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Review of Brain-Computer Interfaces based on the P300 evoked potential

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Abstract: Brain-computer interfaces (BCIs) can be used as a communication and control system for people with severe motor disorders. A BCI is a communication system in which intensions can be sent to the external world without the use of normal peripheral nerves or muscles. Several electrophysiological characteristics can be extracted from the human EEG to control the BCI system. The P300 evoked potential is used in many BCI systems because it is a typical and naive response to a desired choice. An important advantage of a P300-based BCI is that it requires no user's training. However, the P300 can be influenced by different human factors such as attention, motivation and fatigue. The extent to which such factors affect BCI operation remain to be explored. The same applies to BCI operation in real life situations. Important applications are word-spelling devices (e.g. P300 speller) wheelchair control using a P300-based BCI.

Present day BCIs still have shortcomings (e.g. low transfer rates) that prevent their widespread deployment. Future research should not only focus on improving transfer rates and accuracy, but also on using bit rates more efficiently. The use of BCIs in home environment by both people with severe motor disorders and healthy people need to be explored before BCIs can be introduced to the population.

Conclusions:

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Contents

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1. Introduction

Brain-computer interfaces (BCIs) can serve as communication and control systems for people with severe motor disorders such as amyotrophic lateral sclerosis (ALS) (Wolpaw et al., 2002). Communication with computers and controlling electrical devices based on brain activity sounds futuristic, but during the last two decades significant progress has been achieved in BCI research. It also opened a new approach for the development of applications for the consumer market. Different applications also require different BCI systems. BCI systems can use a variety of different electrophysiological signals.
This review summarizes the current state of research in P300-based BCI systems focusing on its applications for both patient and consumer market. First, BCI systems in general are discussed then P300-based BCI systems and applications. Finally, we tentatively outline the future of P300-basedBCIs.

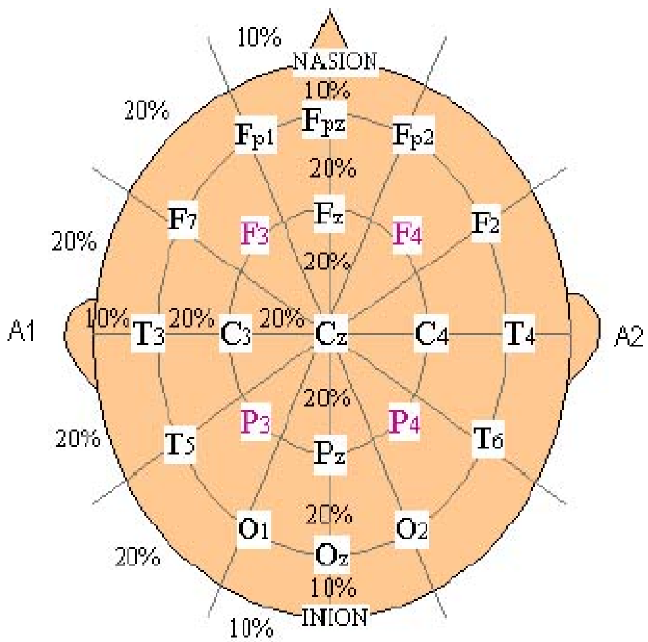
1.1. Definition of a BCI system

A BCI is a communication system in which intensions can be sent to the external world without the use of normal peripheral nerves or muscles (Wolpaw et al., 2002). It is a technological interface between a computer and the user's brain. The last decade it has been speculated that brain activity contains important information about person's feelings, thoughts and intensions (for a review see Knyazev, 2007). Detection of emotions, arousal or attention could be very useful, but such applications are not necessarily BCIs. Incorporating emotion detection can also be beneficial for enhancing BCI operation (Allison et al., 2007).
A BCI system sends a message or command via brain activity to an external device which executes an action. Therefore it concerns not only detection, but also translation and interpretation of the brain activity into commands. Furthermore, feedback and the adaptation of brain activity based on that feedback is important for successful BCI operation (Wolpaw et al., 2002).
Brain activity can be measured using electroencephalography (EEG). By extracting specific components from human brain activity and linking this brain activity to specifically developed algorithms, an interface between a computer and the users' brain is created. The user's brain is now coupled to a computer or external device, which allow communication or controlling devices directly, without implementing any motor action. In addition to EEG, brain activity can also be monitored using other methods such as magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS) (Wolpaw et al., 2002). In contrast to EEG and related methods, MEG, PET, fMRI and fNIRS are technically demanding and expensive. Furthermore, only EEG has a relatively high time resolution which is vital for rapid communication. Therefore EEG is the most practical and suitable method for BCI' development.

1.2. EEG as input for the BCI system

A BCI needs input from the user's brain to convert the brain signals to external operations. Therefore brain signals have to be measured.

EEG signals are recorded with small silver/silver chloride electrodes placed on the scalp at standarized positions (i.e. international 10/20 system), often fixated by a cap (**Fig. 1**) (Teplan, 2002). Conductive gel is used to lower the impedance between the electrodes and the skin on the scalp. When a neuron is activated, a local current flow is produced. Small potential differences (0-100 µV) between electrodes placed at different positions on the scalp are measured (Hoffmann, dissertation). EEG is deduced from apical dendrites of cortical pyramidal cells (Teplan, 2002), thus connectivity with deeper structures can only be studied indirectly. Only a large population of active neurons can generate electrical activity that is recordable with EEG measured over the scalp (Teplan, 2002).



a)

b)

Figure 1: a) Electrode placement following the international 10/20 system. The 10 and 20 refer to the fact that adjacent electrodes are either 10% or 20% of the total left-right or front-back distance of the skull (Teplan, 2002). b) EEG cap to fixate the electrode sites (www.biosemi.com).

The electrodes record brain activity over the scalp which is converted into electrical signals. A sequence of processing steps translates this signal into commands. EEG-based communication requires detailed knowledge of the signals that comprise the EEG. To achieve the goals of feature extraction, characteristics of the signals in three domains can be used (i.e. spatial-, frequency-, and time-domain) (Hoffmann 2007, dissertation). Often data of more than one electrode is available.

