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REVIEW

Optimizing the P300-based brain–computer interface: current status, limitations and future directions

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Abstract
This paper summarizes the presentations and discussions at a workshop held during the Fourth International BCI Meeting charged with reviewing and evaluating the current state, limitations and future development of P300-based brain–computer interface (P300-BCI) systems. We reviewed such issues as potential users, recording methods, stimulus presentation paradigms, feature extraction and classification algorithms, and applications. A summary of the discussions and the panel's recommendations for each of these aspects are presented.

Introduction

Described by Farwell and Donchin (1988), the P300-BCI is an EEG-based BCI system that relies on a brain response known as the P300 to allow individuals to communicate without utilizing voluntary muscle activity. The P300, whose attributes have been studied for four decades, is elicited by rare, task-relevant events and is often recorded in what has come to be called the 'oddball' paradigm (Donchin 1981). The oddball paradigm requires applying a classification rule to a random sequence of events so that each event belongs to one of two categories, one of which is presented infrequently. The participant is required to perform a task that cannot be accomplished without categorizing the events. The P300-BCI presents the participant with random intensifications of either a row or a column in a matrix. Each cell of the matrix contains a character or a symbol. The participant focuses attention on the cell containing a character to be communicated. The BCI system identifies the row and the column that elicited a P300, and in this way the chosen character is identified (i.e. the intersection of the row/column targets). Note that successful use of the system does not require any training of the user. Rare events in an oddball sequence elicit a P300 in just about every subject (Fabiani *et al* 1987). However, as is true for all event-related potentials (ERPs), P300 signals are subject-specific and vary even between recording sessions of the same subject. Therefore, to allow optimal and stable use, calibration of spatiotemporal filters and classifiers is required to adapt the P300-BCI to the individual brain signature of each user.

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Table 1. P300-BCI research in the disabled community 2006–10.

P300-BCI studies	Subjects	Diagnosis	Disability level	Stimuli	Online results (for N subjects)	Chance level	Task
Sellers and Donchin 2006	$N = 3$	ALS	Moderate	Visual Auditory Visual + Auditory	69% ($N = 3$) 61% ($N = 3$) 65% ($N = 3$)	25%	Word selection
Sellers *et al* 2006	$N = 16$	ALS, stroke	Moderate to severe	Visual	>75% ($N = 9$)	3%	Character selection
Piccone 2006	$N = 5$	ALS, stroke, spinal cord injury, Guillain Barre, multiple sclerosis	Moderate to severe	Visual	69% ($N = 5$)	25%	Virtual object movement
Hoffmann *et al* 2008	$N = 5$	Cerebral palsy, multiple sclerosis, ALS, traumatic brain injury, post-anoxic encephalopathy	Moderate to severe	Visual	100%, ($N = 4$)	17%	Image selection
Kübler and Birbaumer 2008	$N = 11$	ALS	Moderate to severe	Visual	66% ($N = 11$)	3%	Character selection
Nijboer *et al* 2008	$N = 6$	ALS	Moderate to severe	Visual	62% ($N = 4$).	2%	Character selection
Kübler *et al* 2009	$N = 4$	ALS	Severe	Auditory	13% ($N = 4$)	4%	Character selection
Silvoni *et al* 2009	$N = 21$	ALS	Mild	Visual	78% ($N = 21$)	25%	Cursor movement
Sellers *et al* 2010, at press	$N = 1$	ALS	Severe	Visual	>80% ($N = 1$)	1.3%	Character selection
Townsend *et al* 2010	$N = 3$	ALS	Severe	Visual	86% ($N = 3$)	1.3%	Character selection

In general, members of the panel agreed that an optimal P300-BCI should be simple to operate, affordable, accurate, and efficient for communication on a daily basis. In such a case, we need to make a balance between technological advancement and practical use in a real-world situation. In the following paragraphs we will present the major challenges of current P300-BCIs and the panel's recommendations for practical solutions.

