EEG Brain-Computer-Interfaces

A review

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Concentration Exam Review

In requirement for the Ph.D. in Psychology

with a concentration in ***Cognitive Neuroscience***

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Introduction

Brain Computer Interfaces (BCI) seek to provide humans with control of machines using their thoughts alone. In their current state, electroencephalography (EEG)-based BCIs do not look promising as a control method for people in good health. They are slow and cumbersome compared to modern control techniques like the mouse and keyboard. Yet as dry active electrodes and artifact rejection procedures continue to mature, EEG is finding its way outside of the laboratories. By viewing the BCI as a properly-designed *alternative channel* of control, rather than a *replacement to* current control schemes EEG-based BCIs may find their way into more widespread use.

EEG measures the electric potential observed between various scalp locations along the head . These signals represent propagated dynamic electric currents arising from the brain. It is believed that superficial excitatory cortical neural networks firing in synchrony are the main contributors to the EEG signal [Mountcastle,2003; Nunez & Srinivasan,2005]. Although other neuro-imaging techniques like electromyography (EMG), functional magnetic resonance imaging (fMRI), and others have begun to prove effective for BCIs [*e.g.* Weiskopf, 2003, 2005; Hinterberger, 2005], their respective acquisition devices are expensive and more cumbersome than EEG. EEG appears to be the most promising neuroimaging technique for development of near-future BCI applications. The *EEG-based BCI* is herein referred to simply as *BCI*.

BCIs are a type of Human Computer Interaction (HCI) methodology and seek to provide an alternate control paradigm - one which bypasses overt motor commands altogether. BCIs are one of many various interfacing techniques currently being explored to enhance human computer interaction [Jacko, 2009]. Progress in developing such alternative control schemes may be attributed to advances in applied neuroscience and statistics (*i.e.,* machine learning) and to hardware availability. Various HCI implementations have already begun to penetrate the commercial market. The Microsoft *Kinect* offers an inexpensive computer vision solution for video game control. Users interact with their virtual game world through physical gestures. The Kinect camera system recognizes poses with modern machine learning and computer vision techniques and updates the game according to the user's gestural cues. Automatic speech recognition (ASR) is another control scheme which continues to gain in popularity. Most smart-phones come equipped with some speech recognition engine built-in, and anyone who has dialed an automated telephone service has likely spoken verbal commands into an ASR machine learning algorithm. As each HCI paradigm develops, its costs and benefits will become apparent. Applications will materialize in the niche areas for which that specific modality is best suited. For example, eye-gaze control interfaces have proven effective for applications which require hands-free control environments. Given the state of modern BCIs, it is unclear whether they will be accepted as a suitable alternative to other HCI control methods. Low communication speeds, high setup time and subject training relative to other HCI modalities pose obstacles to widespread adoption of BCI.

Different BCI implementations may be compared by measuring the speed of communication for each system. One such measure, the information transfer rate (ITR), has been adopted from information theory to help measure BCI efficiency. Descriptors of BCI performance may be found in the appendix. Such criteria are integral to advancements in known BCI control modalities, though this view of maximizing the information sent over time as the *sole criterion* for BCI design is flawed. Recently, alternative uses of EEG for HCI have been considered [Blankertz, 2010] - applications emphasizing less the importance of computer control and more the importance of subject monitoring. In the near future, BCI may find uses in niche applications - whether it will do so alone or as a component of a grand hybrid control scheme is unclear. It is with this perspective that the BCI is reviewed - not as the be-all-end-all of control schemes, rather as an HCI channel.

EEG/Brain Primer

The EEG technique - now nearly a century old [Berger, 1928] - is unique as a neuroimaging technique in that it provides high temporal resolution, relative ease of use and low hardware cost. However, these features come at the cost of low spatial resolution in relation to that found with other methods like fMRI. Electrode scalp locations are usually based on the standardized 10-20 system (see Figure 1 below). Each electrode is labeled with an alphanumeric tag pertaining to the lobe it lies over: occipital (O), temporal (T), frontal (F), central (C) andp (P), followed by an even number denoting a location to the right of midline or an odd number to the left (figure 1 below). Label numbers are replaced with a 'Z' for electrodes lying on the midline.

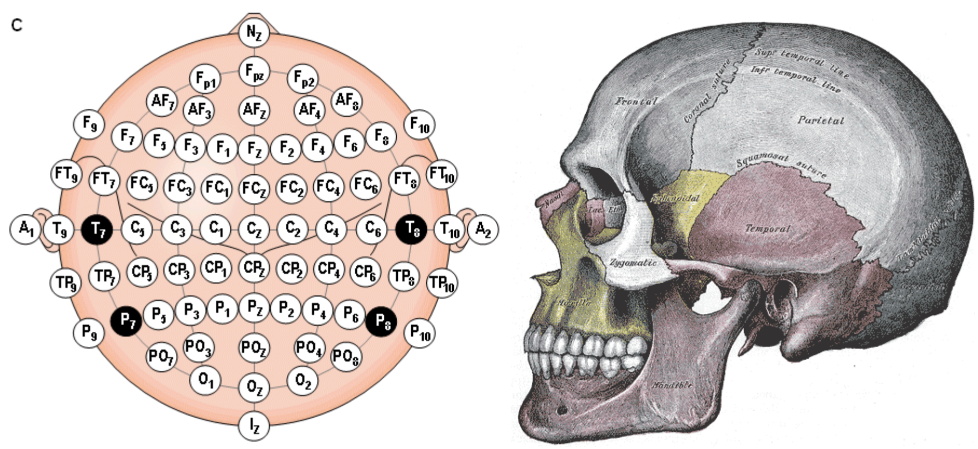

Figure 1 - 10/20 locations and human skull- (left) 10-20 electrode locations with electrode labels. (Nz is over the nose)Highlighted are left and right temporal and parietal electrodes. (Right) – human skull regions with labels. From Niedermeyer and Da Silva [2004]

Brain anatomy reflects the gradual addition of ontogenetic units over many generations of evolution by selective mechanisms [Mountcastle, 2003]. The triune brain is a model which explains human brain development by evolutionary selective mechanisms. It partitions the human brain into the reptilian, paleomammalian and neomammalian complexes. The latest evolutionary addition, the neomammalian complex, consists of the cerebral neocortex - the most superficial brain region and primary contributing brain area to the EEG signal. The neocortex is divided into four *lobes* - occipital, parietal, temporal and frontal. These names reflect not differentiations in the respective cortical regions, rather the bones of the skull that lie superficial to them. These lobes therefore carry little if any functional significance, save for the occipital lobe which is dedicated primarily to vision processing.