1.2.1 Spatial domain

Even if EEG has a low spatial resolution, global discrimination between brain regions can be achieved. The electrodes over brain regions that are associated with the particular cognitive task usually show stronger changes in band power or P300 amplitudes (Hoffmann 2007, dissertation). Because EEG is deduced from apical dendrites of cortical

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pyramidal cells, activity deeper structures can only be studied indirectly. The activity travels through numerous layers of different tissues which may damp and influence the electrical signal (Allison, dissertation). This makes it difficult to locate the exact source of the oscillation. Nevertheless, global discrimination between brain regions (e.g. frontal, central, temporal, posterior and occipital) and between the two hemispheres can be achieved.

1.2.2 Frequency domain

Frequency domain features are related to changes in oscillatory activity (Hoffmann 2007, dissertation). The human EEG can be roughly categorized into 4 frequency bands, namely: delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz) and beta (13-30 Hz) oscillations. Oscillation in particular frequency bands could play a key role in the emergence of percepts, memories, emotions, thoughts, and actions (Cantero and Atienza, 2005; Nunez, 2000; Varela et al., 2001). The (changes in) power of specific bandwidths can be used as control signals for BCI systems.

Delta
The source of delta oscillations is not certain. They are found in cortical regions such as the medial frontal cortex and in subcortical regions such as the nucleus accumbens (NAcc), (Leung and Yim, 1993), the ventral pallidum (Lavin and Grace, 1996), and dopaminergic neurons in the ventral tegmental area (VTA), (Grace, 1995). Noteworthy, these structures (medial PFC, NAcc and the VTA) appear to play an important role in the brain reward system (Gray, 1999).

Theta
Theta activity can be generated in the anterior cingulate cortex (Hayashi et al., 1986; Lang et al., 1987; Mizuki et al., 1980). Recent findings showed that frontal theta is phase-locked to hippocampal theta (Siapas et al., 2005; Jensen, 2005), indicating strong connections between these two structures, although this can only be studied indirectly. Furthermore, there is also evidence that the amygdala produces theta activity during (emotional) arousal (Pare, 2003; Pare and Collins, 2000). Animal researchers have provided evidence for interrelations of theta activity with learning, attention and behavioural inhibition (Sainsbury, 1998). Additionally, it has been suggested that theta activity declines when a task becomes familiar (Knyazev, 2007).

Alpha
Alpha power has come to be considered as a reverse measure of activation. Alpha oscillation is associated with inhibitory behavioural processes and these processes contribute to a variety of cognitive operations such as attention and memory (e.g. Babiloni et al., 2004; Klimesch, 1999). Furthermore, involvement of the lower alpha band in the attention processes is confirmed in recent EEG (e.g. Babiloni et al., 2004; Dockree et al., 2004; Sauseng et al., 2005) and fMRI (Laufs et al., 2003) studies.

Beta
Beta oscillations are linked to the behaviour of inhibitory interneurons in the central nervous system (Whittington et al., 2000). Beta activity has been associated with attention, perception and more generally with cognitive control processes (Schutter and van

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Honk 2005). It seems that alpha along with beta oscillations play a special part in the maintenance of attention to environmental stimuli (Knyazev, 2007).

1.2.3 Time domain

Time domain features are related to changes in amplitude of electrophysiological signals, occurring time-locked to the presentation of stimuli (Hoffmann 2007, dissertation). Phase-locked EEG activities include all kind of ERPs (e.g. P300 evoked potential), whereas non-phase locked EEG activities include event/stimulus-locked oscillations such as induced alpha or beta activities (Kalcher and Pfurtscheller, 1995).
Combining features from several domains can increase classification accuracy and operation speed (McDonald et al., 2000; Teder-Salejarvi et al., 2002). Simultaneously presenting audio (i.e. noise bursts) and visual (i.e. flashes) stimuli results in faster responses and higher accuracies in contrast to unimodal target stimuli (Teder-Salejarvi et al., 2002).
Thus, BCI systems can be controlled using various EEG components. For the major EEG rhythms and most evoked potentials their specific relationship with brain functions are known (Wolpaw et al., 2002). To develop a successful BCI system, understanding of the origin of EEG rhythms and evoked potentials is necessary. Specific characteristics of the human EEG must be controlled and correctly interpreted for successful BCI operation. Therefore several important steps have to be made, including feature extraction and interpretation of the brain activity of the user by translation algorithms.

1.3. Functional BCI model

A BCI system needs several features to extract, translate and operate correctly (i.e. the action should match the users intent, preferably as fast and accurate as possible). It has input, output, components that translate input into output, and a protocol that determines the onset, offset and timing of operation (Wolpaw et al, 2002).
In the BCI discussed here, the input is EEG recorded from the scalp. The digitized signal is sent to the signal processing phase (**Fig. 2**) which extracts relevant features through applying, spatial filtering and spectral analyses (Wolpaw et al., 2002). The feature extraction is of great importance to encode the user's intents or commands. To extract the messages from the signal, BCIs can use signal features that are in the time domain (e.g. evoked potential amplitudes, like the P300 evoked potential), the frequency domain (e.g. alpha or beta rhythms), the spatial domain or a combination (Donchin et al., 2000; Pfurtscheller et al., 2000; Schalk et al., 2000). By filtering the raw EEG data, different frequencies (e.g. delta, theta, alpha or beta) can be selected. Lowpass filters remove higher frequencies whereas highpass filters remove lower frequencies. A bandpass filter is a combination between those two which allow a band of frequencies to pass and a notch filter removes all frequencies in a certain range (Allison, dissertation). The power spectrum from the raw EEG can be derived using a Fourier transformation (Teplan, 2002). This allows direct comparison of the different spectral densities.
After the feature extraction, the signal is translated into device commands using algorithms which change independent variables (i.e. signal features) into dependent variables (i.e. device commands) (Wolpaw et al., 2002). These device commands convey the user's intent.