Users

The goal of BCI research for the past three decades has been to create a brain-controlled communication device for individuals who have lost all voluntary muscle control but are cognitively intact (locked-in). P300-BCI-related publications have been dominated by results from young healthy adults while reports from users with disabilities are limited (Sellers and Donchin 2006, Piccione *et al* 2006, Kubler and Birbaumer 2008, Nijboer *et al* 2008, Silvoni *et al* 2009, Sellers *et al* 2006b, 2010, Hoffmann *et al* 2008, Kubler *et al* 2009, Townsend *et al* 2010). Table 1 presents a summary of publications in which different P300-BCI paradigms were used by small groups of patients with various levels of disabilities resulting in a wide range of accuracy. The variability in the classification accuracy may be due to diversity in experimental designs, subject characteristics, or stimulation paradigms and tasks. Current methods of optimizing BCI systems to account for individual differences, again, rely on data from a population dissimilar to the potential users. The members of the panel suggested that further investigation should be done to examine whether knowledge acquired from healthy subjects could be generalized to patients with different pathologies.

Most P300-BCI studies among the disabled community have evaluated subjects diagnosed with amyotrophic lateral sclerosis (ALS). Successful use of a P300-BCI for communication over a two year period has been documented in one individual severely disabled with ALS (Sellers *et al* 2010), while another study indicated that some individuals with ALS might be unable to use the P300-BCI due to challenges related to disease progression (McCane *et al* 2009). Loss of ocular motor function in late-stage ALS and vent-dependent patients (Pinto and de Carvalho 2008, Mizutani *et al* 1990) suggests a possible link between impaired vision and below chance level of classification in these subjects. Although some attempts to test auditory paradigms have been initiated (Kubler *et al* 2009), more research is needed to determine if an auditory presentation would provide a reliable form of communication for locked-in individuals with no eye movement.

The group recognized that the BCI community has traditionally selected subjects based on the BCI system capabilities and this approach may only benefit a very limited population. Conversely, augmentative and alternative communication (AAC) professionals select devices based on an individual's physical capabilities, cognitive abilities, and the needs of the user and caregiver. Improvements in system performance, together with a reduction in complexity (software operation and electrode application), and also the need for ongoing technical support and training could accelerate the use of the P300-BCI in a broader range of disabled users.

Recording methods

Most of the current scalp EEG collection methods allow efficient recordings, but require proper electrode application (i.e. skin preparation, application of conductive gel, and correct positioning of electrodes, etc). This could be a challenge to caregivers and might cause discomfort to long-term BCI users. The development of more user-friendly dry electrodes (Taheri *et al* 1994, Fonseca *et al* 2007, Popescu *et al* 2007, Gargiulo *et al* 2010) offers a more convenient way for recording brain signals and may enhance the usability of the P300-BCI system, as long as signal quality is comparable (Searle and Kirkup 2000) with that of standard EEG wet electrodes. Other than dry electrodes, efforts have been made by researchers to develop tripolar concentric electrodes with enhanced recording capability via advanced engineering techniques (Koka and Besio 2007). Reported superiority of the tripolar concentric electrode over the standard disc electrode in capturing imagined motor activity (Besio *et al* 2008) and source separation (Cao *et al* 2009) calls for the examination of its performance in the P300 and other ERP-based BCI systems.

The performance of the P300-BCI depends on the quality and amount of information acquired from the scalp surface of the user. Previous exploratory work by Krusienski and colleagues (2008) has identified an optimal subset of electrode sites that could provide reliable and satisfactory classification by a P300-BCI. The suggested 8-channel electrode set (Fz, Cz, P3, Pz, P4, PO7, PO8, Oz) requires less preparation time than the traditional 10–20 sets, and therefore appears to be more practical for long-term home-use of a P300-BCI (Vaughan *et al* 2006). However, it is possible that a different montage would be required for patients with various neuromuscular pathologies. The recommendation by the members of the panel is to start with a full set of electrodes according to the 10–20 system (covering all areas of head), and then develop an individualized montage by drastically reducing the number of required EEG channels while keeping the classification rate optimal. Further discussion on the relationship between number of EEG channels utilized and classification performance will be addressed in the *Feature extraction and classification algorithms* section.