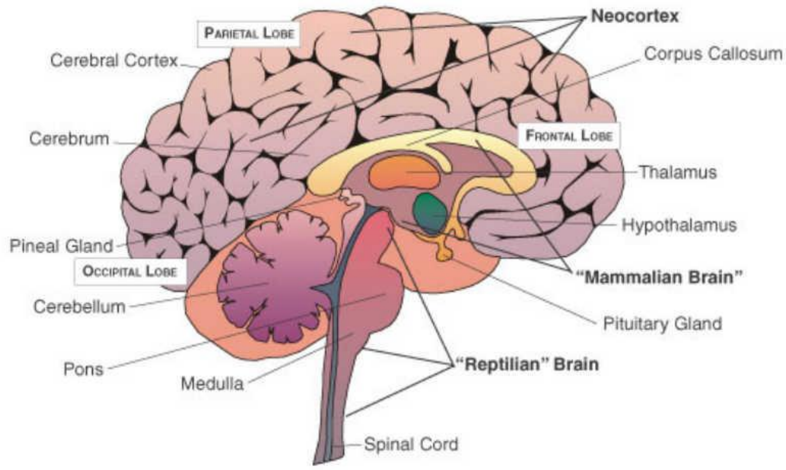

Figure 2 - Triune Brain Regions. - The triune brain consists of the reptilian complex, the paleomammalian complex (limbic system), and the neomammalian complex (neocortex) viewed as structures sequentially added to the forebrain in the course of evolution. From Kazlev and Alan [2003]

To maximize the potential for cognitive information extraction from EEG, one must understand the technique's inherent limitations. For current to be measured on the scalp it must survive the journey from the active brain regions of its origin to the scalp surface. Individual neuron action potentials are very weak in voltage/current production. A single scalp electrode will capture the smeared spatial activity of roughly 500 million neurons located directly beneath the electrode at a measured potential in the range of 20 - 50 microvolts [Nunez & Srinivasan, 2006]. Highly synchronous activity between proximal neurons is necessary for the superposition of these current sources to penetrate the blood-brain, skull and scalp barriers which separate neural sources from sensors. An additional factor which modulates the scalp signal coherence of synchronized neurons is their spatial distribution. Specifically, active neural populations should lie perpendicular to the scalp plane for maximum signal transfer; neuron dendrites should point toward the nearest point in the scalp surface. Cortical pyramidal cells are arranged in such a fashion and are highly interconnected throughout the cerebrum. They can generate highly synchronous neural activity along the cortical surface. Although deeper brain sources may be measured from the scalp, they are attenuated quickly as EEG amplitude falls off with the square of distance between sources and scalp locations [Baillet, 2010]. Therefore, EEG is primarily dominated by activity from these cortical columns. High-level neural activity that represents perceptual neural mechanisms is believed to take place in superficial cortical regions [Mountcastle, 2003] and EEG provides an excellent tool for neuroimaging the cortical surface with high temporal resolution.

Significant spatial smearing occurs due to the inconsistent conductivity between concentric bio-layers and thus limits the degree of certainty with which one may localize scalp potentials to neural sources. This issue of volume conduction is addressed in the form of forward modeling and blind source separation techniques. Many computational methods have been developed to address the issue. For a comprehensive review, see [Baillet, 2010]

Due to miniscule signal amplitude (microvolts), considerable amplification and filtering must be performed on the raw scalp signal before it can be digitized and stored in a computer. Because of considerable amplification gain required to digitize the EEG, care must also be taken to mitigate the introduction of artificial artifacts in the signal. Such artifacts may be the result of muscle movements (blinks, yawns, jaw clenches, talking) and external electrical interference (line noise). Statistical methods have developed to salvage soiled EEG signals [Delorme, 2007; Correa 2006], and such artifact rejection procedures are the focus of many EEG researchers.

To develop BCIs, scientific experiments must be performed with carefully chosen control conditions and with enthusiastic subjects. It has been shown that BCI performance relies strongly on the vested interest of the subjects [Falkenstein, 2000; De Pascalis 2010]. Once one has acquired EEG signals of subjects performing tasks of interest, one must classify between conditions to make the EEG usable in a BCI scheme. To be most effective for direct, councious EEG-based control, stimuli must be found which maximize such effect sizes while minimizing trial length. In general, EEG data suffer from the *curse of dimensionality* [Bishop, 2004]. With experimental trials on the order of tens or hundreds, and EEG sampled in the range 256-1000 samples/sec, data dimensionality almost always exceeds trial order. In order to decompose the high-dimensional spatiotemporal EEG signal, source localization and component techniques have been developed which allow a reduction in the data dimension from the order of the number of sensors (32,64,128…) to the order of components or sources, which may be chosen somewhat arbitrarily. Typically EEG classification procedures utilize one of these dimensionality reduction techniques, followed by feature extraction and classification in these subspaces of the original EEG [Lotte, 2007; Dietterich, 2002].

EEG remains highly elusive, as the majority of the behavioral and background factors which contribute to dynamic, non-stationary trends of the signal are as of yet unexplained. Advancements in fundamental neuroscience and computational EEG methods are essential to progress in BCI [Srinivasan, 1999].

From Mind to Machine

In many instances, BCIs should be *adaptive systems*. The learning algorithms adapt to us, and we adapt to them. One is able to model such recursive systems with control system theory [Mason et al., 2003]. For each new BCI implementation, a unique *control interface* is invoked. The control interface describes the BCI implementation at a system level and is generally designed to serve three main functions:

1) Make the state of the controller application visible with a Control Display
2) Make the state of the user's neural signals visible via a Neural Display
3) Provide a representation of control tasks for the BCI

Control interfaces must also address the "midas touch" problem. As with King Midas, who turned everything he touched into gold, BCIs should pay careful attention to only instigate a machine command when appropriate [Tan, 2010]. Some groups have implemented multiple BCIs concurrently, using one BCI as an on/off mechanism for the others [Pfurtscheller, 2010]. Other Hybrid schemes may use alternate HCI channels [Jacko, 2009] along with a BCI to improve the control interface [Vilimek, 2009]. These and other multiple-BCI implementations, referred to as hybrid BCIs, are reviewed in the final section of this review. However, current BCI implementations require extensive subject training, and certain subjects, referred to as the 'BCI illiterate', do not have any success at all with BCI [Tan, 2010].

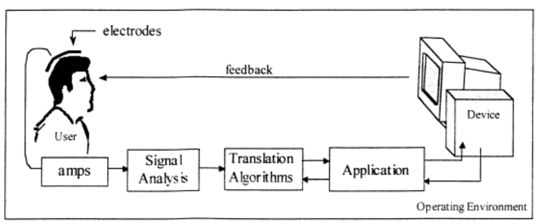

Figure 3a

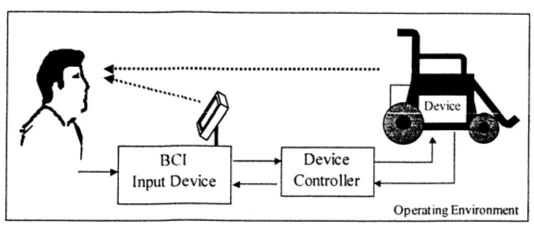

Figure 3b

Figure 3- Feedback in a generic BCI implementation – proposed functional model for BCI control. Figure 3a - The controller application is part of the user-application feedback loop. Figure 3b – wheelchair is in the loop [Mason et al., 2002].

The mental effort made by users to provide a control signal to EEG-based BCIs varies from one BCI implementation to the next. Control tasks may use either exogenous (evoked stimuli responses) or endogenous (self-generated) tasks. Exogenous tasks include BCI implementations such as P300-BCIs and steady-state evoked potential (SSEP) BCIs. In these tasks, the control interface generally provides various classes of visual stimuli from which the user makes a selection, embedding the response characteristic of their choice into their EEG signal. Endogenous control tasks include event-related-desynchronization [Wolpaw, 2003] - a self-paced imagined movement task. Although visual stimuli are not explicitly required for this type of task, performance feedback has been shown to play a large part in the training of subjects for the task [Wolpaw,2003]. The control task may vary wildly from implementation to implementation. Overall, It has been shown that experimental designs which keep subjects actively engaged and vested in the outcome of the BCI experiment provide higher single-trial classification results [Pailing, 2004].