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The ability of the translation algorithm to adjust online (in real-time use) for spontaneous adaptations and for other changes in the signal features is crucial to maintain optimal speed and accuracy (Daly and Wolpaw, 2008). Otherwise, the translation algorithm will not adapt to variations of the subject's mental state.
The output device can be a computer, a wheelchair or a neuroprosthetic limb. For most current BCIs a computer is used as output device, for example word-processing programs (P300 speller). This output allows the user to communicate words without the use of motor actions. This output is at the same time the feedback that the brain uses to maintain and improve the accuracy and speed of communication (Wolpaw et al., 2002). The user must control the signal features, and the BCI must correctly interpret that control into device commands (Wolpaw et al., 2002). For successful use of the BCI a certain protocol must be followed. The protocol describes how the BCI should be turned on and off, and determines the timing of the operation (Wolpaw et al., 2002). However, most operating protocols used in BCI research are not completely suitable for the traditionally aimed target group (i.e. people with severe neuromuscular disabilities). For example, switching the system on and off is often controlled by the investigator (Wolpaw et al. 2002). Training protocols must be adapted to the subject to be effective (Ron-Angevin and Diaz-Estrella, 2008). In addition, in real life the user must choose the message instead of performing a standard task used in laboratories. Such differences can complicate the transition from laboratories to real home environment (Wolpaw et al., 2002).

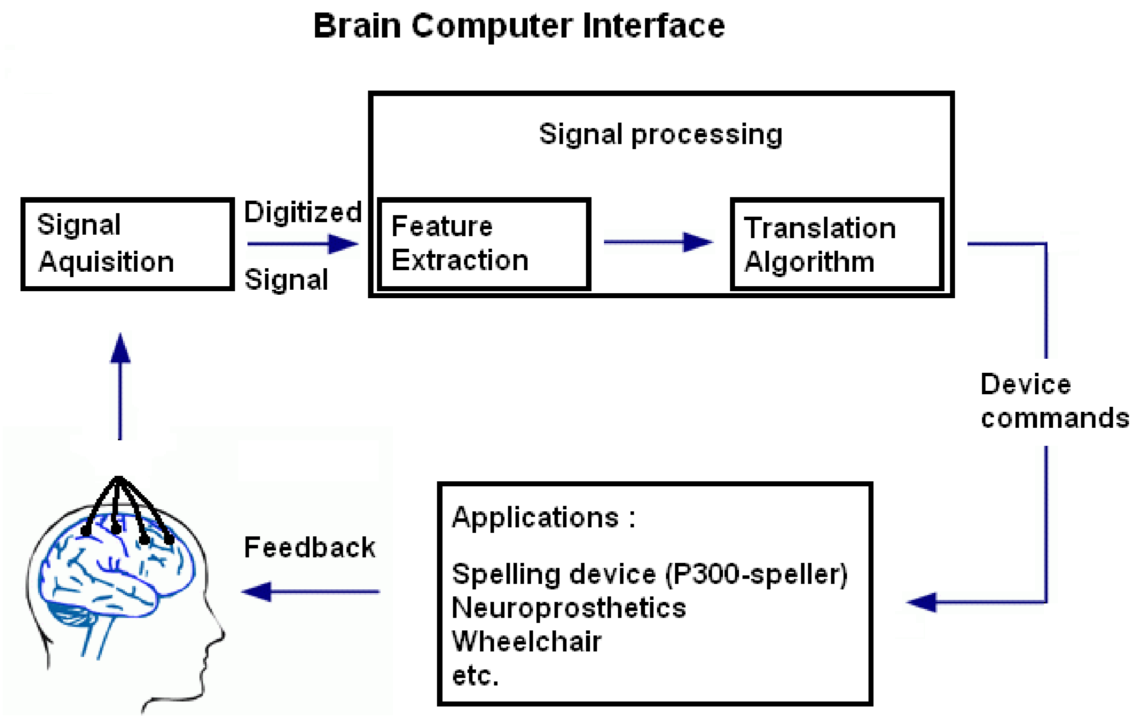

Figure 2: Functional model of a BCI system. Brain activity measured with EEG is converted to an electrical signal in the signal acquisition phase. Next, the user's intent is extracted from the signal. Therefore a variety of different electrophysiological characteristics can be used. Algorithms that are developed in specific for the BCI, interpreted the desired action and send this to an output device. The output device can be a computer with letters or targets as output (e.g. P300 speller). Also a wheelchair or neuroprosthetics (e.g. a robotic arm) can be used as output device for a BCI. Feedback helps to maintain and improve the accuracy and speed of communication/actions.

1.4. Dependent and independent BCI systems

BCIs can be categorized into two classes: dependent and independent. A dependent BCI does not use the brain's normal output pathways to convey the message, but the activity in these pathways is needed to generate the brain activity (Wolpaw et al, 2002). For example, using visual evoked potentials (VEPs) as control signals for BCIs depend on muscular control of gaze direction. By recording the VEP from the scalp over the visual cortex, it is possible to determine gaze direction and thus the direction in which a user intended to move an object on a screen (Wolpaw et al. 2002).

In contrast, an independent BCI system does not depend at all on the brain's normal output pathways. The message is not conveyed by peripheral nerves and muscles and the activity in these pathways is not needed to generate the brain activity (Wolpaw et al, 2002). For example, the P300 evoked potential can be used as a control signal to select certain items flashed on a screen. The generation of the P300 does not depend on the precise orientation of the eyes, but mainly on the user's intent (Sutton et al., 1965; Donchin, 1981; Fabiani et al. 1987). Because the normal output ways of peripheral nerves and muscles may be lacked for people with severe neuromuscular disabilities, independent BCIs are likely to be more useful for this group (Wolpaw et al. 2002).

1.5. BCI-systems based on 4 different groups of electrophysiological signals

As mentioned, different non-invasive electrophysiological signals can be used as input for BCI systems. Present day BCI systems can use VEPs, slow cortical potentials (SCPs), mu and beta rhythms and P300 evoked potentials (Wolpaw et al., 2002).

Using VEPs as control signals requires muscular control of gaze direction and is therefore a dependent BCI (see section 1.4). The other three electrophysiological signals are believed to be independent BCIs, though this still need complete confirmation (Wolpaw et al., 2002).