Stimulus presentation paradigm

The P300-BCI system relies on an oddball paradigm to elicit the P300. To date, there are three main visual paradigms for the P300-BCI: The original, and most commonly used, is the row/column paradigm (RC) (Donchin *et al* 2000, Farwell and Donchin 1988), where the rows and columns of a visual matrix are flashed in a random order while the user attends to his/her desired selection within the matrix. Another paradigm, the single cell paradigm (SC), simply flashes each element of the matrix individually instead of within a row or column. The SC paradigm elicits a larger P300 (Guan *et al* 2004), but accuracy and speed of communication are reported to be lower than that of RC (Guger *et al* 2009). In the checkerboard paradigm (CB) (Townsend *et al* 2010), groups of matrix elements are flashed in a quasi-random pattern that controls for directly adjacent flashes and double flashes (i.e. two consecutive flashes of one single element within the matrix). A recent study with the CB paradigm reported a better classification performance when compared with the RC presentation (Townsend *et al* 2010). In addition to the type of visual presentation, other parameters have been shown to influence performance, e.g. flash rate (McFarland *et al* (at press)), matrix size (Sellers *et al* 2006a), inter-stimulus interval (Sellers *et al* 2006a), and stimulus intensity (Ma and Gao 2008).

The P300 is not modality specific and can also be elicited by auditory or tactile stimuli (Donchin 1981), although the visual paradigm is the primary choice for most P300-BCI systems as it allows the presentation of multiple stimuli simultaneously. However, for severely disabled individuals who have impaired vision, a non-visual P300-BCI might be of benefit. Recent work by Furdea and colleagues (Furdea *et al* 2009) demonstrated the feasibility of BCI communication based on the auditory evoked responses user performance was relatively low when compared to visual P300-BCIs. In another study, a multi-class auditory P300-BCI based on spatially distributed auditory cues was presented (Schreuder *et al* 2010). This paradigm was able to generate high accuracy results by adding spatial information to the cue. However, the information transfer rate was still low when compared to the visual P300-BCI. Another attempt to develop a P300-BCI that is independent of vision used a tactile paradigm that has two to six vibratactile stimuli around the waist of subjects (Brouwer and van Erp 2010). This paradigm resulted in 58% accuracy for six possible selections and 73% for a binary selection, again lower than the P300 visual paradigms.

As comparative data on P300-BCI visual paradigms are limited; the panel advises further systematic comparisons of CB, SC and RC, and other novel paradigms (Treder and Blankertz 2010) be conducted in the future. Also, it is possible to find a set of stimulation parameters that work best for one paradigm may not generalize to the other visual paradigms. The current recommendation of the panel is to allow the selection of a specific visual paradigm and base parameters based on user preference and performance. Development of non-visual P300-BCIs are promising, but currently still in their infancy. Continuous effort should be made to explore non-visual paradigms for the P300-BCI, and testify their use in patients with various levels of disabilities.

Feature extraction and classification algorithms

One major challenge in optimizing the performance of the P300-BCI is enhancing the real-time detection of the ERP elicited by the chosen stimuli. The process of real-time detection consists of extraction of ERP features which best represent the user's intentions and classification of the extracted features into an appropriate output by the selected algorithm.