EEG BCIs have traditionally been developed using one of three neural response classes: (I) event related potentials, (II) event-related desynchronization and (III) steady state evoked potentials. Each BCI modality is presented [below] with relevant BCI applications. The costs and benefits of each BCI should help to illuminate application directions for which each is likely to be successful. Finally, one threat to widespread BCI use is often overlooked in the majority of BCI publications - the problem of BCI illiteracy. For each given BCI modality, roughly 20% of subjects are simply unable to elicit the control signal [Tan, 2010; Blankertz, 2008]. The cause of illiteracy may vary from cortical population synchronization strength and spatial distribution variations in subjects to lack of motivation and interest in the experiment [Falkenstein, 2000]. To circumvent this issue, it is possible to train a subject within each BCI modality and use the one in which they produce best performance [Tan et al., 2010].

Event Related Potentials

ERPs are fluctuations in the background EEG activity generated by "a given neuro-anatomical module when a specific computational operation is performed." [Luck, 2005]. ERP's are labeled based on their sensory modality (visual, auditory, etc..) followed by polarity (P/N) and stimulus-relative lag latency in ms. For example, the visual P300 component refers to the positive deflection that occurs roughly 300 ms post-stimulus. Though the modality tag is often omitted even though there exist visual and auditory components which share polarity and latency, though lack functional similarity. ERPs are distinct from the other EEG BCI characteristic signals in that they are visible in the raw signal and need no advanced signal processing methods for recognition. Most ERP experiments simply average together multiple trials and test for effect sizes in the grand-averaged data. ERPs are therefore very easy to analyze statistically however the need for averaging across many trials hinders ERP application in single-trial BCI application.

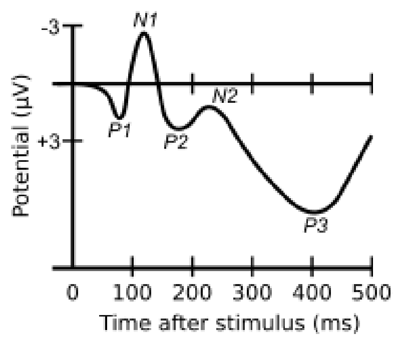

Figure 4 - Averaged waveforms of select ERPs including the P1,N1,P2,N2 and P3 potentials. Negative polarity is in the positive vertical direction. From [Luck,2005]

Neuroscientists have discovered numerous conditions which elicit ERPs in humans. The component attracting most attention from BCI researchers has been the P300, or P3, component [Chapman et al., 1964], which arises upon presentation of infrequent yet task-specific targets. Its relatively large amplitude and 'oddball' function lends it nicely to multi-class selection BCI designs. The P300 will be reviewed briefly followed by a summary of other well-known ERP components. They describe visual, auditory, language, and error and response-related domains. Components are presented based on relevance for potential BCI application.

Component Families

P3 family – The P300 is arguably the most thoroughly-studied ERP within the BCI community. P300 experimentation dates back as far as the mid 1960's, when Chapman and Bragdon [1964] discovered the ERP response to visual stimuli differed depending on whether the stimuli had meaning to the subject or not. Since then, many factors which modify the P3 response including stimuli frequency, subjects' physical and background mental states have been identified. There are two subcomponents which make up the P300: the novelty P3, or P3a, followed temporally by the classic P3, or P3b. The classic P3 is often referred to simply as the P3. The novelty P3a occurs in response to a rare but non-target stimulus, as opposed to the infrequent target stimulus which gives rise to the classic P3. The P3a generally peaks 250-280ms post-stimulus at fronto/central cites and is believed to play a role in human attention circuits [Luck, 2005; Polich, 2007].

N2 family - The N2 wave, often appearing in combination with the later P3 signal, has been shown to reflect executive cognitive and motor control functions as well as stimulus mismatch detection. It consists of numerous subcomponents, including the N2a, N2b and N2pc [Folstein, 2008].

The 'Basic' N2 component: Repetitive non-target stimuli elicit a deflection at 200ms which is considered the basic N2. If other deviant stimuli are infrequently presented within this repetitive train, larger amplitudes are observed in the N2. If the deviants are task-irrelevant tones, the effect consists of a mismatch negativity, referred to as the N2a, while task-relevant deviants produce a slightly delayed N2 effect, called the N2b [Folstein, 2008]. The component's amplitude increases for less frequent targets and thus is considered to reflect stimulus categorization processes. Visual mismatches, however, do not elicit this response. This component is often seen in subjects performing the oddball task, most well-known for eliciting the P3. Some subjects do not produce a reliable P3 in the oddball task, but do produce an N2 large enough for detection [Tan, 2010]. In the visual domain, the deviance which causes the N2 component is often studied spatially rather than temporally. For example, it is common to compare the ERP elicited by a stream of homogeneous items to the ERP elicited by that same stream containing one deviant item [Luck, 2005]. The N200 has also been used to study human semantic and phonological processing. Using a go/no-go task with semantic and phonological stimuli, Schmitt and colleagues found that peak N200 latency occurs earlier when responses are contingent on semantic information and later when they are contingent on phonological information [Schmitt, 2000].

Visual Components

The visual components are presented in a table for quick reference. For a comprehensive review of ERP's associated with visual stimuli see [Luck, 2005].

Name	**Onset (ms post stimulus)**	**Polarity**	**Neural Location of Origin**	**Brief description**	**Factors affecting amplitude**
P1	70-120	+	Lateral Occipital	attending to an incorrect spatial position [Hillyard, 1994],[Mangun, 1991]	Attentional distance from intended target
N1	150-200	-	Global response, peaks frontal	Discrimination tasks, Stimulus angularity and luminance	Selective attention [Wascher, 2009]
P2	150-275	+	Anterior, Central	Infrequent yet simple target stimuli. Part of larger **visual evoked response** (VER)	Target Infrequency, direction of attention [Furutsuka 1989]
N170	170	-	Occipito-temporal	Negative deflection when presented with human faces, and highly familiar words [Schendan, 1998]	Face inversion[Jacques, 2000], facial race[Vizioli, 2010] and emotional expressions [Righart, 2008]
P3	300	+	parietal	Infrequent but relevant and complex stimuli [Polich, 2007]	Frequency and importance of stimulus
N400	250-550	-	Central-parietal	wide array of meaningful and potentially meaningful stimuli, including visual and auditory words (and strings of letters), acronyms, signs, pictures, environmental sounds, and gestures [Kutas, 2000]	Frequency, orthographic neighborhood size, repetition, semantic/associatve priming, attention
P600	500-600	+	Central-parietal	Language-related errors (heard or read) and other syntactic anomalies [Patel,1998]	Familiarity, attention

Auditory Components

N1 occurs over fronto-central regions and is sensitive to attention, the surprise associated with an auditory stimulus, and features of speech sounds like voice onset time. More infrequent and unpredictable auditory stimulus yields a larger N1. Like the visual N1, this component has several subcomponents [Naatanen, 1987]

The Mismatch Negativity (**MMN**) is observed when subjects are exposed to a train of similar stimuli followed by an outlier, for example several 800-Hz tones followed by a 1200 Hz tone. The mismatched stimuli elicit a negative-going wave that is largest at central midline locations and peaks between 160-220 ms. This component arises even if the subject is not paying direct attention to the stimulus. Similarly, Luck [2005] states that the MMN is thought to be a fairly automatic process which compares incoming stimuli to a sensory memory trace of preceding stimuli.

