample-by-sample and the EEG data revealed that foot motor imagery could be detected in 18.2 ± 6.4 % of the run time.

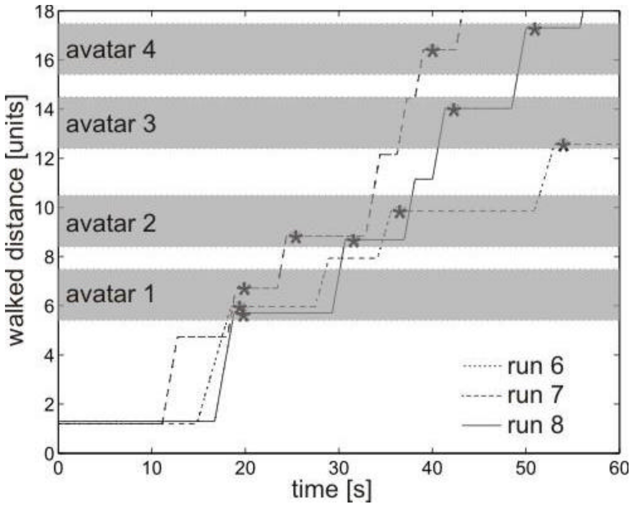

Figure 3: Spatial-temporal tracking data of the first four avatars of three runs (run 6 – run 8). The communication spheres of the avatars are indicated with gray rectangles. The time and position of the contact with the avatar is marked with a "*". In run 7 the third avatar was missed.

3.2 Interview

In an interview after the experiment the patient confirmed that "moving" occurred only during periods of foot motor imagery, but he reported that it was hard to stop precisely. Especially when the avatars were placed very laterally and it was hard to find the correct distance to the avatar.

He stated that the experience he had during the Cave experiment was different compared to the experiments he did in Graz the month before: "*It is really easier for me, to sit in the CAVE and to image a foot movement, as to sit in front of the computer monitor and watch a bar-graph going up and down*. *It's more motivating and more exciting*".

While doing the experiment the subject was able to notice what was going on around him and did not only concentrate on the motor imagery, because it is automatic for him now; so he can imagine the movement, speak at the same time, and move his shoulders at the same time. Concerning the experience with the interaction he mentioned, that "*It has never happened before, in the sense of success and in interaction. I think that I was on the street and so the people come to me, and not some much speak to me, but they come to me, so 'imagine the movement' and go to the people.*" He said that he had the feeling of being in that street and forgot that he was in the lab and people were around him. "*Of course the image on the wall didn't looked like your or me, but it still felt moving in a real street, not realistic, but real. I checked the people (avatar), we had 14 girls and 1 man.*" The subject stated that he felt surprised as one avatar walked through him; he wanted to get out of the way, to go back. Additionally the subject mentioned that there was a big difference between stereo and mono presentation (one run was performed in mono to shot some photos) and he liked stereo more.

His biggest wish is to be more independent: "*…maybe I can sit in the wheelchair, but feel independent, fell that I can move my hands, my fingers to do normal things all day … in virtual reality and also in the real world using some mechanical aid …*".

4. DISCUSSION

For the first time it could be demonstrated that a tetraplegic patient, sitting in a wheelchair, could control his movements in VE by the usage of an asynchronous (self-paced) BCI based on one single EEG recording. The mentally induced beta ERS in our patient is an unique phenomenon and probably the result of the intensive and long-lasting BCI feedback training with the goal to achieve control over brain waves.

The usage of a visually-rich VE with avatars which were talking to the subject ensured that the experiment was diverse and even distracting for the subject. The simulation power of the VE ensured that he had the sense of being in the street and going to the people; therefore the experiment was similar to a task in a real street. Nevertheless, the subject was able to succeed with 90 %. The reason for the missed avatars was the invisible communication sphere around the avatars, which was reported by the subject as the biggest disadvantage of this VE. So it was not clear for the subject where the sphere started or ended, especially when the avatars were placed further away from the middle of the street and the sphere was therefore very small. Sometimes he thought to be close enough, but maybe missed it by a hairbreadth, so an additional very small "step" (very short foot MI) was necessary to come inside the sphere. Unfortunately, it could happen that this step was too large (too long) and the sphere already passed by. Oscillatory EEG components need some time to appear and stop, so very short bursts (necessary for such small steps) are very unlikely to be produced.

For a person who is wheelchair-bound VEs are especially attractive. First, simply using a VE that includes, for example, immersion in an almost all-surrounding stereo world with the freedom to move at will, can give such persons access to experiences that may be long forgotten (or which they have never had). Another advantage here is that the simulation power of VEs can be used to create virtual prototypes of new navigation or control methods, and give potential users experience of them in a safe environment, before they are ever built physically. In other words VEs can be used for ergonomic design and evaluation. For patients who have almost no mobility at all, special interfaces can be constructed based on whatever mobility they may have, and in the last resort the use of physiological signals that can be learned to be under voluntary control could also be used as input to the interaction capability of VEs. A VE can be controlled by any signal that the patient is capable of producing voluntarily, and hence the utility of such interfacing can be relatively easily and inexpensively be tested prior to actual production. It is known that the development of skills or knowledge that are obtained while someone is in a VE can be transferred to real-world behavior and performance [11,20]. Indeed VEs have also been shown to amplify effects - that self-movements perceived in an VE that did not actually occur can help to build new neural pathways, and hence be used for rehabilitation [8].

Controlling a VE (e.g. the virtual wheelchair) is the closest possible scenario to controlling the real wheelchair in a real street, so virtual reality allows patients to perform movements in a safe environment. So a further step of transferring the BCI from laboratory conditions towards real-world applications could be performed.

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Game-like Training to Learn Single Switch Operated Neuroprosthetic Control

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ABSTRACT

Brain-Computer Interfaces (BCIs) are systems that establish a direct connection between the human brain and a computer, thus providing an additional communication channel. In patients suffering from a high spinal cord injury (SCI), BCIs can be used to control neuroprostheses such as functional electrical stimulation for grasp restoration. In this paper, we describe a training procedure that allows subjects to produce one brain pattern (elicited with motor imagery) of two different durations (e.g., 1s and 3s). For this purpose a "Jump and Run" game was implemented. Results of 5 able-bodied subjects show that it is possible to elicit one brain pattern over two different durations.