Due to the high inter-trial variability and unfavorable signal-to-noise ratio (SNR), ensemble averaging is commonly performed to detect a reliable P300 or other task-related potentials. The need for signal averaging results in a tradeoff between speed and accuracy of communication. To improve the information transfer rate, research has focused on minimizing the amount of signal averaging required for reliable detection of P300, moving toward the goal of single-trial ERP detection. Single-trial ERP detection is known to be challenging, as P300 potentials and/or other task-related signal components are buried in a large amount of noise (ongoing task-unrelated neural activities and artifacts). The essential goal is to improve the SNR significantly, i.e. to separate the task-related signal from the noise content. Artifact removal is an important step before the extraction of task informative features, i.e. the P300. Different methods have been proposed to remove common sources of artifacts in raw EEG signals such as eye movement (Mennes *et al* 2010), eye blink (Li *et al* 2006), muscle contraction (Gao *et al* 2010) and body movement (Gwin *et al* 2010). Feature extraction plays a key role in P300-BCI system operation. Instead of modeling the entire ERP waveform, different spatial and temporal filtering methods have been proposed by researchers to *extract* the most representative ERP features, components, or patterns that could best represent the user's intent. These includes methods based on orthogonal linear transformation (Dien *et al* 2003), blind source separation (Xu *et al* 2004, Li *et al* 2009a, Li *et al* 2009b), wavelet transform (Quian Quiroga and Garcia 2003, Bostanov and Kotchoubey 2006) and other advanced techniques (Rivet *et al* 2009). These advanced feature extractors reduce the dimension of the feature space and capture the most distinctive information in a single-trial ERP for subsequent binary classification.

Reliable P300-BCI operation requires accurate classification of features extracted from the EEG signal. Numerous studies have attempted to enhance the classification algorithm by linear methods (Bostanov 2004, Krusienski *et al* 2006), nonlinear methods (Krusienski *et al* 2006, Kaper *et al* 2004), neural network (Cecotti and Graser (at press)), and a combination of classifiers (Rakotomamonjy and Guigue 2008). While debate continues about the best classification method for a P300-BCI system, most current BCI designs pair up highly complex feature extractors with a relatively simple linear classifier (Farquhar 2009). This arrangement is probably due to the preference for simplicity and the belief that linear classification would be sufficient after a decent feature extraction process (Muller *et al* 2003). For a practical P300-BCI with only eight channels, stepwise linear discriminant analysis (SWLDA) has been shown to provide the best overall performance over other classification methods (Krusienski *et al* 2006). Thus, it has been widely used in the P300-BCI community. However, in the context of single-trial ERP classification, more channels will be required to provide sufficient information for a either an efficient feature extraction or a competitive classification (Blankertz *et al* (at press)). To achieve high classification accuracy with high dimensional spatiotemporal features, regularization techniques for classifier have been proposed (Blankertz *et al* (at press), Farquhar 2009, Tomioka and Muller 2010) to avoid the degradation of performance due to small sample-to-feature ratios. A recent report by Blantertz *et al* (at press) compared the performance between SWLDA and a regularized LDA using the shrinkage technique. Their results showed a superior performance of shrinkage LDA over SWLDA when the number of training samples is small.

The panel recommends that data preprocessing, feature extraction and classification should not be regarded as isolated processes. Too often researchers have tackled each of these tasks separately while ignoring the inter-relationship between them. Recent evidence suggested that these tasks are not independent of each other and a unified discriminative approach might provide a better overall performance (Mirghasemi *et al* 2006, Farquhar 2009, Tomioka and Muller 2010). Moreover, for successful implementation of the practical home system, the panel suggests a systematic examination of current advanced feature extraction and classification methods under the framework of an ergonomic BCI with minimal system complexity and a practical number of recording channels (i.e. limited information).

Applications

BCI for languages with logographic writing system

Most BCI systems for assistive communication have focused on spelling languages having an alphabetic writing system, such as English and German. This approach can be easily adapted for languages with other types of segmental writing systems, e.g., Arabic, Devanagari, or a syllabary, e.g., Japanese *kana*. However, languages with a logographic writing system, such as Chinese, pose significant challenges to P300-BCI systems since only a handful of the thousands of distinct logograms in the writing system can be presented to the user at any moment. While some progress has been made in developing a P300 speller for Chinese (Jin *et al* 2010, Minett *et al* 2010), further development is required to make P300-BCIs accessible to individuals whose language has a logographic writing system.