Error Detection

In trials where a mistake is made or observed by the subject [Schie, 2004], a negative-going potential arises, sometimes followed by a positive component [Holroyd, 2002]. The error potential (EP) has two components: a primary 'error negativity'(ERN), a negative-going deflection maximal at 80-150 ms post-error, and a subsequent 'error positivity'(ERPe), which occurs 200-500ms post error, if it occurs at all. The error potential is a functionally sensitive component [Falkenstein, 2000]. Its amplitude is modulated by a number of factors pertaining to the task. The less likely the error is to occur, the higher the amplitude of the Ne component. In general, subject investment in task outcome has shown to increase amplitude [Falkenstein, 2000; D'Antuono, 2010; Pailing 2004; De Pascalis 2010]. It is dominant in fronto-central locations, and is believed to originate in the superior portion of Anterior Cingulate Cortex (See figure 5 below). In observed vs. self-performed errors, the ERN is of significantly lower amplitude and higher latency (around 250ms) [Schie, 2004].

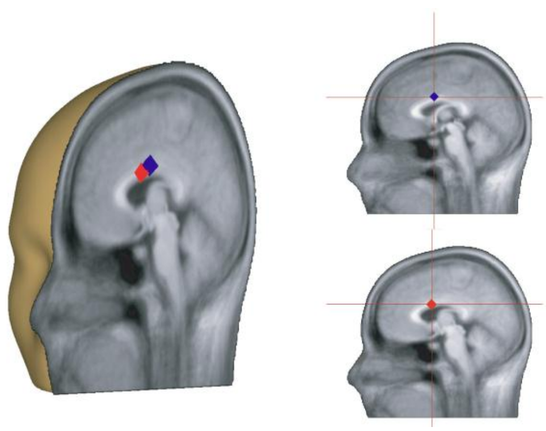

Figure 5- ERN in Anterior Cingulate Cortex. Superior portion of ACC supports cognitive processing including error recognition. Best dipole model for performed (blue) and observed errors (red). From [Schie, 2004]

Various Other Components

The readiness potential **(Bereitschaftspotential**, or BP) – Subjects who are asked to make a series of self-paced movements, show a slow negative shift at frontal and central cites, documented in two distinguishable components. The early one, BP1, lasts from -1.2 to -.5 s, and the late one (BP2), lasting from -.5 up to -.05 s before the movement. The BP has been recorded accompanying willful movements of the wrist, arm, shoulder, hip, knee, foot and toes, as well as preceding speaking, writing and even swallowing. In one experiment, the BP was used along with ERD (described below) to obtain single-trial classification rates as high as 84% of self-paced keypresses [Kornhuber, 1990]. A special form of the BP – the lateralized readiness potential (LRP) - reflects preparation of motor activity [Mordkoff, 2000].

Late positive component (LPC) – The LPC reflects explicit recognition memory. It occurs 400-500 ms post stimulus, and lasts a few hundred milliseconds. The component which came to be known as LPC was associated with episodic memory and was first discovered in studies observing repetition or recognition effects on EEG. Results showed that ERPs to old items were characterized by decreases in negativity in the 300 -500 ms range (N400) and increases in a subsequent, partially overlapping positivity (LPC). The joint increase in positivity across these two responses was termed the "old/new" effect [Friedman, 2000].

ERP BCI Implementations

As more is understood about ERPs and the factors which contribute to their amplitude and latency, it is likely that they will prove more useful in BCI settings. For a comprehensive review of classification procedures for single trial ERP components see [Blankertz, 2010].

P300 Applications

Due to its unique stimulus type, minimal training time, and high information transfer rate (between 30-50 bits/minute [Mak,2011; Meinicke, 2003; Nam, 2009]) the P300 signal provides the foundation for many BCI implementations. It first made the leap from esoteric neuroscience technique to applied BCI in the seminal paper '*Surprise!... Surprise?*' [Donchin 1980]. As with all ERPs, it is necessary to average multiple trials to increase SNR - so less frequent stimuli means a lower ITR. However since less frequent stimuli also means higher P3 amplitude, there is a tradeoff between stimulus frequency and trial length which must be maximized for an optimal P3 BCI. BCI designers will find comprehensive reviews of factors contributing to P3 amplitude and latency in [Polich, 2007; Gonsalves, 2002].

P300 speller

The P300 speller is the most well-known BCI implementation due to its ease of use and extensive list of relevant publications. The speller requires subjects to choose and attend a symbol from an alphanumeric matrix. As the rows and columns flash periodically, the chosen symbol flashes infrequently, and the P300 is elicited. (See Figure 6 below)

Figure 6 - P300 speller with column highlighted. Rows and columns flash while subjects attend their chosen letter. The algorithm recovers the user's choice at the intersection of row/column which elicits highest P3 amplitude. From [Schalk, 2004]

Although they are most popular of the BCI implementations, P300 spellers as well as most BCIs suffer from an unnatural 'probing' of the subject for a response. That is, in order to elicit the P300, subjects must maintain attention on the class choices available in the event of a flash. Other P300 applications reviewed next leverage the need for subject probing to explore alternative P300 BCI functionality.

Cortically-Coupled Computer Vision

Other P300 BCIs leverage the quick and reliable recognition speed of humans to boost computer image search performance. In this experiment, subjects are presented a rapid serial visual presentation (RSVP) in the 6-10Hz range and asked to search for a *class of targets* within the images. For example, subjects were presented images of natural landscapes and asked to look for humans in a scene. Subject-aided categorization of the images improved algorithm performance by 300% [Sajda, 2010].

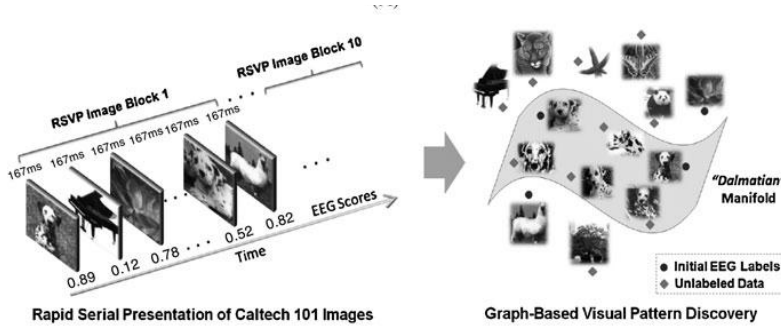

Figure 7 - RSVP of images containing target images (Dalmatians) in a list of images containing dogs(left), and the human-aided image classifications (right) [Sajda et al., 2001]

BrainBrowser

The BrainBrowser is a variant of the P300 speller, using the P300 for internet browsing [Tomori, 2003]. Subjects attended their choice of navigation-related selections (next page, previous page, etc.) as they flash below an active web browser (see image below).