Categories and Subject Descriptors

H.5.2 [**Information Interfaces and Presentation**]: User Interfaces - *Input devices and strategies.*

General Terms

Measurement, Human Factors.

Keywords

Brain-Computer Interface (BCI), electroencephalogram (EEG), spinal cord injury (SCI), "Jump and Run" game, neuroprosthesis.

1. INTRODUCTION

Brain-Computer Interfaces (BCIs) are systems that establish a direct connection between the human brain and a computer [7], thus providing an additional communication channel. For people suffering from severe palsy e.g. amyotrophic lateral sclerosis or brain stem stroke, such a BCI is potentially their only way to communicate with the environment. In patients suffering from a high spinal cord injury (SCI), BCIs can be used to control neuroprostheses such as functional electrical stimulation for grasp restoration with surface electrodes [5] or implanted devices, e.g. the Freehand (R) system [4].

The problem in high SCI patients (lesion above cervical level C4) is that these patients loose control over their grasp function and also their elbow function. In addition to these functional deficits, the ability to control external levers or joysticks also decreases. Eye-tracking systems in the combination with a computer screen can be easily used for spelling. In the case of a prosthesis control, the user has to watch his moving arm; therefore the use of an eye-tracker is difficult in such a scenario. In those cases, a BCI seems to be a good alternative method to control such devices. A first realization of a two axis control for a prosthetic device using steady-state visual evoked potentials (SSVEP) was recently published [2].

In this work, we introduce a one-channel EEG-based controlled "Run and Jump" game to allow subjects to get pulse width modulated control. After a multi-channel screening procedure, one Laplacian channel and a maximum of three spectral components were automatically selected and used for cue-based and later for self-paced feedback training. To train the generation of one brain pattern over two different durations a "Jump and Run" game was implemented. Results of 5 able-bodied subjects are presented.

2. METHODS

2.1 Subjects

Ten subjects (mean age 28.1 years, median age 24.5 years, SD 10.3), 4 female and 6 male participated in a screening study. The subjects were without any medical or psychological diseases, had normal or corrected to normal vision and got paid for attending to the experiments. At the beginning of the study, subjects were informed about the aim of the research and gave their written consent to participate. The study was approved by the local ethic committee.

During screening 3 types of movement imaginations (left hand, right hand, and feet) had to be performed. Using Distinction Sensitive Learning Vector Quantization (DSLVQ) algorithm [6] one Laplacian channel and two best separating MI were selected. After this screening 3 subjects quitted their participation. Seven remaining took part at the cue-based training and 5 (2 female, 3 male) reached a classification accuracy of about 80% in a two class paradigm (basket game, [1]). During this training they leaned to establish two different brain patterns by imagining hand and/or feet movements. After further DSLVQ analyses one pattern was selected to be trained for a pulse width modulated brain switch.

2.2 EEG Recording

Five Ag/AgCl electrodes were placed either over C3, Cz or C4 (according the international 10-20 system), dependent on the results of the screening procedure performed prior this study. Electrodes were placed in a way that a single orthogonal derivation was possible, means one electrode was directly over e.g. C3, the remaining four were placed 2.5cm anterior, posterior, lateral and medial to this position. The reference electrode was mounted at the left mastoid; the ground electrode was mounted at the right mastoid. EEG was recorded using gBsamp (g.tec, Guger Technologies, Graz Austria) amplifier, 0.5 – 50 Hz band pass filter, Notch filter on, and a sensitivity of 100uV. The sampling rate was 250 Hz.

2.3 Data Processing

The real-time Graz-BCI system is based on Matlab and Simulink using RealTimeWindowsTarget toolbox (The Mathworks Inc, Nattick USA). Online Laplace derivation C_{LAP} was computed applying equation (1) in a sample by sample basis. Here C_{center} was e.g. C3, C_{surr} were the orthogonally surrounding electrodes.

$$C_{LAP} = C_{center} - \frac{1}{4}\sum_{i=1}^{4} C_{surr,i} \qquad (1)$$

Further, logarithmic band power features were computed by filtering, squaring and averaging (window was 1s) the EEG data, also in a sample by sample way. By applying Fisher's linear discriminant analyses (LDA), which weights were trained during the cue-based training period, a classification was realized. The LDA distance was then used to evaluate the brain pattern.

2.4 "Jump and Run" Game

For the purpose of subject training a computer game like paradigm was created in form of a "Jump and Run" game. Subjects were controlling a jumping ball and had the task to leapfrog obstacles presented in random intervals between 10s and 15s along the way. The obstacles were presented in form of small hills with the length of 1 or 3s. Each time the LDA output was exceeding a selected threshold (TH = class mean plus one time its standard deviation) the difference between the actual LDA output and the threshold was mapped to the height of the ball. Subjects were instructed to perform motor imagery only to over jump the obstacles (Fig.1) and not in the periods in-between. Six runs (each lasted 300s) with ten short and ten long obstacles each were performed. At the upper left corner of the screen, a number corresponding to the game performance was displayed. It increased, when the ball moved over the obstacles.

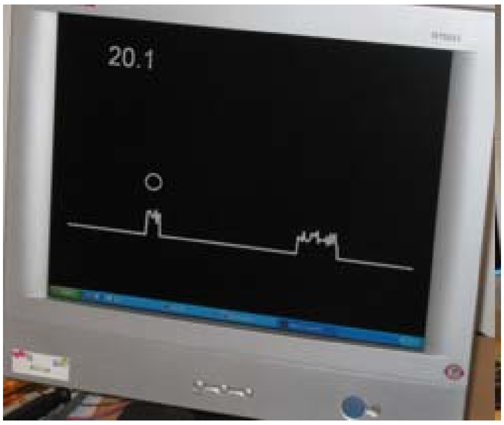

Figure 1: "Jump and Run" game. The task was to leapfrog short and long obstacles.

For further analyses EEG data, landscape and the way of the ball are stored.