VEP

VEPs may reflect the electrophysiological mechanisms underlying the processing of visual information (Gao et al., 2003). Transient VEPs occur when there is some resting period between two stimulations, whereas steady state VEPs (SSVEP) are the result of high repetition rates (Gao et al., 2003). Different visual stimuli are presented on a panel and flicker with different frequencies. When a subject gazes at a certain target stimulus, the SSVEP is induced in the brain. The flickering frequency of the target stimulus is equal to the evoked SSVEP (Gao et al., 2003), which allow determination of the stimulus where the subject is looking at. Coupled to a word processing program, healthy volunteers can operate at 10-12 words/min (Wolpaw et al., 2002).

SCP

SCPs are slow voltage changes generated in the cortex. People can learn to control SCPs although it mostly requires long training procedures. When high accuracy levels are consistently achieved, they can use language support programs, enabling users to choose letters by a series of two-choice selections (Perelmouter and Birbaumer, 2000). With this program users can write about 0.15-3.0 letters/min (Wolpaw et al., 2002).

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Mu rhythms

Mu rhythm is 8-12 Hz EEG activity in primary sensory or motor cortical areas when they are not engaged in processing sensory input or producing motor output (Neidermeyer, 1999). A decrease in mu and beta rhythms is associated with movement or preparation of movement, whereas an increase of mu and beta rhythms is associated with relaxation (Pfurtscheller, 1999). The decrease is labelled 'event-related desynchronization' (ERD), whereas an increase is labelled 'event-related synchronization' (ERS) (Pfurtscheller, 1999). Interestingly, they also occur with motor imagery (i.e. mental rehearsal of a movement) (Pfurtscheller and Neuper, 1997), which makes it relevant for BCI use.

P300

Finally, P300 evoked potentials might be used as control signals in BCIs. In the next chapter, BCIs based on the P300 evoked potential will be discussed.

2. P300 Evoked Potentials

ERPs have been of major importance for the study of cognitive processes (Nieuwenhuis et al., 2005). One widely studied component of ERPs is the P300 evoked potential. The P300 is present in many sensory-evoked waveforms (Nieuwenhuis et al., 2005) and it does not require extensive training. P300 based BCIs are independent which makes the P300 an interesting EEG component for BCI systems.
Recently, three studies have been published in which P300-based BCI systems were tested with disabled subjects:

1. Piccione et al. (2006) tested a 2D ball/cursor control system with five disabled subjects. Upward, rightward, downward and leftward arrows were randomly flashed on a screen and the user had to pay attention to the arrow indicating the desired direction (Piccione et al., 2006). The target stimulus elicits the P300 which can be recognized by the system and result in movement of the ball in the desired direction. The results showed that the P300 is a suitable control-signal for disabled subjects.
2. Sellers and Donchin (2006) used also a four-choice oddball paradigm ('yes', 'no', 'pass', 'end') in their study, either in the visual modality, in the auditory modality, or in a combined modality. Subjects had to focus on either the 'yes' or 'no' during each series of flashes (Sellers and Donchin, 2006). The results showed that P300-based communication is possible for subjects suffering from ALS, in both modalities. However, the average communication speed in both studies was relatively low (i.e. 7.67 bits/min and 1.80 bits/selection on average, respectively).
3. Nevertheless, Hoffmann et al. (2008) showed that it is possible to use P300 based BCIs with higher transfer rates. They used six different images (i.e. a television, a telephone, a lamp, a door, a window and a radio) in their study with five disabled subjects. The subject had to count silently how often a prescribed image was flashed (Hoffmann et al., 2008). Results showed bitrates range between 10 – 25 bits/min indicating that a P300 based BCI could be used efficiently by disabled people.

2.1. EEG and P300

As mentioned in the introduction, EEG-signal features in the time domain can be used in BCI systems. Event Related Potentials (ERPs) represent brain activity that is elicited in response to events (Donchin et al., 2000). ERPs can be divided into two classes: exogenous ERPs which are the result of early, automatic processing of stimuli, whereas endogenous ERPs are the result of later, more conscious processing of stimuli (Hoffmann 2007, dissertation). Conscious processing occurs at about 100 ms latency when the visual signal is under way towards extrastriate areas and areas in the parietal and temporal cortex (Lamme, 2006). Although 30-40 ms after stimulus onset the visual signal already reaches the primary visual cortex (Lamme, 2006), behaviour response is based on unconscious processing (i.e. reflexes) in the first 100 ms.
Endogenous ERPs are suitable for BCIs because they depend on stimulus context and subject's attention, which could reflect the intention of the subject. The P300 is an endogenous ERP that gained much attention in BCI research.

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The P300 is a positive deflection in the human EEG (**Fig. 3**), approximately 300 ms after the presentation of rare or surprising, task-relevant stimuli (Sutton et al., 1965). It is an endogenous component most frequently elicited in what has come to be called the "odd-ball paradigm" (Donchin et al., 2000). The P300 is a slow wave oscillation associated with behavioural relevant and attention processes. Users can change the amplitude of the P300 by paying more attention to a specific event (Allison et al., 2007). Therefore the P300 is used in many BCI systems to unravel intents or messages hidden in the EEG. However, the P300 is also influenced by many other factors (Hoffmann 2007, dissertation), making it more complicated to correctly interpret the signal. The amplitude of the P300 is influenced by the target probability, the inter-stimuli interval, habituation effects, attention and task difficulty (Hoffmann 2007, dissertation).