Figure 8- Brainbrowser - P300 controlled web browsing. Active web browser is controlled by flashing navigation-related choices below it. From Tomori [2003]

Lie Detection - 'Brain Fingerprinting'

Another P300 implementation is *brain fingerprinting* [Farwell, 1991] – a technique similar in function to cortically-couple computer vision which acts as a lie detector test. In this work, Farwell expanded P300 analysis to include observations up to 1400ms post-stimulus and named the lie-detection-specific ERP application MERMER [Farwell, 2001]. In this scheme, suspected criminals are displayed a RSVP of images of the crime scene or murder weapon flanked by other objects. In this manner the MERMER was shown to reliably discriminate guilty from non-guilty suspects with a high accuracy [Farwell, 2006].

Error-Potential Applications

Error detection in humans may be used in a BCI setting as well. When humans interact with other humans, we share experiences, mimicking the emotional state of those observed in order to learn from them [Falkenstein, 2000]. Upon performing and observed errors, error potentials may be recognized by a BCI. In this manner subjects provide passive feedback to a learning algorithm. For example in one experiment, subjects' ERN was used to modify an algorithm's behavior to optimize task performance [Chavarriaga, 2010]. The algorithm performed a binary selection task initially blindly, and through the subject's Ne, learned the correct decision choice over trials. An actor-critic reinforcement learning update rule was used [Sutton & Barto, 1998] where the subject acted as critic and the computer (actor) moves about in an initially random fashion. Feedback from the critic helps to guide the belief of the actor to learn the correct binary decision with over 90% accuracy. In most subjects adaptation to the binary selection task converged within 20-30 trials (see figure 9).

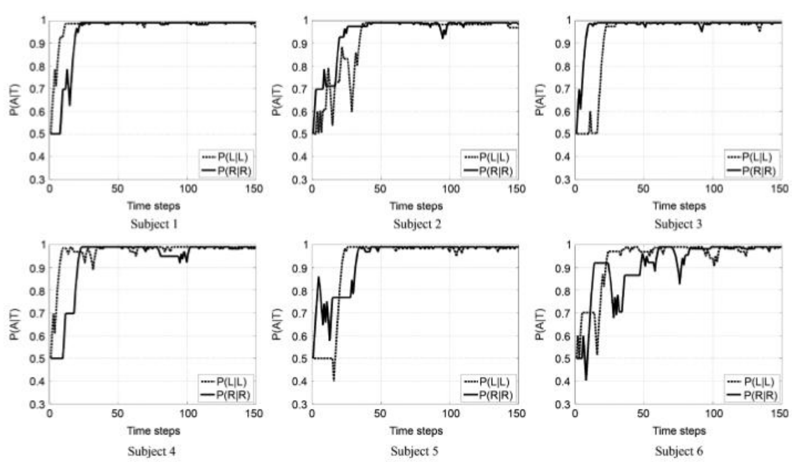

Figure 9 - ERN BCI performance. A reinforcement learning algorithm learns the correct choice in a binary decision task using observer feedback in the after 20-30 trials for most subjects. From [Chavarriaga, 2010]

Steady-State Evoked Potentials

Steady-state evoked potentials (SSEPs) are responses found in EEG to stimuli which are amplitude-modulated at a particular frequency. SSEPs provide a “frequency-tagging” method of tracing brain responses to the modulated stimuli. The modulated stimuli can be visual ones, in which case EEG signals at the tagged frequency are interpreted in terms of visual processing and the potentials themselves are known as steady-state visual evoked potentials (SSVEPs) [Reagan, 1977, 1989; Srinivasan, 2004, 2006], but they can also be auditory ones (SSAEPs) [Horton *et al*., 2011, 2012] or even somatosensory ones (SSSEPs) [*e.g.,* Zhang, 2007]. SSEPs have amplitudes which are sensitive to whether a subject is paying attention to the modulated stimuli, so that considerable information can be learned about attentional mechanisms [*e.g.*, Horton *et al.*, 2011, 2012] in addition to sensory ones. Finally, SSEPs reflect nonlinear stimulus processing as revealed through significant EEG responses often found at harmonics of the fundamental modulation frequency [Reagan, 1977, 1989]. Frequency-tagging using SSEPs has been used in a variety of ways to track visual and auditory processing, including studies of the effects of varying stimulus position in visual space [Morgan, 1996; Muller *et al*., 1998, 2003] and the effects of binocular rivalry [Tononi *et al*., 1998; Srinivasan *et al.*, 1999; Ding *et al*., 2006].

The vast majority of BCIs which use SSEPs use visual stimuli. SSVEPs provide information about the electrophysiological mechanisms underlying visual information processing. Visual stimuli must be modulated for these to be evoked; static visual stimuli do not appear to affect any significant alterations in the EEG [Sutter, 1992]. Although SSVEPs are found using visual stimulus flicker frequencies that vary over a wide range (see Fig. 10 below)[Herrmann, 2001], the strongest SSVEPs are generated by visual stimuli modulated at a rate in the range 8-25Hz [Reagan, 1989; Morgan, 1996].

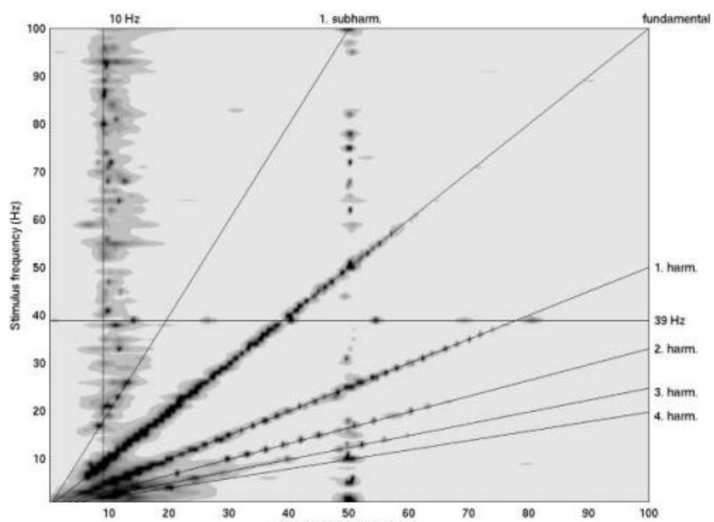

Figure 10. SSVEP response curve - stimulus frequencies vs EEG response frequencies. EEG is modulated at the fundamental flicker frequency and up to 4 harmonics. From [Herrmann, 2001].

SSVEP BCI Implementations

SSVEPs are robust responses in EEG to amplitude-modulated visual stimuli and so are ideally suited for use in BCIs. Their ease of use and minimal training requirements have led to successful implementations with dry-sensor systems [Luo, 2010]. SSVEP-based BCIs are often similar to P300-based BCIs insofar as the subject selects among some discrete set of possibilities (*e.g.*, a set of buttons). Each member of the set of possibilities (*e.g.*, a particular button) is flickered at its own identifying frequency. Subjects attend the desired item for some period of time, and the result is that the SSVEP evoked by the desired item, at the identifying frequency, is increased relative to the SSVEPs evoked by the unattended items.