2.5 Data Analyses

To receive a more detailed analyses compared to the performance measure during the game, the ball movement was analyzed. Therefore, four parameters were defined. The true positives (TPs) display whether the ball was correctly moving over the obstacles. Here the maximum number was 40s (100%). The false positives (FPs) give the time when the ball was jumping without moving over the hills (maximum 260s, 100%). Taking into account that a user will starting earlier to jump before the hill begins, and also jumps a little wider then the hills' duration, the number of TP and FP was calculated in a second way. Additionally to the duration of the hill, one second was attached at the beginning as well as at the end of the hill, receiving hill durations with 3 and 5s (see Figure 2).

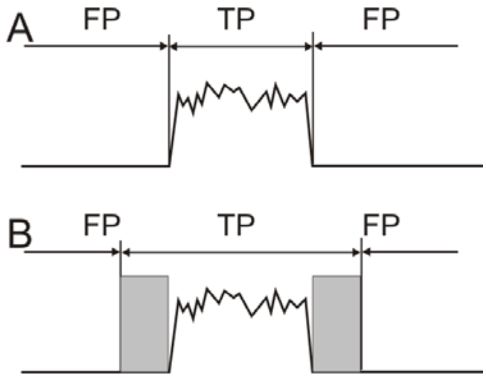

Figure 2: Definition of TP and FP. A) Using the strict criteria, TPs are defined only for the duration of the hill. B) TPs with additional time to start jumping before the hill begins and time after the hill ended. This time was defined with 1s.

3. RESULTS

Table 1 represents the number of TPs and FP for both, the strict and weak conditions during 6 runs (total 30min) of 5 subjects.

Table 1. Results of pulse-width modulated brain switch during 6 runs (total 30 min) "Jump and Run" game. Electrode position and the type of imagination is presented in column 2 and 3 (R.. right hand, L.. left hand, F.. feet). TP% and FP% during strict conditions, TPw% and FPw% during weak conditions. Numbers in () represent the maximum time for each condition.

subject	electr. pos.	type imag.	TP% (40)	FP% (260)	TPw% (80)	FPw% (220)
ak10	C3	R	55	29	51	26
al4	C4	L	94	37	92	27
al7	C3	F	51	49	52	48
al9	C3	R	56	24	54	19
al10	C3	L	95	41	90	33

After averaging the LDA output for short and long jumps mean and standard error give a qualitative overview over the system performance. Exemplarily, the averages of subject al4 are presented in Figure 3.

4. DISCUSSION

In this work we report on a game-like training procedure for establishing a pulse width modulated brain pattern to further control a neuroprosthetic device. Five subjects participated in this study and four of them learned during the training to elicit one brain pattern for two different time durations. The results given in Table 1 show that two subjects were very good. They were able to jump with a high accuracy (about 94.5%) over the hills. A further measure for the good performance is the low number of FPs (39%) between the hills. Further two subjects reached about 55.5% TPs and also only 26.5% FPs. The remaining subject was not able to achieve a good performance (TPs of 51%, FPs of 49%). This subject could jump over half the hills but was jumping also during half of the non-jumping periods.

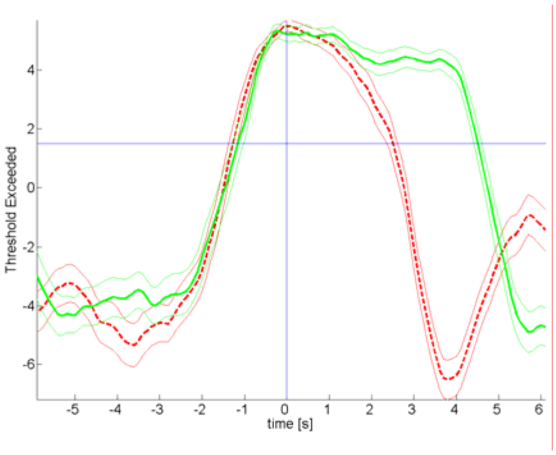

Figure 3: Averaged result of subject al4. Dashed line represents the short jumps, solid lines the long jumps. Additional, the standard error is given.

For a real self-paced control it is important to reduce the number of FPs to avoid any unwanted switching.

A novelty of this work is the use of a single Laplacian EEG channel. Applying the BCI e.g. with patients, it is important to minimize the number of EEG electrodes, while keeping a certain performance. This type of derivation ensures that the recorded EEG is focal and also removes phase-locked influences from the surrounding.

The four good subjects were then able to use their skill for the control of an artificial arm by this pulse width modulated (PWM) brain switch. The PWM switch translates the self-paced motor imagery related brain activity of two different durations into device control commands. The short pattern was used to open and close the grasp and the long pattern was used to trigger the elbow function (more details in [3]).

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EEG-based interaction with virtual worlds: A self-paced three class Brain-Computer Interface

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ABSTRACT

In this paper, we present self-paced Brain-Computer Interface (BCI) based interaction with a computer game. The BCI is able to detect three different motor imagery related brain patterns (imagination of left hand, right hand, foot or tongue movements) in the ongoing brain activity by using three bipolar electroencephalogram (EEG) channels only. To ensure that brain activity was used for control, on-line reduction and detection of eye movements and other muscle artifacts were used. The task of the game was to navigate through a virtual environment and collect scattered coins within a limited time. Results of three subjects are reported. All three subjects managed to control the BCI by using the self-paced operation mode and collect coins. Two out of the three succeeded to collect all of them.

Categories and Subject Descriptors

H.5.2 [**Information Interfaces and presentation**]: User Interfaces—*input devices and strategies, interaction styles*; I.5.4 [**Pattern recognition**]: Applications—*Signal processing*

General Terms

Experimentation, Human Factors

Keywords

Brain-Computer Interface (BCI), electroencephalogram (RRG), self-paced operation mode, Virtual Reality (VR), Classification

1. INTRODUCTION

Direct Brain-Computer Communication is possible due to on-line analysis and translation of spontaneous brain activity into device control sequences. For this purpose, however, one specific type of mental activity is necessary to modify brain signals in a predictable way. From a technical point of view, signals can be transmitted either synchronously or asynchronously. Synchronous (cue-based) information transfer requires an additional "synchronization" signal. This implies that (i) the system is sending the signal to the user asking him/her to switch to the next mental state and consequently that (ii) the timing is predetermined. In contrast, the asynchronous mode allows users to switch into the next mental state at any time, because the synchronization signal is part of the conveyed data. Self-paced systems are furthermore capable to detect whether the ongoing brain activity belongs to the class of intentionally induced chances and should therefore be translated into a control command (intentional-control) or not. Self-paced operation is the most natural way of interaction.