BCI as a switch and as an environmental control

Since the P300-BCI can use matrix entries with symbolic meaning, the output can be used for many tasks. Although communication may be foremost among these, environmental control can provide additional quality of life benefits and can be used in parallel with communication. The output can be directed to assistive technology (AT) software such as word prediction, standalone AT devices, or other environmental control platforms. For several of these applications, software interfaces may be defined that will perform adequately. Other applications, such as interfacing with standalone AT devices or environmental control devices designed for switch inputs, may require a hardware interface which ideally would utilize standard protocols and connections to provide easy setup

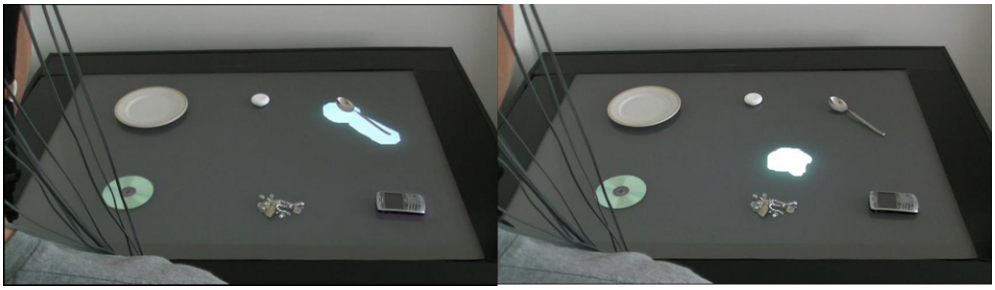

Figure 1. A participant using the P300-based BCI with real-world objects on a multi-touch surface. Left: the spoon is being flashed by surrounding the area underneath it with light; Right: a non-object flash.
(This figure is in colour only in the electronic version)

without customization. In a commercial BCI, such interfaces (e.g. USB) could be built in, but for researchers investigating a particular application, the multi-purpose BCI output device (Thompson *et al* 2009) can be used to provide plug-and-play switch, USB keyboard, and USB mouse outputs.

Novel applications of P300 BCIs

Using physical objects in an oddball paradigm, a P300-BCI system reported by Yuksel *et al* (2010) allows users to directly select their object of interest. Real-world objects were randomly placed on a multi-touch surface, and areas of light were flashed underneath and around the objects (figure 1). The mean accuracy rate of 99% was achieved by 20 participants. This demonstration of a novel application of the P300-BCI hints at a future scenario where physical objects are overlaid with virtual flashes. For example, in a 'smart home', a projector can highlight physical objects. Computer vision techniques can be used to recognize objects from scenes and select target objects for use in the P300 paradigm.

Conclusion

The P300-BCI appears to be the most commonly used BCI system, and the only system for which regular home use by locked-in patients has been reported. Despite its popularity among researchers, it is apparent that many P300-BCI systems must be improved before they can be considered as an alternative communication device for individuals who are in or near a locked-in state. In this paper, the panel has made recommendations in different areas of P300-BCI operation to optimize the speed, accuracy, consistency and convenience of the current system. Further work in all these areas is needed for P300-BCIs to be used more effectively in real-life environments.

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References

Besio W G, Cao H and Zhou P 2008 Application of tripolar concentric electrodes and prefeature selection algorithm for brain–computer interface *IEEE Trans. Neural. Syst. Rehabil. Eng.* **16** 191–4

Blankertz B, Lemm S, Treder M, Haufe S and Muller K R Single-trial analysis and classification of ERP components—a tutorial *Neuroimage* at press

Bostanov V 2004 BCI competition 2003—data sets Ib and IIb: feature extraction from event-related brain potentials with the continuous wavelet transform and the t-value scalogram *IEEE Trans. Biomed. Eng.* **51** 1057–61

Bostanov V and Kotchoubey B 2006 The t-CWT: a new ERP detection and quantification method based on the continuous wavelet transform and Student's t-statistics *Clin. Neurophysiol.* **117** 2627–44

Brouwer A M and van Erp J B 2010 A tactile P300 brain–computer interface *Front. Neurosci.* **4** 19