In general, the less probable the eliciting event, the larger the amplitude of the P300 is. To evoke a reliable P300, the probability for the target stimulus is normally set to values around 10% (Hoffmann 2007, dissertation). In addition, when many nontarget stimuli precede a target stimulus, the P300 amplitude is higher than if a small number of nontarget stimuli precede the target stimulus (Squires et al., 1976). Furthermore, if the amount of time between two stimuli is long (long inter-stimuli interval), the amplitude of the P300 is higher, whereas short inter-stimuli intervals result in lower amplitudes (Hoffmann 2007, dissertation). Because the P300 is evoked by attention processes, repeatedly presenting the same target stimulus could result in habituation which decreases the P300 amplitude, but only when short inter-block-intervals and many trial blocks are used (Ravden and Polich, 1998). Ravden and Polich (1998) showed that the P300 amplitude decreases across a 10-block session of trials in about 1 hour (Ravden and Polich, 1998). When the subject loses his attention and/or concentration, the P300 can completely disappear. Finally, the amplitude of the P300 can be decreased when the task is more difficult. Polich et al (1987) showed that the P300 was larger when target tones were very different from nontarget tones in contrast to little difference between target and nontarget tones (Polich et al., 1987).

Because the P300 is a slow wave oscillation, lowpass filtering combined with downsampling removes unimportant information from high frequencies (Hoffmann 2007, dissertation). To distinguish the P300 from the background activity (i.e. uncorrelated activity, noise, signal variability), several samples need to be averaged. Generally, dozens or hundreds ERPs are elicited from each subjects and averaged together (Allison, dissertation). By averaging such a large number of ERPs, the noise influence gets cancelled. The noise is reduced with the square root of the number of averaged trials (Coles et al., 1986).

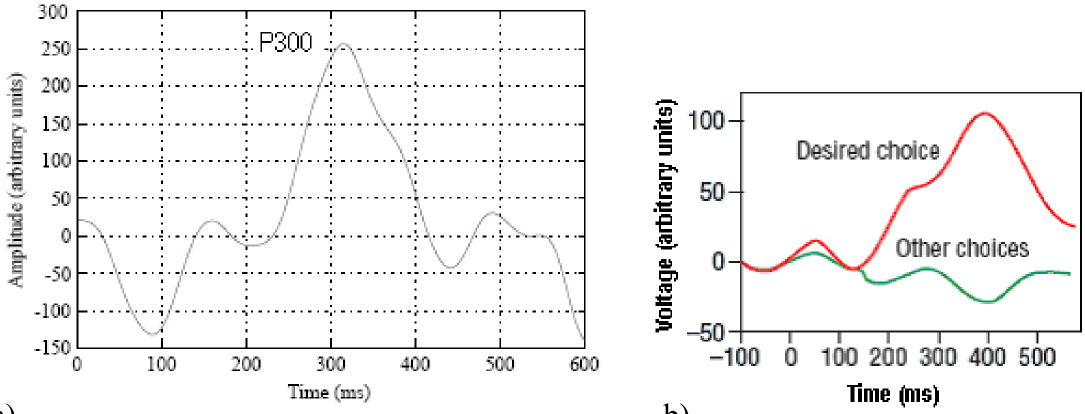

Figure 3: (Hoffmann 2007, dissertation; Rebsamen et al., 2007). a) Illustration of a P300 wave. The P300 is a typical positive deflection in the EEG, approximately 300 ms after the presentation of a rare, surprising or desired stimulus. The scalp distribution of the P300 has a maximum over central-parietal midline electrodes (Nieuwenhuis et al., 2005) b) Because only the oddball stimuli (which require focused attention of the user) evoke the P300, it can be used as control signals in BCIs to select the desired choice.

2.2. P300 used in (visual) BCIs: the P300-speller

The P300 has been used in many BCI systems because users can change its amplitude by paying more attention to a specific event (Allison et al., 2007). Polikoff et al., (1995) used a P300-based BCI to allow users to control a 2D cursor. While in their study actual cursor movement was not implemented, offline analysis showed that in principle it was possible to control a cursor based on the P300 (Polikoff et al., 1995). In addition Piccione et al (2006) further explored cursor control based on the P300. They showed that it is possible for disabled subjects to use a P300-based BCI for communication.
However, Farewell and Donchin (1988) were the first who used the P300 as a control signal in a BCI system. They described the P300 speller system which allowed subjects to communicate a sequence of letters to a computer (**Fig.5a**). To create an oddball paradigm, a 6x6 matrix containing the letters of the alphabet was displayed on a computer screen. Rows or columns, containing 6 characters, were randomly flashed to the subject. The subject can select a specific letter by focusing attention on the cell containing that specific letter. Because the task-relevant stimulus results in larger P300 amplitude, an algorithm can select this letter and put it on a computer screen. It is worth mentioning that, the P300 is only elicited if the subject is looking at the flashed row and columns. In subjects that have visual impairments, auditory or tactile stimuli might be used (Glover et al. 1986; Roder et al., 1996).

2.3. Auditory P300 based BCIs

BCI systems can maintain communication in paralyzed patients suffering from neurological or muscular diseases, such as ALS. As the disease progress, different states can be classified. In the complete locked-in state all voluntary muscular control is lost (Nijboer et al., 2008). Many ALS patients that reach this state have impaired vision, and may not be able to use a visually based BCI (Nijboer et al., 2008). Usually the auditory system is unimpaired in these patients, thus exploring the possibility to use auditory based BCI could be of great importance.

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Just a few studies investigated auditory BCIs based on the P300. Hill et al. (2005) studied P300 evoked potentials that occurred in response to two simultaneously presented auditory stimulus streams. When attention was focussed on the target stimuli, a classification based on the EEG responses could be made between target stimuli and control stimuli (Hill et al., 2005). Although variation between participants existed and the speed was low (about 4-7 bits/min), it provided a useful basis for an auditory BCI.
Furthermore, as mentioned in the beginning of this chapter, Sellers and Donchin tested healthy volunteers and patients with ALS with a P300-based BCI. The words were presented visually, auditory or both. The authors were able to show that although the visual and visual + auditory reach higher accuracy levels, a P300-based BCI using the auditory modality is feasible for both healthy and disabled subjects (Sellers and Donchin, 2006). This study did not focus on the speed of the system. Because spoken words were used, the speed with which the system could operate was reduced (1.80 bits/selection) (Sellers and Donchin, 2006).
Two other studies also investigated auditory based BCIs, but they used slow cortical potentials (Hinterberger et al., 2004) and sensorimotor rhythms (Nijboer et al., 2008) as control signals for the BCI. Both studies conclude that auditory BCI control can be achieved with auditory feedback, although visual BCIs are superior to auditory BCIs. As the number of stimuli averaged increases, the accuracy increases more for the visual and auditory + visual mode than for the auditory mode (Sellers and Donchin, 2006). Furthermore, auditory P300s occur 140 ms earlier than visual P300 showing that there are differences in P300 latency for auditory and visual stimuli (Squires et al., 1977).
It is important that a BCI system can function effectively using different presentation modalities, because a user may have impaired visual or auditory systems. Although recent studies showed that auditory BCIs can be feasible, achieving high transfer rates (say, > 20 bits/min) seems to be a major problem.