The main motivation for the development of such a non-muscular communication channel is to provide people suffering from severe motor disabilities (e.g. "locked-in" state) a possibility to interact with their environment. An additional hands-free communication channel, however, can be useful for many other applications as well.

Important aspects for the practical realization of such Brain-Computer Interface (BCI) systems are (i) the number of sensors used to acquire the brain activity, (ii) the available number of discriminable mental states and (iii) to detect and reduce (muscle) artifacts on-line in order to ensure that only brain activity is used for control.

In this paper, we introduce an enhanced version of the Graz-BCI, based on the detection of oscillatory changes in sensorimotor electroencephalogram (EEG) induced by motor imagery (MI) [2, 5]. For practical reasons only three bipolar EEG channels were used to discriminate between three different motor imagination tasks and determine whether the ongoing EEG is intended as a control sequence or not. On-

Table 1: Bipolar electrode channels (international 10-20 system) and motor imagery strategies for each subject. Deviation from predefined position is given as anterior (a, +3.5cm) and posterior (p, -3.5cm).

	Electrode position	Motor imagery
s1	C3a-C3p, Cza-Czp, C4a-C4p	Left, Right, Tongue
s2	C3a-C3, Cza-Czp, C4a-C4	Left, Right, Foot
s3	C3a-C3, Cza-Cz, C4a-C4	Left, Right, Foot

line muscle artifact detection and electrooculogram (EOG) reduction was implemented to prevent users to use muscle activity for control. Three able-bodied subjects were trained to gain self-paced control of the 3-class BCI and therewith to navigate through a Virtual Environment (VE) with the aim to find and collect scattered items. The adopted training procedure is described and results of the on-line experiment are presented.

2. METHODS

2.1 Subjects and data acquisition

Three healthy subjects (s1, s2 and s3; 2 male and 1 female), already familiar with BCI experiments, participated in this study. Three bipolar EEG-channels were recorded with six sintered Ag/AgCl electrodes placed over hand and foot representation areas. The exact electrode locations are summarized in Table 1. Electrode Fz served as ground. Additionally three EOG electrodes were positioned above the nasion, and below the outer canthi of the eyes, forming a rectangular triangle (for more details see [7]). The signals were analog band pass filtered between 0.5 and 100 Hz and sampled with 250 Hz.

2.2 Signal processing

Logarithmic band power (BP) features were extracted on a sample-by-sample basis from the ongoing EEG by band pass filtering, squaring and applying a moving average filter over the past second. Fisher's linear discriminant analysis (LDA) was chosen for classification.
In order to reduce EOG artifacts in the EEG, the fully automated correction method presented in [7] was used. Transient electromyographic (EMG) spike activity was detected in the ongoing EEG by means of the "inverse filtering" method [6]. We used a time-invariant autoregressive (AR) model (Order 11) to molder the EEG. The AR parameters were estimated from a 2 min segment of EEG without artifacts, recorded at the beginning of each experimental session. Each time the root-mean-square (RMS) value of the inversely filtered process exceeded the selected detection threshold (five times RMS from artifact-free EEG), a yellow warning signal was presented for 1-s on the computer screen. Subjects were instructed to relax until the warning signal disappeared.

2.3 Training procedure

In this work, we opted for a multi-level procedure to train subjects to gain self-paced control.
First, according to a cue-based paradigm (trial duration t=6.0s, cue from t=2.0s to t=3.25s, motor imagery period from t=2.0s to t=6.0s), monopolar multi-channel EEG recordings of four motor imagery tasks were collected. Subjects were instructed to perform kinesthetic [1] imagination of left hand, right hand, foot and tongue movements. In total, 144 trials per class were collected on two different days.
Secondly, by applying the Distinction Sensitive Learning Vector Quantization (DSLVQ, [3]) method to bipolarly derived channels, highly subject-specific parameters like electrode positions, reactive frequency components and motor imagery task was identified. For each subject maximal 6 band power features in the range between 8-30 Hz (bandwidth 2 Hz, step size 1 Hz) were selected from maximal 3 bipolar channels arranged symmetrically over both hemispheres. The 3 MI tasks which achieved the best overall classification accuracy were selected for feedback experiments. Since Fisher's LDA classifier is designed to solve 2-class problems, as in [4], we used three independently pairwise trained LDA functions in combination with Majority voting to discriminate between the three motor imagery tasks.
Thirdly, cue-based feedback training was performed. The task was to move a smiley-shaped feedback cursor according to a cue to the left/right/down(up) by performing left hand, right hand or foot (tongue) motor imagery respectively (see Table 1). The duration of each trial was 8s. At t=0s the smiley was positioned in the center of the screen. At t=2.0s a warning tone was presented followed by the cue at t=3.0s. Feedback was given from t=3.0s to t=7.5s. Five to seven sessions were recorded on different days with at least 4 runs with 10 trials per class each.
Fourthly, after subjects reached a classification accuracy of 75% or higher, one single LDA discriminant function was trained to detect the intentional control (IC) class, consisting of the three motor imagery tasks pooled together in the spontaneous EEG activity. To identify the most discriminative band power features DSLVQ was applied to the last cue-based feedback training dataset. For each subject band power features were extracted from each trial at two time points t and $t{+}1s$ around the best on-line classification accuracy during motor imagery (class IC). In contrast to the IC class, the non-control class (NC) was composed of features extracted from each trial at the time of cue presentation (before motor imagery) and features extracted in 1-s steps from the 2 min recording used to set up the inverse filter coefficients. Each feature-set consisted of ninety-three band power features. Form each of the three bipolar EEG channels thirty-one band power features between 6 - 36 Hz with a bandwidth of 2 Hz (1 Hz overlapping) were extracted. The 6 most reactive frequency bands were selected and used to train the LDA classifier. To increase the robustness of this LDA an additional threshold TH was introduced which had to be exceeded for a subject-specific transition time t_T. By increasing or decreasing the threshold, the classifier, at least in some extend, could be adapted to non-stationary changes of the EEG.
Fifthly, to obtain a self-paced operated BCI system, the cue-based 3-class classifier and the IC vs. NC LDA were combined. Each time the latter detected IC, the actual classification result of the former classifier was the BCI output. Otherwise the output was "0" and consequently NC.
At this stage self-paced training was performed. The feedback smiley (see point three, cue-based training) was visible and reactive all the time. Cues were presented in random intervals between t=7.0s an t=17.0s and the subject's task was to move the smiley towards the highlighted target. Subjects had t=8.0s time to hit the target. About 1.5 hours of