Cao H, Besio W, Jones S and Medvedev A 2009 Improved separability of dipole sources by tripolar versus conventional disk electrodes: a modeling study using independent component analysis *Conf. Proc. IEEE Eng. Med. Biol. Soc.* **2009** 4023–6

Cecotti H and Graser A Convolutional neural networks for P300 detection with application to brain–computer interfaces *IEEE Trans. Pattern Anal. Mach. Intell.* at press

Dien J, Spencer K M and Donchin E 2003 Localization of the event-related potential novelty response as defined by principal components analysis *Brain Res. Cogn. Brain Res.* **17** 637–50

Donchin E 1981 Presidential address, 1980. Surprise! . . . Surprise? *Psychophysiology* **18** 493–513

Donchin E, Spencer K M and Wijesinghe R 2000 The mental prosthesis: assessing the speed of a P300-based brain–computer interface *IEEE Trans. Rehabil. Eng.* **8** 174–9

Fabiani M, Gratton G, Karis D and Donchin E 1987 The definition, identification, and reliability of measurement of the P300 component of the event-related brain potential *Advances in Psychophysiology* ed P K Ackles, J R Jennings and M G H Coles (New York: JAI) p 2

Farquhar J 2009 A linear feature space for simultaneous learning of spatio-spectral filters in BCI *Neural Netw.* **22** 1278–85

Farwell L A and Donchin E 1988 Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials *Electroencephalogr. Clin. Neurophysiol.* **70** 510–23

Fonseca C, Silva Cunha J P, Martins R E, Ferreira V M, Marques de Sa J P, Barbosa M A and Martins da Silva A 2007 A novel dry active electrode for EEG recording *IEEE Trans. Biomed. Eng.* **54** 162–5

Furdea A, Halder S, Krusienski D J, Bross D, Nijboer F, Birbaumer N and Kubler A 2009 An auditory oddball (P300) spelling system for brain–computer interfaces *Psychophysiology* **46** 617–25

Gao J, Zheng C and Wang P 2010 Online removal of muscle artifact from electroencephalogram signals based on canonical correlation analysis *Clin. EEG Neurosci.* **41** 53–9

Gargiulo G, Calvo R A, Bifulco P, Cesarelli M, Jin C, Mohamed A and van Schaik A 2010 A new EEG recording system for passive dry electrodes *Clin. Neurophysiol.* **121** 686–93

Guan C, Thulasidas M and Wu J 2004 High performance P300 speller for brain–computer interface *2004 IEEE Int. Workshop on Biomedical Circuits and Systems* pp S3/5/INV–S3/13-6

Guger C, Daban S, Sellers E, Holzner C, Krausz G, Carabalona R, Gramatica F and Edlinger G 2009 How many people are able to control a P300-based brain–computer interface (BCI)? *Neurosci. Lett.* **462** 94–8

Gwin J T, Gramann K, Makeig S and Ferris D P 2010 Removal of movement artifact from high-density EEG recorded during walking and running *J. Neurophysiol.* **103** 3526–34

Hoffmann U, Vesin J M, Ebrahimi T and Diserens K 2008 An efficient P300-based brain–computer interface for disabled subjects *J. Neurosci. Methods* **167** 115–25

Jin J, Allison B Z, Brunner C, Wang B, Wang X, Zhang J, Neuper C and Pfurtscheller G 2010 P300 Chinese input system based on Bayesian LDA *Biomed. Tech. (Berl)* **55** 5–18

Kaper M, Meinicke P, Grossekathoefer U, Lingner T and Ritter H 2004 BCI competition 2003—data set IIb: support vector machines for the P300 speller paradigm *IEEE Trans. Biomed. Eng.* **51** 1073–6

Koka K and Besio W G 2007 Improvement of spatial selectivity and decrease of mutual information of tri-polar concentric ring electrodes *J. Neurosci. Methods* **165** 216–22