SSVEP-based BCIs have been used for a variety of purposes. The majority of successful SSVEP implementations for BCI communication use flickering targets distributed across the screen. In much of this work, flashing checkerboard patterns are used as target stimuli since they provide maximal contrast when flickered [Reagan, 1989]. Many SSVEP-based BCIs use checkerboards as ways for the user to select either a particular location on the display screen or to select a direction of movement. Four examples of this design are shown in Figs. 11, 12, 13, and 14, respectively. Successful implementations include the control of avatars in interactive virtual worlds (Figs. 11, 12) [Mehta, 2010; Lalor, 2005], the control of telephone dialing [Cheng, 2002], the control of racecar travel direction on a virtual track (Fig. 13) [Martinez, 2007], and an SSVEP-based speller (Fig. 14) [Volosyak, 2011; Friman, 2007].

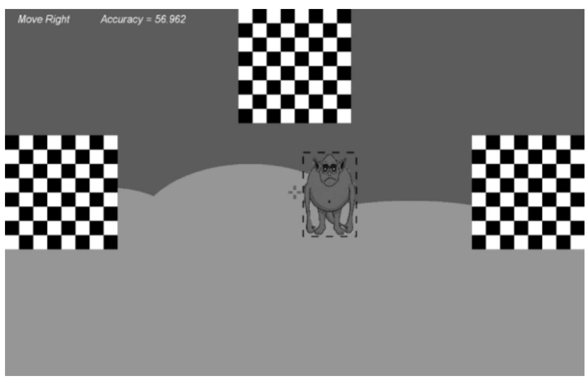

Figure 11 - Representation of the visual interface for an interactive virtual environment. Subjects attend one of the flickering checkerboards to control avatar movement through the environment. Three checkerboards reverse square contrast (black/white) at 15, 12, and 20 Hz, from left to right, respectively. From [Mehta, 2010].

Figure 11- SSVEP control of a virtual avatar. Subjects attend one of the checkerboards to balance a virtual avatar on a pedestal. From [Lalor, 2005]

Figure 12- SSVEP racing game. Subjects attend one of the flickering checkerboards to direct a racecar through a virtual track. From [Martinez, 2007]

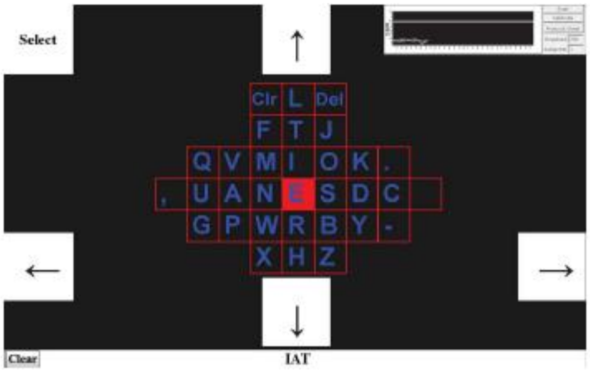

Figure 13 - SSVEP speller. Subjects attend to flickering arrows to select symbols from a letter matrix. Selections are made by attending the flickering 'select' target. From [Volosyak, 2011]

Event-Related Desynchronization (ERD) / Synchronization (ERS)

The third major means of BCI control at present - the ERD/ERS scheme - is naturally suited for controlling direction. Subjects control two-dimensional movement (*e.g.*, a computer cursor) by imagining movement (*e.g.*, the left or the right side of the body). Such BCIs require extensive training. The result of performing certain imagined and real movements is activity modulation among cortical motor and sensorimotor neurons in the hemisphere contralateral to the side on which the movement takes place (see Fig. 15) [Pfurtscheller et al, 1999]. Contralateral EEG mu (9-12 Hz) and beta (12-30 Hz) band signals are *attenuated* during movements both real and imagined [Sterman, 1999]. This attenuation is attributed to the desynchronization of neuronal activity. At movement offset, beta-band signals over motor/sensorimotor regions quickly return to normal levels and exhibit fast and short-lasting bursts ("pops"), while mu-band signals recover more slowly [Neuper *et al*., 2001]. These post-movement increases in signal strength are thought to represent a resynchronization of neuronal activity. In particular, post-movement beta-band "pops" represent a resynchronization of motor cortical neurons which were active during motor preparation [Pfurtscheller *et al.,* 1996]. Spectral power of the post-movement beta ERS has been shown to vary within the beta band for different types of imagined movements and recording locations [Neuper *et al.*, 1996].

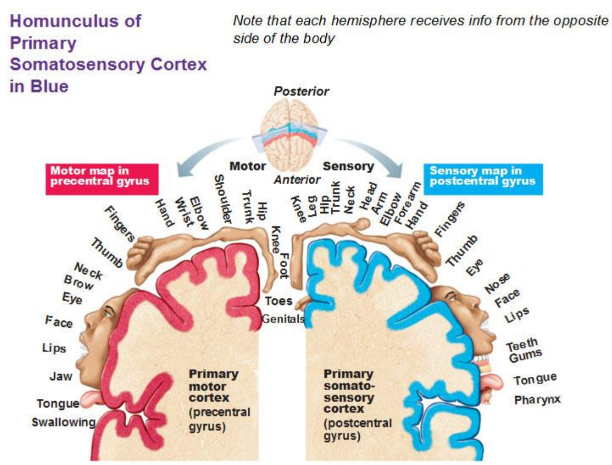

Figure 14. The motor (left) and somatosensory (right) homunculi, which show the areas of cortex devoted to moving or sensing different parts of the body. From Antranik [2009].

ERD/ERS-based BCIs have been developed which provide control of one, two, or three dimensions of cursor movement. Yet these BCIs do *not* work out of the box [Tan, 2011]. Subjects and algorithms must be trained extensively (4-8 hours) with trial-by-trial feedback provided to optimize subject and recognition algorithm performance [Wolpaw *et al*., 2004, 2010]. Training methods are used which let both the subject and the algorithm adapt to one another during the training period, so that the joint system achieves optimal performance through *co-adaptation* made possible through feedback [*e.g.* Sanchez, 2009; Wolpaw, 1998]. Others continue to investigate the factors which contribute to the ERD control signal. For example, Yuan and colleagues [2008] showed that there is a correlation between the speed of imagined hand clenching and power in mu and beta bands.

ERD applications

As stated above, the primary application for ERD/ERS in BCI work has been to the control of cursor position. Through extensive training involving feedback, subjects can learn to control cursor movement in one, two, or three dimensions [Wolpaw, 2002; Wolpaw, 2010]. The training for 2D cursor control depends on earlier training developed for 1D control, while the training for 3D cursor control depends on earlier training for 2D control.

The details of training are as follows. In each trial, subjects face a blank screen with a target location and a cursor. Subjects are asked to move the cursor to the target within the allotted time (seven seconds). Feedback is provided through periodic (every 50 ms) updates of cursor position that are determined through analysis of the preceding 400 ms of EEG. Using this real-time feedback, subjects learn to modulate their ERD/ERS for maximum signal transfer, while the computer's learning algorithm is optimized concurrently. Training starts by having the subject acquire control in a single dimension of movement, for horizontal, vertical, and depth-axis dimensions. Subjects then train for a prescribed number of trials for movement in each plane possible by combining two dimensions. They then train in all three dimensions until sessions no longer improve performance. The overall training period ranges from three-eight hours across subjects.

After training, scalp maps which relate EEG spectral power to scalp position are consistent with the notion that subjects control cursor movement through imagined motor movements (see Fig. 16).