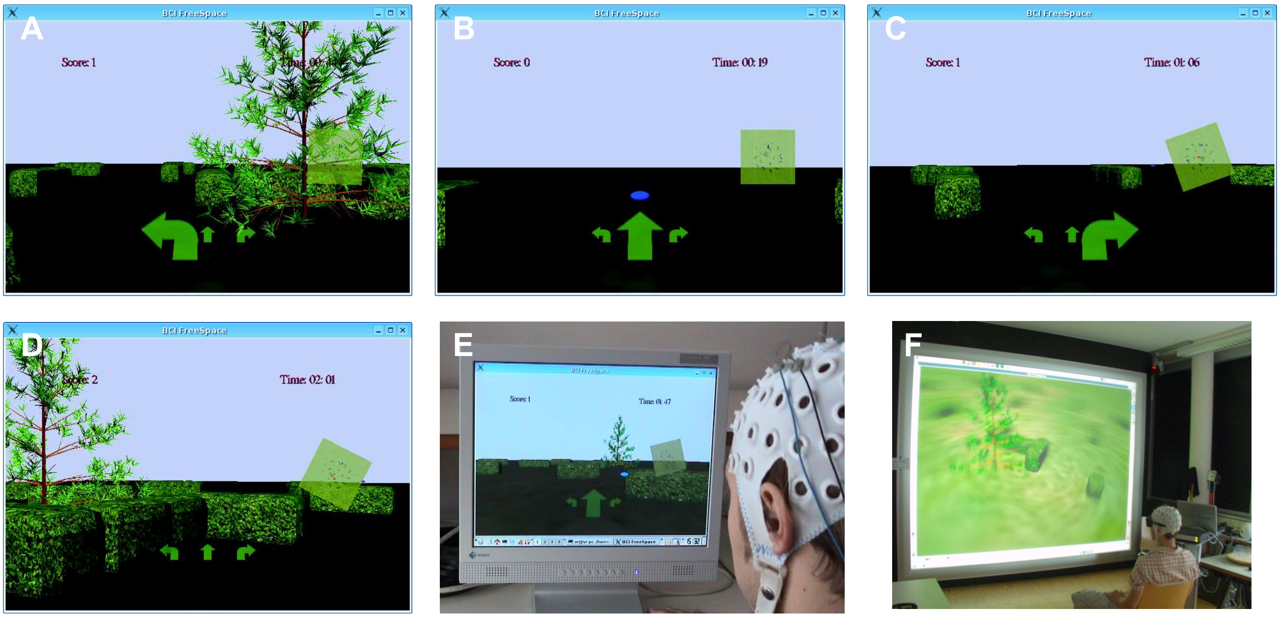

Figure 1: A-E. First person view of the freeSpace VE presented to the subjects on a standard computer screen (E.). A tree, some hedges and a coin (in B.) are visible. The big arrow represents the BCI classification result and navigation command (A. turn left, B. move forward, C. turn right, D. non-control). On the upper left side the scoreboard and on the right side the elapsed time was presented. For an easier navigation on the right side a rotating map of the freeSpace was shown. F. Stereoscopic visualization of the VE on a projection wall.

training were performed on two different days.

2.4 Virtual Environment and experimental paradigm

The 3-D modeling software Maya (Alias Wavefront, Toronto, Canada) was used to create and the Qt application framework (Trolltech, Oslo, Norway) to visualize and to animate the "freeSpace" Virtual Environment (VE). The virtual park, dimension 30x30 units, consisted of a flat meadow, several hedges and a tree. Three items (coins) were positioned on fixed locations inside the park. Subjects had the task of picking up these three coins within a three minute time limit. From a randomly selected starting point (same position for all subjects), subjects could explore (first-person view) the park in the following way: Left/right hand MI resulted in a rotation to the left/right (45°/s) whereas foot or tongue MI resulted in a forward motion (1 unit/s). Whenever NC was detected, no action was performed. With this control, each part of the park could be reached. Like in computer games, coins were automatically collected by contact; hedges and three had to be bypassed (collision detection). For orientation a map of the VE, showing the actual position was presented. In this study the VE was presented in 2-D on a conventional computer screen. Figure 1 shows screen snapshots and pictures of the VE. No instructions on how to reach the coins were given to the subjects.
Two sessions with 3 feedback training runs were recorded. Each session started with free-training lasting about 20 minutes. At the beginning of that period the subject-specific LDA threshold and transition time (maximum value 1s) were identified empirically according to the statements of the subjects and fixed for the rest of the session. At the end of each session subjects were interviewed on the subjective-experienced classification performance.

3. RESULTS

The identified bipolar EEG channels, reactive frequency components and motor imagery tasks allowed all three subjects to control the BCI after about 4 hours of feedback training with an accuracy of 80% and higher.
The found frequency components relevant for the detection of the three motor imagery tasks (intentional-control IC) in the ongoing EEG achieved off-line classification accuracies (10x10 cross-validation) of 77%, 84% and 78% for subject s1, s2 and s3, respectively.
Each subject was able to navigate through the VE and collect items. Subject s2 and s3 succeeded in collecting all three items within the 3 minutes time limit. Subject s1 was able to collect only 2 of the 3 coins. The best performance of each subject is shown in Figure 2.A. Interesting is that best results were achieved from each subject independently when starting from the same starting position. The routes, however, show that subjects had different strategies (depending also on the ability to control the BCI) and have chose different ways to collect the coins. The distribution of the BCI classification output (both feedback sessions) showed that all four classes occurred during the experiment (Figure 2.B). Interviews with the subjects confirmed that all 3 motor imagery mental states as well as NC were deliberately used for navigation. It was necessary that no navigation command was sent to the VE during non-MI related mental activity, like e.g. orientation or routing, or whenever subjects needed a break.