Krusienski D J, Sellers E W, Cabestaing F, Bayoudh S, McFarland D J, Vaughan T M and Wolpaw J R 2006 A comparison of classification techniques for the P300 speller *J. Neural. Eng.* **3** 299–305

Krusienski D J, Sellers E W, McFarland D J, Vaughan T M and Wolpaw J R 2008 Toward enhanced P300 speller performance *J. Neurosci. Methods* **167** 15–21

Kubler A and Birbaumer N 2008 Brain–computer interfaces and communication in paralysis: extinction of goal directed thinking in completely paralysed patients? *Clin. Neurophysiol.* **119** 2658–66

Kubler A, Furdea A, Halder S, Hammer E M, Nijboer F and Kotchoubey B 2009 A brain–computer interface controlled auditory event-related potential (P300) spelling system for locked-in patients *Ann. NY Acad. Sci.* **1157** 90–100

Li K, Sankar R, Arbel Y and Donchin E 2009a Single trial independent component analysis for P300 BCI system *Conf. Proc. IEEE Eng. Med. Biol. Soc.* **2009** 4035–8

Li R, Keil A and Principe J C 2009b Single-trial P300 estimation with a spatiotemporal filtering method *J. Neurosci. Methods* **177** 488–96

Li Y, Ma Z and Lu W 2006 Automatic removal of the eye blink artifact from EEG using an ICA-based template matching approach *Physiol. Meas.* **27** 425–36

Ma Z W and Gao S K 2008 P300-based brain–computer interface: effect of stimulus intensity on performance *J. Tsinghua Univ.(Sci. Technol.)* **48** 415–8

McCane L M, Vaughan T M, McFarland D J, Zeitlin D, Tenteromano L, Mak J N, Sellers E W, Townsend G, Carmak C S and Wolpaw J R 2009 Evaluation of individuals with ALS for in home use of a P300 brain computer interface. Program No. 664.7 *Society of Neuroscience Annu. Meeting (Chicago, IL)*

McFarland D J, Sarnacki W A, Townsend G, Vaughan T M and Wolpaw J R The P300-based brain–computer interface (BCI): Effects of stimulus rate *Clin. Neurophysiol.* at press

Mennes M, Wouters H, Vanrumste B, Lagae L and Stiers P 2010 Validation of ICA as a tool to remove eye movement artifacts from EEG/ERP *Psychophysiology* **47** 1142–50

Minett J W, Gang P, Lin Z, Hong-Ying Z and Wang W S Y 2010 An assistive communication brain–computer interface for Chinese text input *4th Int. Conf. on Bioinformatics and Biomedical Engineering (iCBBE)* pp 1–4

Mirghasemi H, Shamsollahi M B and Fazel-Rezai R 2006 Assessment of preprocessing on classifiers used in the P300 speller paradigm *Conf. Proc. IEEE Eng. Med. Biol. Soc.* **1** 1319–22

Mizutani T, Aki M, Shiozawa R, Unakami M, Nozawa T, Yajima K, Tanabe H and Hara M 1990 Development of ophthalmoplegia in amyotrophic lateral sclerosis during long-term use of respirators *J. Neurol. Sci.* **99** 311–9

Muller K R, Anderson C W and Birch G E 2003 Linear and nonlinear methods for brain–computer interfaces *IEEE Trans. Neural Syst. Rehabil. Eng.* **11** 165–9

Nijboer F *et al* 2008 A P300-based brain–computer interface for people with amyotrophic lateral sclerosis *Clin. Neurophysiol.* **119** 1909–16

Piccione F, Giorgi F, Tonin P, Priftis K, Giove S, Silvoni S, Palmas G and Beverina F 2006 P300-based brain computer interface: reliability and performance in healthy and paralysed participants *Clin. Neurophysiol.* **117** 531–7

Pinto S and de Carvalho M 2008 Amyotrophic lateral sclerosis patients and ocular ptosis *Clin. Neurol. Neurosurg.* **110** 168–70