2.4. Accuracy, speed and transfer rates

Two very important characteristics of a BCI system are the accuracy and the transfer rates. If a system is not accurate enough and/or the transfer rates are too low, the system is not efficient. The bit rate of the system is an objective measure of information transfer and often an issue in current BCI systems, although the importance of the accuracy must not be overshadowed. An increase in accuracy from 75 % to 90 %, given four choices, nearly doubles the bit rate (**Fig. 4**) (Sellers and Donchin, 2006). In addition, accuracy of at least 70% is needed for effective communication (Sellers et al. 2006).
Most P300-based BCI system reaches transfer rates of about 10 bits/min. However recent studies showed efficient P300-based BCIs with high accuracy rates up to 100% in disabled subjects. In addition, transfer rates up to 25 bits/min can be reached for these disabled subjects (Hoffmann et al., 2008). Meinicke et al. (2002) report a maximum bit rate of 84.7 bits/min using a 6x6 matrix speller. However, the accuracy level was less than 50 % leading to a net result system that is not able to correctly spell a single word (Sellers and Donchin, 2006). In addition, Kaper et al. (2004) achieved high transfer rates up to 97.57 bits/min (mean = 47.26 bits/min) using an algorithm based on support vector machines to analyze EEG data from the P300 speller. However, the method has not been implemented online and it is not clear how this would be achieved (Sellers and Donchin, 2006). Thus developing a P300-based BCI system that has an accuracy of at least 70%

and has also rapid transfer rates that reaches nearby the bit rate of real keyboards and mice (up to 350 bits/min) would be a daunting challenge. Although the low transfer rates is a disadvantage for all present day BCIs. P300-based BCIs have an important advantage compared to BCIs using other electrophysiological signals.

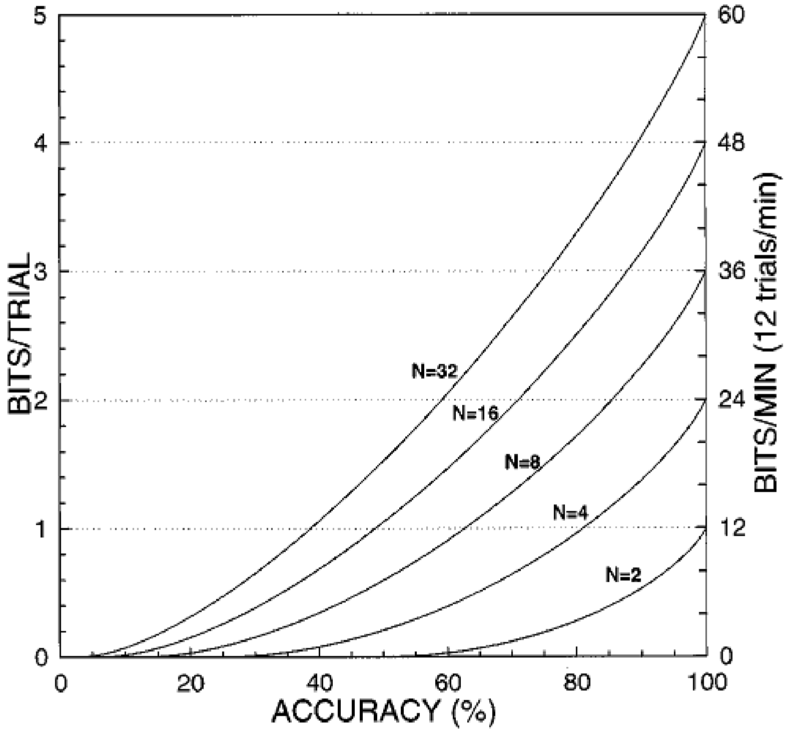

Figure 4: Transfer rates in bits/min (for 12 trials/min) and in bits/trial. N is the number of possible choices. Each choice has the same probability of being the one the user desires. If the probability (P) that the desired choice will actually be selected is always the same, and if each of the other (i.e. undesired) choices has the same probability of selection (i.e.(1-P)/(N-1)), then the bit rate, or bits/trial (B), is: $B=\log_2 N + P \log_2 P + (1-P)\log_2[(1-P)/(N-1)]$. For each N, bit rate is shown only for accuracy ≥ 100/N (i.e. ≥chance). (Figure and legend from Wolpaw et al., 2000).

2.5. Advantages and disadvantages of P300-based BCIs

A P300-based BCI has the very interesting property that it requires no initial user training to generate a P300 in response to the desired target. BCI systems that do require training, demand also interaction between the operator and the user. This could be challenging in case of disabled patients. P300-based BCIs require no training and the user can immediately start using it. The P300 is a typical, or naive, response to a desired choice (Wolpaw et al., 2002). This holds for every human being, although individual differences in P300 latency and amplitude have also been reported (Fabiani et al., 1987). Studies have indicated that some ALS patients may have abnormal evoked potentials. Paulus et al. (2002) reported that 12 of 16 ALS patients displayed abnormal P300 patterns, as compared to an age-matched control group (Sellers and Donchin, 2006). ALS might damage the prefrontal cortex that is associated with attention processes and thereby affect BCI use (Rockstroh et al., 1989; Müller et al., 1997). Beside attention, also other human factors like motivation and fatigue influence BCI use (Wolpaw et al., 2002). This is important to keep in mind, because BCI systems are in particular developed as

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communication devices for severely disabled patients. Thus it should serve the needs of the people with disabilities and take into account the possible limitations of the user.