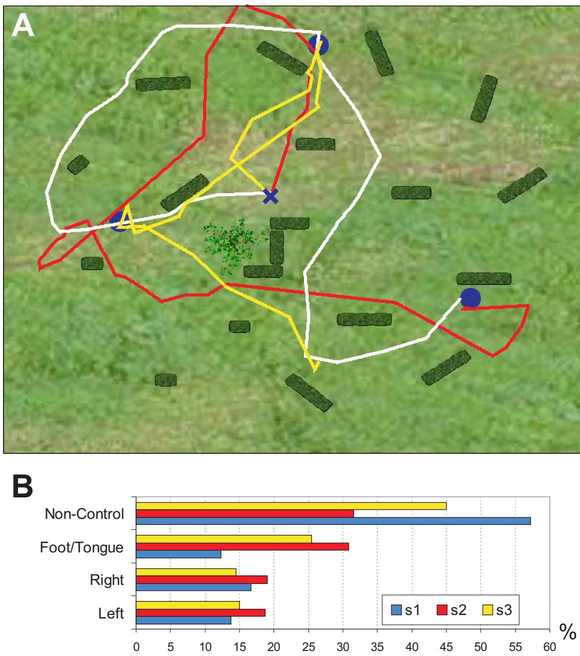

Figure 2: A. Map of the "freeSpace" virtual environment showing the best performance (route) for each subject. The rectangles indicate hedges, the circles the pickup areas (collision detection) and the "x" marks the starting point. Subject s2 (red) and s3 (white) successfully collected the 3 coins. Subject s1 (yellow) succeeded in picking up only 2 coins. B. Overall motor imagery task distribution in percentage.

4. DISCUSSION

The applied signal processing method and training procedure enabled subjects to gain self-paced control of the Graz-BCI. In order to minimize the influence of muscle artifacts on the BCI classification result, on-line EOG reduction and EMG detection was performed. The proposed algorithms are simple to implement, computationally not demanding and can easily be adapted at the beginning of each feedback session. One still open issue, however, is the long-term stability of the methods.

The key factor of the presented BCI system, however, is that only three bipolar EEG channels were used to detect three different motor imagery tasks in the ongoing brain activity. This makes the system suited for home application.

Although a very simple methodology was used to solve the "intentional control versus non-control" problem, subjects were relatively satisfied with the BCI classification performance. Further investigations and modeling of motor-imagery related changes in the EEG are necessary in order to improve the detection accuracy. Equally important for the realization of stand-alone systems is finding an automatic (or adaptive) method for the computation of the detection threshold TH and the transition time t_T. In this work an empirical approach was adopted and the parameters were changed according to the statements of the subjects.

The "freeSpace" paradigm was introduced because no instructions, except the overall aim to collect coins, had to be given to the subjects. The paradigm is motivating and entertaining. Moreover there is an endless number of ways to collect the coins, an important and decisive factor.

In this work the virtual environment was presented on a standard computer screen. However, to further increase motivation and entertainment, as depicted in Figure 1.F, also an immersive stereoscopic visualization is possible.

The results of the study show that subjects learned to navigate through the "freeSpace" VE successfully and were able to collect coins by autonomously switching between different mental states. The main advantage of the system is the reduced number of electrodes needed to realize self-paced 3-class direct Brain-Computer interaction.

5. ACKNOWLEDGMENTS

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Serious gaming requires serious interfaces

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ABSTRACT

This paper focuses on the application of intuitive game interfaces (including brain machine interfaces) to serious gaming, in particular real-time, interactive, and highly realistic environments for advanced concept development, experimentation and training.

General Terms

Performance, Design, Experimentation, Security, Human Factors.

Keywords

Serious gaming, brain machine interfaces.

1. SERIOUS GAMING

Serious games have become known as computer and video games used as persuasive or experience technology for educational purposes. These games are intended to provide an engaging, self-reinforcing context for motivating and educating the players, most often at secondary school level. However, serious gaming is rapidly finding its way in the fields of marketing and in-game advertisement (Coca-Cola Zero in X-Box games), recruitment (America's Army), health care (Pulse!!), post-traumatic stress disorder (virtual reality treatment of Iraq War veterans), public policy making (Cyber-Budget), humanitarian issues (Food Force), climate changes (Climate Challenge), cultural awareness (Real Lives), crisis management for first responders (Dubai Police), business processes (Eduteam, GY$T) and military operations (DARWARS Ambush!, Dangerous Waters).

Important drivers for the expansion of game technology in the field of military operations and crisis management are that the current generation game technology enables on-line multi-player participation and distributed communication, offers highly realistic visuals and real time complex object and avatar behavior and that games can be run on relatively low-end platforms. Obvious advantages of applying game technology versus real world scenarios are: safely experiencing large scale and high risk scenarios (reducing cost and physical and environmental damage), full controllability of scenarios (high relevant incident density), distributed multi-player participation (flexibility of location), autonomous intelligently acting characters (availability of virtual counter parts and instructors), behavior monitoring and feedback (enhanced learning), etc. Furthermore, web-based game technology can be used to exploit the brain power of large communities by challenging them to test concepts.

2. TNO AND SERIOUS GAMING

TNO is a large R&T organization (over 5000 fte) with the mission to apply scientific knowledge for strengthening the innovative power of industry and government. It has a strong position in the field of ICT and Modeling & Simulation, including the development and application of game technology. For example, for the entertainment sector, TNO has developed the mobile entertainment game Triangler. In Triangler teams try to enclose each other within 150 m geometric equilateral triangles using mobile devices. Triangler recently received the Grand Prix and the Most Innovative Game Award of the prestigious International Mobile Gaming Awards (IMGA). Triangler addresses strategic, tactical and operational co-ordination skills which may make the game useful for large-scale training programs, for example for first responders.

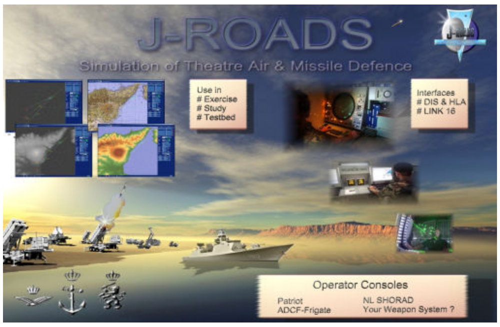

Figure 1. J-ROADS: a scenario and analysis game for joint theater air defense studies.