Popescu F, Fazli S, Badower Y, Blankertz B and Muller K R 2007 Single trial classification of motor imagination using 6 dry EEG electrodes *PLoS One* **2** e637

Quian Quiroga R and Garcia H 2003 Single-trial event-related potentials with wavelet denoising *Clin. Neurophysiol.* **114** 376–90

Rakotomamonjy A and Guigue V 2008 BCI competition III: dataset II—ensemble of SVMs for BCI P300 speller *IEEE Trans. Biomed. Eng.* **55** 1147–54

Rivet B, Souloumiac A, Attina V and Gibert G 2009 xDAWN algorithm to enhance evoked potentials: application to brain–computer interface *IEEE Trans. Biomed. Eng.* **56** 2035–43

Schreuder M, Blankertz B and Tangermann M 2010 A new auditory multi-class brain–computer interface paradigm: spatial hearing as an informative cue *PLoS One* **5** e9813

Searle A and Kirkup L 2000 A direct comparison of wet, dry and insulating bioelectric recording electrodes *Physiol. Meas.* **21** 271–83

Sellers E W and Donchin E 2006 A P300-based brain–computer interface: initial tests by ALS patients *Clin. Neurophysiol.* **117** 538–48

Sellers E W, Krusienski D J, McFarland D J, Vaughan T M and Wolpaw J R 2006a A P300 event-related potential brain–computer interface (BCI): the effects of matrix size and inter stimulus interval on performance *Biol. Psychol.* **73** 242–52

Sellers E W, Kubler A and Donchin E 2006b Brain–computer interface research at the University of South Florida Cognitive

Psychophysiology Laboratory: the P300 speller *IEEE Trans. Neural Syst. Rehabil. Eng.* **14** 221–4

Sellers E W, Vaughan T M and Wolpaw J R 2010 A brain–computer interface for long-term independent home use *Amyotroph Lateral Scler.* **11** 449–55

Silvoni S, Volpato C, Cavinato M, Marchetti M, Priftis K, Merico A, Tonin P, Koutsikos K, Beverina F and Piccione F 2009 P300-based brain–computer interface communication: evaluation and follow-up in amyotrophic lateral sclerosis *Front. Neurosci.* **3** 60

Taheri B A, Knight R T and Smith R L 1994 A dry electrode for EEG recording *Electroencephalogr. Clin. Neurophysiol.* **90** 376–83

Thompson D E, Baker J J, Sarnacki W A and Huggins J E 2009 Plug-and-play brain–computer interface keyboard performance *4th Int. IEEE/EMBS Conf. on Neural Engineering, 2009 (NER'09)* pp 433–5

Tomioka R and Muller K R 2010 A regularized discriminative framework for EEG analysis with application to brain–computer interface *Neuroimage* **49** 415–32

Townsend G, LaPallo B K, Boulay C B, Krusienski D J, Frye G E, Hauser C K, Schwartz N E, Vaughan T M, Wolpaw J R and Sellers E W 2010 A novel P300-based brain–computer interface stimulus presentation paradigm: moving beyond rows and columns *Clin. Neurophysiol.* **121** 1109–20

Treder M S and Blankertz B 2010 (C)overt attention and visual speller design in an ERP-based brain–computer interface *Behav. Brain Funct.* **6** 28

Vaughan T M, McFarland D J, Schalk G, Sarnacki W A, Krusienski D J, Sellers E W and Wolpaw J R 2006 The Wadsworth BCI Research and Development Program: at home with BCI *IEEE Trans. Neural Syst. Rehabil. Eng.* **14** 229–33

Xu N, Gao X, Hong B, Miao X, Gao S and Yang F 2004 BCI competition 2003—data set IIb: enhancing P300 wave detection using ICA-based subspace projections for BCI applications *IEEE Trans. Biomed. Eng.* **51** 1067–72

Yuksel B F, Donnerer M, Tompkin J and Steed A 2010 A novel brain–computer interface using a multi-touch surface *Proc. 28th Int. Conf. on Human factors in Computing Systems ACM (Atlanta, GA, USA)*