Moreover, several P300-based BCI studies found slight reduction in performance during the sessions, which might be due to a habituation effect (Sellers and Donchin, 2006). Because the P300 is largest for new, relevant, desired events, repeatedly presenting rare events results in decreased P300 amplitudes and thus reduced performance. However, when unexpected experimental sessions were performed, the P300 amplitude spontaneously returned to the same level as the first session (Sellers and Donchin, 2006). On the other hand, it has been shown that the P300 of individual trials are relatively stable (Cohen and Polich, 1997; Polich, 1989). In addition, reliability factors of 0.70 or higher were reported within and between sessions (Fabiani et al., 1987). Thus, it seems that although response habituation might occur, it does not seem to be a likely source of poor performance.

Because using a P300-based BCI requires attention and concentration, the user should not be distracted. This could be difficult if the P300-based BCI is used in normal life. Therefore testing BCIs by patients in home environment is of great importance.

2.6. Applications of P300-based BCIs

Although BCI systems are mainly developed for people with severely disabilities, it could also provide healthy persons a futuristic experience by controlling the environment only with thoughts. However, present day BCI systems still have shortcomings that prevent their widespread application.

An important P300-based BCI application is the spelling device (P300-speller, **Fig 5a**) which allows disabled patients to communicate. A BCI might give the ability to answer simple yes or no questions with a transfer rate up to 20 bits (yes/no)/min. In addition, a BCI might provide slow word processing with a transfer rate of about 2 words/min (Wolpaw et al., 2002). Although the transfer rates are low, it can improve the quality of life of completely locked-in ALS patients.

Moreover, a BCI might be used to control a wheelchair (**Fig 5b**). Although there are some prototypes of BCIs steering a wheelchair, the possible movements are strongly constrained. This is necessary because steering a wheelchair is a complex task and the system has to be extremely reliable. Rebsamen et al (2007) developed a brain-controlled wheelchair prototype which uses a P300 EEG signal and a motion guidance strategy to navigate in a building safely and efficiently (Rebsamen et al., 2007). With the P300 EEG BCI, the user can select a destination item on a menu by counting the number of times the destination flashes. The wheelchair then moves to the selected and desired destination on a predefined path (Rebsamen et al., 2007). Importantly the BCI system has to know what his location is to find the right path. The software of the navigation can easily be modified if the environment changes (Rebsamen et al., 2007).

Besides steering a wheelchair, controlling neuroprosthetic devices is also an important application for people with severe motor disabilities. BCIs can be used to control movement of limbs, for example a robotic arm. Taylor et al. (2002) showed that a BCI based on the activity of cortical neurons, is able to control 3D movements of a robotic arm (Taylor et al., 2002). Although this experiment was conducted with monkeys, it opens the opportunity for patients to use neuroprosthetics. However, P300-based neuroprosthetics have not been reported so far.

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Moreover, in theory all electrical devices coupled to a BCI system could be controlled more or less. In home environment one might think of lights, music devices and the television. Gao et al. (2003) presented a BCI system (i.e. an environmental controller) based on steady state visual potentials (SSVEPs), that is successfully coupled to an electric apparatus (Gao et al. 2003). In addition Bayliss (2003) describes the control of a virtual apartment based on the P300 evoked potential. She showed that the P300 can be used in different environments (i.e. also in virtual reality) (Bayliss, 2003).
Although the aim of BCI technology was to provide disabled users a communication or device controlling system, it also opens new ideas for the consumer market to provide futuristic experiences. It is more like a mental remote control, to control light, music, television etc. P300-based BCIs are very well suitable for these applications. There is no need for training making it easy to use, and it reflects intents and desires of persons, thus approaching feelings of the user. Furthermore, the game industry might benefit from the introduction of BCIs. Expert computer gamers often use a variety of keys requiring several fingers on both hands to effectively control the game (Allison et al., 2007). BCIs could assist these gamers by providing supplemental control. However, BCI-systems often require full attention which makes it hard to perform several tasks at the same time. Therefore, the so called ‘BCI distraction quotient’ needs to be explored (Allison et al., 2007).
In sum, a BCI might give the ability to answer simple questions quickly (i.e. 20 bits/min is 20 yes/no answers/min), control the environment (e.g. lights, temperature, television etc.), perform slow word processing (i.e. 2 words/min), or even operate a neuroprosthesis or wheelchair (Wolpaw et al. 2002). Also the healthy population might benefit from BCIs.

Figure 5: Examples of applications of P300 based BCIs. a) The P300 speller is a BCI that use an oddball paradigm to allow a user to communicate letters to a computer. Rows or columns containing the letters of the alphabet are randomly flashed to the user, who can select a letter by focusing attention on that specific letter. If the row or column containing that letter is flashed, it results in a larger P300 amplitude, which can be detected by an algorithm. The algorithm computes 36 average ERPs, one for each cell. The discriminant score for each cell is computed and the cell with the maximum discriminant score is selected. Finally, it can be send to an output device which should perform the desired action (e.g. write the desired/selected letter on a screen) (Sellers et al., 2006). b) Rebsamen et al. (2007) developed a P300 based BCI which allow the user to navigate a wheelchair through an apartment by selecting desired locations. The wheelchair finds his way by following a predefined path (Rebsamen et al., 2007).

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3. Future of P300 based BCIs

BCIs can be valuable for people with severe motor disabilities. However, present BCI systems have some drawbacks relative to other interfaces such as keyboards and mice. Beside their lower transfer rates and lower accuracy, BCI systems require an electrode cap and a computer with specific developed software. Furthermore the user often cannot setup the system by her/himself and the system is very sensitive to noise induced by the environment and the user her/himself. Therefore it is unlikely that BCI will replace conventional interfaces in the near future (Allison et al. 2007). Nevertheless, complete locked in ALS patients can take advantage of BCIs because it could be the only way to communicate with the outer world. For them, present BCIs can be of great value although they are not as efficient yet as conventional interfaces. Furthermore, BCIs can be a valuable supplemental controlling device that can also be used just for entertainment. Different applications require different BCI systems; the BCI system should serve the needs of the user.