In the field of defence, security and safety, TNO is actively developing specific serious game technology to meet the demands of its most important stakeholders, that is the Ministry of Defence, the Ministry of the Interior and first responder organizations, including intelligence organizations, the police force, firefighters, and medical emergency organizations. Amongst its track record of developing and applying serious games are:

- The real time multiplayer networked war game Kibowi for training staff officers battalion, brigade and division level in so-called Train As You Fight exercises. (http://www.kibowi.com/)
- J-ROADS, a scenario and analysis game for joint theater air defense studies capable of simulating ground and sea-based air defense systems and combining virtual and real entities (see Fig. 1). J-ROADS was used to demonstrate the interoperability of air defence personnel (joint/combined) of participating nations (USA, NL, GR, GER) in a large-scale exercise for extended air defence, called JPOW in 2006 (Taylor et al., 2006). (http://www.tno.nl/downloads%5Cdef_alg_JROADS.pdf)
- Mission simulation in urban area's based on the commercial game Unreal Tournament. Using position tracking of team members in virtual urban areas we tested the operational benefits of a wearable display called Soldier Digital Assistant (SDA).
- The Networked Enabled Capability field lab, a serious crisis management game for studying the civil-military cooperation at large-scale disaster situations. The game was developed in cooperation with the MoD and Police.
- Interactive Disaster Management Trainer (IDM): TNO developed the IDM-trainer for training individual and team behavior of multidisciplinary crisis management teams. (http://www.nifv.nl/web/show/id=66285)

The above projects rely heavily on game technology for developing new doctrines and capabilities at strategic, tactical and operational levels. This is known as Concept Development and Experimentation (CD&E). CD&E is an approach for designing complex systems characterized by many and culturally diverse stakeholders, a wide variety of technologies and disciplines involved, and various external factors and political dimensions. For these situations traditional knowledge-based engineering approaches no longer suffice. Only highly interactive and attractive game technology can facilitate the creative processes required. For this purpose TNO has developed an Advanced Concept Development & Experimentation facility called ACE, consisting of networked group facility rooms, mission simulation centers, next generation command & control centers and high-end vehicle and flight simulators. ACE allows people to actually experience concepts, see causal relations, think laterally and combine implicit knowledge to arrive at innovative and effective solutions. The concept development process is an iterative process with increasing fidelity as the concept develops into a fielded capability.

ACE can support different phases of CD&E:

- Concept *development* gives broad and sometimes ill-defined ideas a chance to be examined by groups of experts in a logical process. These ideas can come from different sources: e.g. the Ministry of Defence, industry, servicemen, organizations or partners. It is important to facilitate creativity and lateral thinking, to stimulate multidisciplinary group processes and bring solutions from one domain to another. In practice this process is non-time critical and is usually supported by non-validated public information sources and low-tech visualization platforms. The aim of the game technology in this phase is to create awareness and team spirit and to confront.
- Concept *testing and experimentation*: Promising concepts must be tested for their feasibility, specific hypotheses must be tested and demonstration experiments must provide insight into the realization of the concept. At this point decisions may have substantial impact on doctrine, organization, training, and material for future operations. Therefore, it is crucial to base such decisions on validated models and realistic scenarios in which time critical aspects and interdependencies can be tested. Usually high-end game technology with realistic interactive real-time scenarios is used to guarantee that results from the virtual world can be transferred to the real world.

3. GRAND CHALLENGES IN SERIOUS GAMING

Given the tremendous potential of serious gaming substantial research efforts are justified, with a focus on two research challenges:

1. Validated content. Serious games are intended to confront people with the effectiveness of environmental changes, security measures, training methods, policy rules, or governance structures in various scenarios and to support decision making. Particular choices can have high socio-economic and/or financial impact and should therefore be based on validated content. In order to let people experience causal relations in concept testing it is of crucial importance to develop, validate and combine models that define the behavior of the action-response patterns of the simulated world. Some examples of various categories are models of the physical, cognitive and group behavior of virtual characters, public governance models, dispersion models of chemical and biological warfare agents, models of the explosion sensitivity of built constructions, and models of interdependencies within the critical vital infrastructure, etc. Obviously these models can only represent the explicit knowledge available.

2. Intuitive interfaces. Serious games are meant to facilitate creative and educational processes and so they should optimally exploit the cognitive resources of all participants. With current interface technology, however, participants often spend a substantial part of their cognitive resources on understanding and controlling interfaces for communicating with their colleagues (e.g. channel switching in multi-party conferencing, "encoding emotions" using 2D emotion disks), on navigating through the environment and manipulating objects (e.g. 6 DOF mouse control) and on telling the system to change levels and scenarios (e.g. choosing menus). Such a waste of cognitive resources can be eliminated drastically by developing game technology that automatically "reads participants" based on sensor technology (location, movements, non-verbal behavior, emotions) and brain signals (intentions and mental states).

To meet both challenges, TNO has founded the Center for Advanced Gaming & Simulation (AGS) in conjunction with the Utrecht University and the Utrecht School of Arts (www.gameresearch.nl). This center has recently won a Euro 10M government funded program GATE (GAme research for Training and Entertainment) which will be carried out by a consortium of

AGS-partners, Delft University of Technology, University of Twente and Thales industry. GATE focuses on the following research questions:

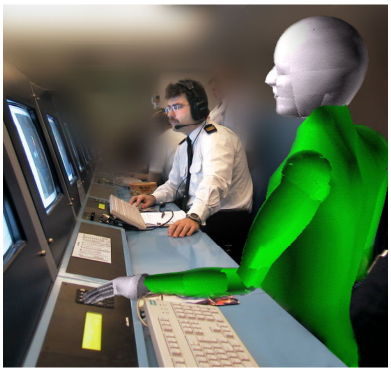

Figure 2. Artist's impression of a Virtual instructor.

- automatic adaptive scenario generation (intelligent behavior of objects requires less scripting),
- automatic world generation (combining geometric databases and public sources),
- intelligent avatar behavior (kinematics, cognitive behavior, multimodal realism), e.g. virtual instructors (see Fig. 2)
- intuitive interface technology (including multimodal system output and brain machine interfaces).