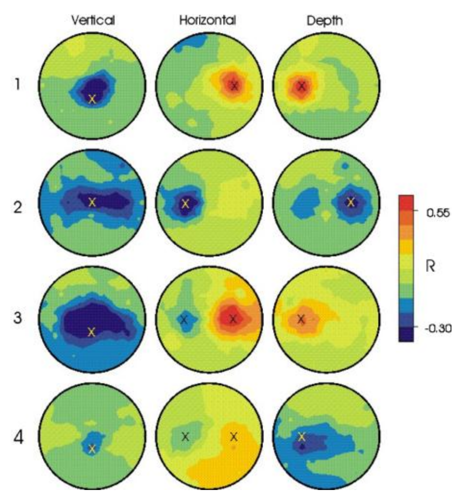

Figure 15. Topographies for all 4 subjects in the 3D ERD control scheme. Scalp maps show correlations between spectral EEG power and each dimension's online control signal. X's indicate locations of electrodes chosen for online classification. From Wolpaw [2010].

Trials are labeled successful if the subject reaches the intended target in less than seven seconds. With training, Wolpaw and colleagues [2010] found that subjects gained two- and three-dimensional control with 90% success or higher on single trials. Subjects reported verbally that as training continued, they seemed be able to elicit control in a fashion more natural than imagining hand and foot movements [Wolpaw, 2010]. Yet much of the success of Wolpaw and colleagues with this cursor-control work is likely due to subjects having received extensive training, which extended to *hundreds of hours* for some subjects [Wolpaw, 2010].

Although the ERD/ERS is well-suited for cursor movement control, other uses have become apparent. For example, it is possible for a P300-like BCI to use instead ERD signals generated by either imagined or real movements. As shown in Fig. 17, one among a set of displayed items is highlighted at any one time; the highlighting moves from one item to the next. When the item which is targeted by the subject is highlighted, the subject signals this by imagining movement and so generating an ERD. In this way it is possible for a subject to choose a target item from among a discrete set of items [Friedrich, 2008].

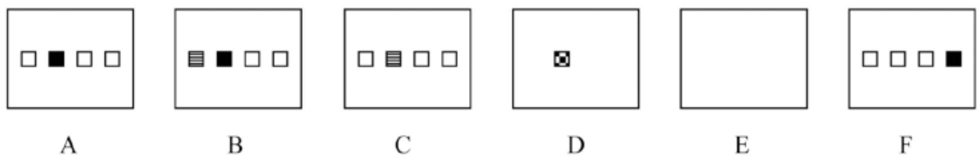

Figure 16. The scanning protocol for a discrete-selection BCI based on ERD/ERS., showing the steps to a successful selection. (A) shows the four choices presented on the screen. One is marked as the current item by highlighting it in red. (B) The scan starts at the left edge of the screen and successively highlights every choice in yellow for 2.5 s each. (C) When the target choice is highlighted, the user can make a selection. (D) If the selection is correct as shown here, the target changes color for 1 s while the other boxes disappear. (E) Trial repeats. From Friedrich [2008].

BCI Application Areas of the Future

BCI researchers have recently explored the use of BCIs for *subject monitoring* [Tan *et al.*, 2011; Blankertz *et al.*, 2010]. In this approach, the BCI is used to collect measurements of background mental states while subjects are engaged in external tasks. The measurements may then be used to optimize the interaction between the subject and the external task.

One application area for subject monitoring BCIs of great importance is *affective computing*. Affective neuroscience research has shown that EEG may be used to discriminate among affective states [Petrantonakis et al., 2010; Davidson, 1992; Müller, 1999; Keil, 2001; Aftanas, 2004; Bos, 2006; Liu, 2011]. For example, the “Affective Pacman” game was designed to induce frustration in subjects. Researchers found that EEG measured during gameplay can be used to discriminate among player affective states [Ruederink, 2009]. A full subject monitoring BCI is but one step away: use the measurements of affective state to alter gameplay.

The Emotiv company produces EEG headsets and software which uses EEG and EMG measures to provide developers with affective, cognitive and (facial) expressive indices for human-computer interaction[Le et al., 2007]. The goal of work like this is to automate recognition of human affect [Picard, 2007]. Certain kinds of affect recognition have been achieved using means other than EEG. For example, facial recognition work in computer vision has succeeded in classifying affect from images of faces [e.g., Zeng,2007]. Yet in absence of overt behavior, user mental state estimation and task optimization may benefit from an EEG-based subject monitoring BCI. Direct BCI implementations may also be optimized based on the users affect [Schoonover, 2011].

Finally, it may be beneficial to model a task to aid subjects achieve a state of *flow*. Positive Psychology describes flow as the intersection of skill and challenge (see figure 19 below), and that people experiencing flow tend to be more relaxed and focused [Csikszentmihayli,1990].

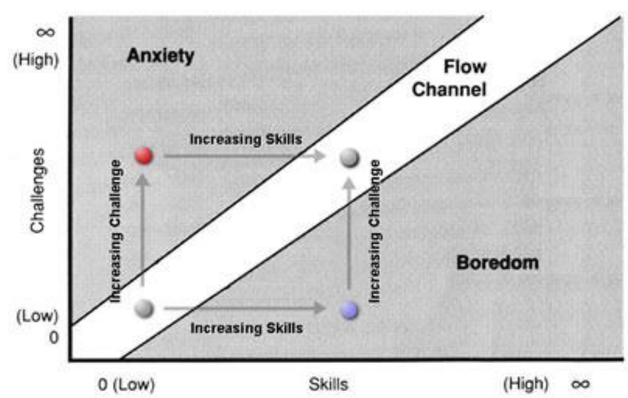

Figure 18 - State of flow. Flow occurs at the boundary between boredom and anxiety, or when the challenges offered by a task are well matched to the subject's skill set [Csikszentmihalyi , 1990].

For example, [Hamilton et. al, 1984] showed significant differences in the visual evoked potentials of subjects who experienced flow more often than those who rarely experienced it. For subjects who did not frequently experience flow, visual evoked potentials raised significantly above baseline in a visual counting task. However for subjects who did experience flow, evoked potentials decreased compared to baseline; indicating that investment of attention seemed to decrease mental effort. Separate behavioral measures of attention confirmed that the group was also more accurate in a sustained attentional task. Educational settings may benefit from applied neuroimaging and knowledge of flow states[Vogel-Walcutt, 2012].

Other areas which may provide alternative HCI channels through the BCI include human information and workload processing [Kohlmorgen, 2010; Berka, 2007], emotion measures in music listening [Lin et al., 2010 ; Blankertz, 2010], subject identification[Brigham, 2010] each may contribute to more widespread BCI adoption.

The Hybrid BCI

It is likely that multiple commercial BCI applications will provide viable contributions to the adoption and acceptance of personal BCIs. Thus it behooves one to consider interface configurations using multiple interaction methods. Such Hybrid BCIs use multiple interaction schemes *concurrently* to improve human-computer interaction [Pfurtscheller, 2010]. There are many classes of hybrid BCIs. As shown in Fig. 19, control schemes may be arranged either sequentially or in parallel. Such configurations create unique opportunities for interaction than provided each interaction method alone. Some hybrid BCIs use only BCI components [Allison, 2010]. In one pure hybrid BCI experiment, subjects performed a binary selection task using both the ERD and SSVEP methods (see figure 19C). When using both ERD and SSVEP paradigms concurrently, single trial performance significantly exceeded that found using each method alone [Allison, 2010]. It was proposed recently to use the P300 and ERD schemes in combination to provide both cursor control as well as a secondary communication channel [Schoonover, 2011].