3.1. Medical or private use

Controlling electrical devices using only thoughts can serve useful purposes. Traditionally, BCI systems have been used as assistance technology for disabled people. However, another interesting path is the use of BCI systems for multimedia applications. In section 2.6 several medical and multimedia applications has been described. The P300 based-BCIs can be used for both groups. The medical applications of BCI systems are widely described. The P300 speller seems to be the most important and far advanced P300-based BCI system, which can be used by patients with neuromuscular disabilities. Also the use of the P300 to control a wheelchair is explored which led to promising results. We will now discuss some multimedia applications that can be used by healthy people.

Gamers seem likely an important target group to use BCI systems. They are strongly attracted to new futuristic technologies (Allison et al., 2007) and often live in their own world when they are in the game. They could easily wear headgear and invest in peripheral devices (Allison et al., 2007). Developing games which are integrated in BCI devices would open a new gaming market.

BCI systems might also be interesting as an assistant interface used by military operations or more important, specialized users such as surgeons, machinists or aircraft mechanics (Allison et al., 2007). But before such applications can be introduced BCI systems must be proved to be reliable, safe and useful. BCI acceptability needs to be increased.

Present BCIs are still more effective than fashionable. However the development of new EEG sensors made significant progress (Allison et al., 2007b). New electrodes can be used without gel and may require no direct contact with the scalp (Allison et al., 2007). These new technologies allow easy integration of the sensors with conventional devices such as headphones, caps or glasses. If technologies such as bluetooth are used, wireless, wearable BCIs might be developed.

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If BCI systems can be fashionable, 'cool' and 'futuristic', some people may want to use such a BCI system simply because it is novel and exciting (Allison et al, 2007). Because a P300-based BCI requires no training, people can immediately start to use such a BCI, which makes it an easy to use gadget.
But the BCI system must add something to conventional interfaces to be really useful. While the P300 may index attention and intentions, P300-based BCIs might provide information available that otherwise will not be available (Allison et al., 2007).
In spite of the controlled conditions, one of the hallmarks of the results achieved is their variability. This variability is likely to be even greater when BCIs are taken out of the protected settings in which they are now typically used and are applied to the day-to-day needs of people with severe disabilities or healthy users (Wolpaw, 2007).
BCI development will depend on different issues. Developing BCIs for medical applications requires other conditions than BCIs developed for the consumer market. Thus the goal of the BCI must always keep in mind. More complex applications depend on achievement of greater speed and accuracy (Wolpaw et al., 2002).
The main issue about the present day BCI systems are their low transfer rates. If transfer rate could be increased with high accuracy, BCI systems can be very valuable for future applications. For the disabled, every possibility of communication or controlling devices would increase their quality of life. For them transfer speed is not that important, although it should be preferable.

3.2. Information transfer rate (speed)

The development of BCIs that are practical, reliable and capable of high-speed complex communication and control is an enormously difficult problem, and one that is far from solution (Wolpaw, 2007). While other communication devices such as a computer mouse can achieve bit rates up to 300-350 bits/min (Krepki et al, 2007), present day BCIs reach transfer rates up to 25 bits/min. Therefore it is unlikely that BCI systems will replace present controlling devices in the near future. However, for severe neuromuscular disabled persons this provide the possibility of basic communication and control functions, such as simple word processing and environmental control (Wolpaw et al., 2002). For the consumer market transfer rate is of great importance. As noted in section 3.1, more complex applications need higher transfer rates and accuracy. The question is how these transfer rates can be achieved, and if this is necessary to speed up BCI operation. Optimal use of present bit rates might also increase transfer rates. Rebsamen et al. (2007) already use this approach by selecting choices of locations (e.g. kitchen, bathroom etc.) to steer a wheelchair instead of moving the wheelchair in certain directions (e.g. left, right). Furthermore, P300 based BCIs using single trials need to be explored. If it is possible to select the desired choice based on a single trial, transfer rates can be increased. Future BCI research should not only focus on how higher transfer rates with high accuracy can be achieved, but also how present bit rates can be used in a more efficient way.

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4. Conclusion

BCI systems allow users to communicate or control devices using brain activity. No motor actions are needed which makes it a valuable communication assistance for the severely motor disabled. Several electrophysiological characteristics can be extracted to control the BCI system. The P300 is used in many BCI systems because it is a typical, and naive, response to a desired choice (Wolpaw et al., 2002), which requires no training. However, the P300 can be influenced by different human factors such as attention, motivation and fatigue (Allison 2003, dissertation). The exact influence of these factors on BCI use needs to be explored as well as the use of BCI in normal life conditions. Present BCIs are often used in laboratories which have strict protocols and supervision of the operator. Because the goal of BCIs is to provide disabled persons a communication device, the BCI should serve the needs and limitations of the user. Beside BCI developed for the disabled population, they can also be introduced to the healthy population. Gamers seem to be the first user group of BCIs for entertainment, or as a supplemental interface for assistance in games. Bayliss already developed a P300-based BCI to control a virtual environment (Bayliss, 2003). Many gamers are attracted to futuristic technologies and already use headgear. In addition, they spend a lot of money on peripheral devices, thus their might be a market for BCI game development (Allison et al., 2007). Important for a successful introduction of BCI in the world population, they need to be easy to use, fashionable and reliable. New electrodes that can be easily integrated with conventional devices such as headphones, caps or glasses opened new possibilities to introduce BCIs in the real world.

In spite of the fact that traditionally BCIs were developed for persons with severe neuromuscular disabilities and the present BCIs are not very fast, they are of significant value for those users. The extent to which BCIs can be used mainly depends on the information transfer rates that will be achieved in the future. Besides increasing bit rates, future BCI research should focus on how present day bit rates can be used more efficiently. Present day BCIs achieve maximum transfer rates up to 25 bits/min, whereas conventional interfaces such as computer mice achieve bit rates up to 300-350 bits/min (Krepki et al, 2007). Therefore it is unlikely that BCIs will replace conventional interfaces in the near future but will rather complement them.

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