Further, GATE includes transfer projects with small and medium size enterprise (SMEs) in the game industry sector (e.g. Guerilla Games, Cyclomedia and Noldus) and pilot projects in the field of education, health care and crisis management (in cooperation with Thales). For the research program on intuitive interface technology, TNO is the leading partner. TNO's laboratory in Soesterberg (TNO Human Factors) employs over 200 researchers in the field of human factors research, including long term research programs in the field of 3D visual, 3D auditory, tactile and multimodal interfaces, mental workload models and physiological measurements.

4. BRAIN MACHINE INTERFACES

Brain-machine interface (BMI) technology in the field of gaming is about to revolutionize gaming and simulation. Let us briefly discuss two directions of brain machine interface research and their application potential: machine-to-brain interfaces and brain-to-machine interfaces.

Examples of machine-to-brain interfaces are (invasive) connections of microphones to the auditory nerve (nowadays 70,000 people have cochlear implants) and cameras to the optic nerve (still embryonic). Further, deep brain stimulation (DBS) is a USA FDA-approved method for treating tremor based on a multi-electrode lead implanted into the thalamus which relays and modulates sensory signals to and from the cortex. Non-invasive machine-to-brain interfaces are still experimental, for example Transcranial Magnetic Stimulation (TMS) which stimulates superficial brain neurons with strong magnetic pulses. TMS is now an experimental therapy for various disorders but may in the near future be used to enhance cognitive functions, memory and learning ability (Jensen, 2005). In all cases machine-to-brain interfaces have serious ethical complications because they may influence personality, free will and mental abilities. Therefore we will concentrate on brain-to-machine interfaces rather than on machine-to-brain interfaces. Moreover, progress in this field has a high priority in the light of developing intuitive interfaces (see Research Challenge 2).

Until recently brain-to-machine interfaces were applied mostly in the therapeutic domain in non-time critical situations due to the generally low signal-to-noise ratio requiring multiple trials. However, emerging technology based on single trial EEG measurements (Millian et al., 2004) enables the application of BMIs in real time control processes such as navigation and communication in game environments. Progress in brain-to-machine interfaces (BMI) is critically dependent on two aspects: measuring brain activity and interpreting brain activity.

- Measuring brain activity can be done invasively (subdurally, or under the skill, for example by placing electrodes in the parietal cortex) and non-invasive (or outside the skull). Invasive measurements have practical and medical problems but are less noisy and therefore preferred over non-invasive measurements, for example in neuro surgery). Non-invasive measurements are usually based on Electroencephalography (EEG). EEG is the neurophysiologic measurement of the electrical activity of the brain by recording from electrodes placed on the scalp measuring postsynaptic (electrical) potentials from a large number of neurons. Alternatively peripheral nerve signals can be used such as the motor commands to the muscles, for example in exoskeleton applications.
- The greatest challenge for BMI performance is the interpretation of brain signals, that is, the decoding of brain activity in terms of distinguishable intended movements (e.g. reach locations) or mental state (e.g. attention, frustration). Most prominent methods are Linear Discriminant Analysis and Support Vector Machines. An example of a meaningful brain signal is the so called Error Related Negativity (ERN) occurring when we push wrong buttons in a speed reaction time task without being able to correct (Parra et al., 2003). User profiles and intentional models may feed Bayesian frameworks to optimize the interpretation of sensor and brain signals.

For serious game applications we concentrate on non-invasive brain-machine interfaces and are particularly interested in finding neural correlates for:

- Navigational intentions: can we extract if the user wants to proceed to the left or right, or rotate? (see also Friedman et al., 2007)
- Mental commands: How well can we extract learned mental commands or mental rhythms?

- Facial expressions: how can we make a virtual character in a game mimic a player's facial expression based on brain signals? (young BMI companies like Emotive and NeuroSky are producing first products).
- Mental state: is the user ready to receive information (related mental load), what is his level of frustration?
- Spatial orientation: Is the user spatially disoriented (the neural correlate of being lost, see Fig. 3)?
- Visual attention: To what objects is visual attention oriented? Have people found their targets?
- Error behavior: Can we determine whether a user knows he made a mistake?

To be more specific, the focus of our study is on the interpretation of event related potentials in game environments. For example, the P300 potential (positive potential with a latency of 300 ms) seems to reflect task relevance, and may be informative in situations where subjects have to actively search for infrequent targets. The N400 potential (negative potential with a latency of 400 ms) seems to be associated with semantic relations and access to explicit memory and may be of interest for detecting error behavior.

Related to this we are interested in collecting data on the interaction between multimodal stimulus presentations and event related potentials. Our objective is to find out to what extent multimodal stimulus representations can reduce the signal-to-noise ratios of event related potentials.

In order to find the answers to these questions and to utilize this knowledge in the domain of serious gaming for security and safety solutions we are very much aware that we have to make use of a transfer of technology and experience in the therapeutic domain (mental state recording) to the domain of gaming and simulation. Finally, we have to connect game researchers, neuron-imaging and neuron-cognition experts, entertainment industries, human factors specialists, (military) domain experts and system engineers for their role as smart integrators.

TNO is a partner in the BrainGain consortium consisting of the Radboud University in Nijmegen, the universities of Maastricht and Twente, and several industrial partners and patient organizations. This consortium has recently won a Euro 10M grant from the Ministry of Economic Affairs (see http://www.nici.ru.nl/braingain/index.htm). Their mission is to apply recent developments in the area of analyzing and influencing brain activity to the improvement of quality of life and performance for both patients and healthy users.

Within this consortium the Human Media Interaction group of the University of Twente leads the theme on BMIs for Healthy Users. TNO Defence, Security and Safety participates substantially in this theme. It has an extended history on using physiological measures (including EEG) in relation to human performance, sensory processing and perception, and adaptive user interfaces. In 2006, it started to concentrate its EEG research in a BMI lab in Soesterberg to optimally facilitate BMI related research with human subjects. It has a second, complementary laboratory in Rijswijk that is involved in BMI related research on non-human species which has a focus on BMI research for patients.

Figure 3. TNO BMI-lab: EEG-measurements for advanced man-machine interfaces

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