Other hybrid BCIs may use BCIs in combination with other user-interface methods (*e.g.*, eye-tracking, see figure 19G) [Vilimek, 2009]. In one experiment, an eye gaze interface was employed with an ERD BCI replacing the common dwell-time selection mechanism. Subjects performed a search-and-select task and their performance was compared in the hybrid BCI and dwell time conditions. The Hybrid BCI provided faster and more accurate control than short (1 ms) dwell times.

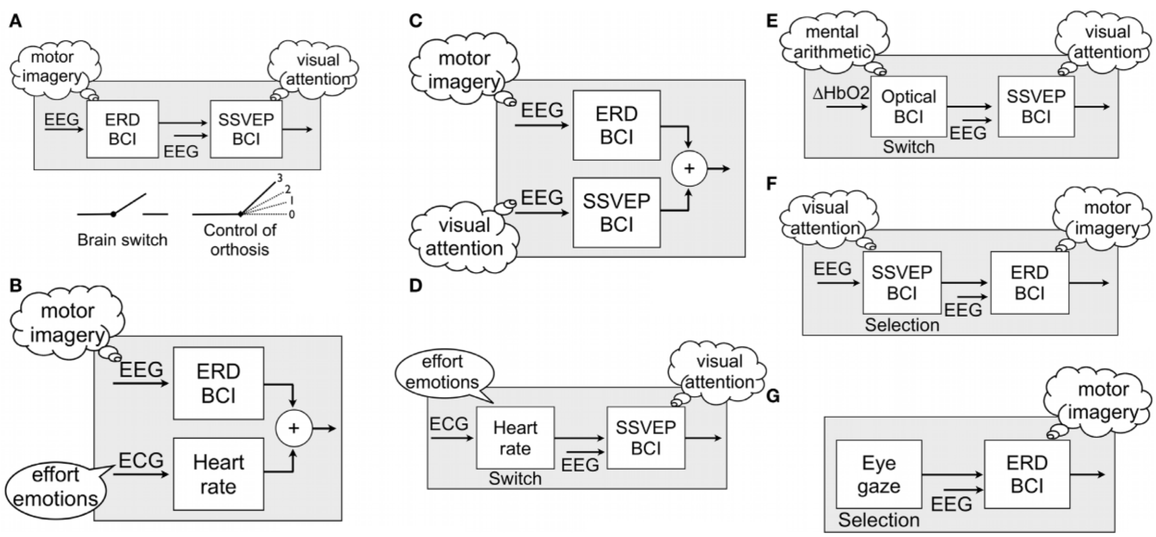

Figure 17 - Examples of Hybrid BCIs with sequential (A,D–G) and simultaneous (B,C) interfaces [Pfurtscheller, 2010]. Certain sequential configurations (A,D,E) may alleviate the Midas touch problem in BCIs by using one interaction method as a "brain switch" to activate and deactivate the alternate scheme. Simultaneous interface combinations (B,C) may be used to improve the accuracy of the joint configuration compared to that of the individual methods. Examples of pure hybrid BCIs (A,C,E,F) and HCI/BCI hybrids (B,D,G) are illustrated. Figure was taken from [Pfurtscheller, 2010].

Hybrid BCIs are a worthwhile approach towards non-communication-and-control BCIs as well. The Emotiv Epoc commercial EEG/EMG headset offers a suite of affective indices measured concurrently – allowing developers to adapt applications to user's varying mental states[Le et al. 2007].

Conclusion

BCIs are likely to expand in application as computational EEG theory [Srinivasan, 1999] leads to higher SNR measurements and as EEG recording becomes more convenient [Luo et al, 2010; Shambroom, 2011]. Communication and control BCIs are already preferred by patient groups who require computer-assisted communication but who would like to avoid invasive techniques. As new communication paradigms are discovered and existing methods mature, BCIs for communication and control may become useful to healthy subjects as well, either on their own or as an additional HCI channel. Alternatively, background mental state assessment by subject monitoring BCIs may generate further applications. As more uses for EEG are explored, new hybrid configurations will become possible. In sum, one can expect BCIs to grow more and more common as components in human-computer interfaces.

Appendix - BCI Optimization

"All BCIs are not created equal"

Since the field has gained popularity with researchers of various technical backgrounds, standards have been developed by which to compare different BCI implementations. To evaluate the performance of different BCIs the speed and accuracy of information transfer may be compared (called information transfer rate or ITR) [Schlogl, 2007]. All things equal, the optimal system is that with the highest ITR. The ITR of a BCI system is a function of two performance characteristics –classification accuracy and communication speed. Typically for communication and control BCIs, as communication speed increases, accuracy is attenuated; this tradeoff must be optimized for a maximum ITR. To find the optimal point in this tradeoff, we may model the BCI as a noisy communication channel and describe the channel behavior probabilistically.

Information theory provides descriptors which describe the characteristics of information. For example, the self-information of a random variable - the amount of information contained in the outcome of an observed event - is defined as a function of how probable that event was. Modeling the outcome of a BCI trial as a discrete random variable X with M possible outcomes denoted { x_1, $x_2..x_M$ }and the probability of each outcome denoted {p_1, $p_2..p_M$} the self-information contained in observing outcome *i* is

$$I(x_i) = \log\left(\frac{1}{p_i}\right)$$

It is easy to see that the maximum-information outcome of an arbitrary random variable has the lowest associated outcome probability. Random variables may exhibit different behaviors with respect to the notion information quantification. The entropy is a measure of a random variable which describes the uncertainty associated with observing its outcome. Shannon produced three criteria [Shannon, 1948] which should embody Entropy*:*

1) It should be maximal when $P_x(x)$ is a *uniform random variable*, and in this case it should increase with the number of possible values *x* might take.

2) It should remain the same if we *reorder* the probabilities assigned to different values of *x*

3) The uncertainty about two independent random variables should equal the sum of the uncertainties of each of them.

The equation which satisfied all three, now call Shannon's entropy, is simply the expectation of self-information over all probabilities. This measure describes the random variable solely in terms of its uncertainty.

$$H(X) = E\big(I(X)\big) = \sum_{i=1}^{n} p(x_i)I(x_i)$$

Entropy for discrete random variables

However, BCI designers have access to more than just the BCI output – during training, the intended (true) class labels are known. This knowledge may be employed to model the BCI classifier input / output relationship probabilistically. The mutual information of two random variables is a measure of their dependence. To optimize the speed-accuracy tradeoff and to calculate the ITR of a BCI system, the amount of mutual information [Cover, 1991], *I(X;Y)* between the true labels and predicted labels must be maximized [Wolpaw, 2002]. The mutual information may be conveniently expressed as

$$I(X,Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) log(\frac{p(x,y)}{p(x)p(y)})$$

The ITR is a very important BCI descriptor – maximizing this function leads to BCI implementations with maximum channel throughput. Measuring BCI performance as a function of ITR alone helps to optimize performance of a given BCI implementation, *though it does not directly assess the functional optimization of the implementation*.

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