Neural Networks 22 (2009) 1329–1333

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet

2009 Special Issue

The MindGame: A P300-based brain–computer interface game

Andrea Finke [a,b,*], Alexander Lenhardt [b], Helge Ritter [a,b]

[a] Research Institute for Cognition and Robotics - CoR-Lab, Bielefeld University, Germany
[b] Neuroinformatics Group, Faculty of Technology, Bielefeld University, Germany

ARTICLE INFO

Article history:
Received 1 October 2008
Received in revised form 30 June 2009
Accepted 8 July 2009

Keywords:
Brain–computer interface
BCI
EEG
P300
Virtual game
Neurofeedback

ABSTRACT

We present a Brain–Computer Interface (BCI) game, the MindGame, based on the P300 event-related potential. In the MindGame interface P300 events are translated into movements of a character on a three-dimensional game board. A linear feature selection and classification scheme is applied to identify P300 events and calculate gradual feedback features from a scalp electrode array. The classification during the online run of the game is computed on a single-trial basis without averaging over subtrials. We achieve classification rates of 0.65 on single-trials during the online operation of the system while providing gradual feedback to the player.

1. Introduction

Various types of brain–computer interfaces (BCI) have been introduced and evaluated in great detail in the past two decades. The vast majority of these approaches relies on electroencephalography (EEG) to acquire signals from the brain – for many good reasons: EEG technology is non-invasive and highly portable while acquisition and maintenance are inexpensive. Several components can be extracted from the human EEG that are suited as input to a brain interface, among them the P300 event-related potential (ERP). For a general overview on current BCI research refer to the book of Dornhege, del R Millán, Hinterberger, McFarland, and Müller (2007). Wolpaw et al. (2002) gives an introduction on the ideas guiding BCI research.

The P300 is time-locked to a stimulus and characterized by a positive polarity. However, it is usually embedded in EEG noise and superposed by other EEG events. It is triggered by unpredictable thus surprising events in a series of background stimuli (Duncan-Johnson & Donchin, 1977). Decades of psychological research have shown that the P300 can be elicited reliably in every neurologically healthy human. The experimental parameters influencing the properties of the P300, which are amplitude and latency, have been studied extensively. Polich (2003, 2007) provides detailed reviews on the P300 potential.

The first P300-based BCI was introduced by Farwell and Donchin (1988). Using data from only one electrode (Pz) and simple, model-based classifiers, they already succeeded in developing a slow but usable communication device for severely paralyzed patients. Their original paradigm, the P300 Speller Paradigm, has since then become the standard benchmark case for P300-based BCIs. It has been successfully implemented by several researchers (e.g. Lenhardt, Kaper, & Ritter, 2008; Serby, Yom-Tov, & Inbar, 2005) in offline and online mode. These approaches usually target at the improvement of information transfer rates. Others, like Bell, Shenoy, Chalodhorn, and Rao (2008), try to control robots with the P300. In the past BCI competitions I to III data from the P300 Speller Paradigm was provided for analysis (see http://ida.first.fraunhofer.de/projects/bci/competition_iii for an overview on the last competition with P300 data).

A very important and so far often ignored advantage of the P300 over other EEG components is that its application in a BCI offers a discrete selection rather than a continuous control mechanism as most of the other components. In a recent report Wolpaw (2007) called this distinction goal-selection versus process control. He argued that the goal-selection approach resembles the natural functioning of the brain much closer since it does not require the brain to learn something completely new. The P300 is produced unconsciously without large additional cognitive load. On a cognitive level the P300 can be seen as a measure for alertness and attention and thus reflecting a subject's general arousal level (Datta et al., 2007).

* Corresponding author at: Research Institute for Cognition and Robotics - CoR-Lab, Bielefeld University, Germany. Tel.: +49 521 10612116.
E-mail addresses: afinke@cor-lab.uni-bielefeld.de (A. Finke), alenhard@techfak.uni-bielefeld.de (A. Lenhardt), helge@techfak.uni-bielefeld.de (H. Ritter).

0893-6080/$ – see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.neunet.2009.07.003

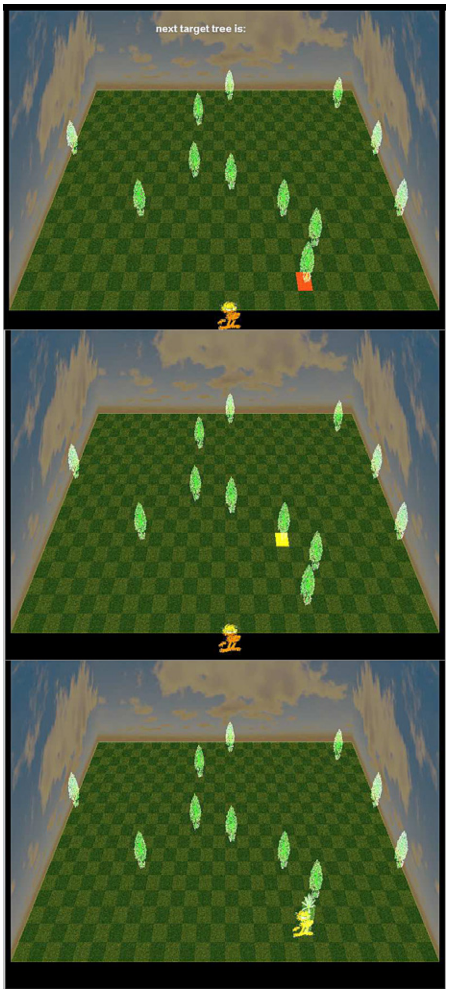

Fig. 1. Screenshots from the MindGame. The subject controls the character by selecting the target of the next move in a P300-based paradigm.

2. The MindGame approach

Our point of departure was the original P300 Speller Paradigm, where a 6×6 symbol matrix containing letters and digits is presented to the subject. The subject has to attend to the symbol while the rows and the columns are highlighted in random order. Since the highlighting events are unpredictable for the subject, they elicit P300 events whose detection allows us to identify the row and column that intersect at the target symbol. The idea that guided the presented study was to extend the most common P300-based approach in BCI research to a *game paradigm* to provide richer interaction possibilities, in particular to study the role and adaptivity of neurofeedback while playing a "thought controlled"game. We employed an adaptive classifier for the identification of P300 events from a scalp electrode array, together with a training scheme, for optimizing the classifier to each player. Additionally, we incorporated gradual feedback into the game to explore the benefits of cognitive control.

Paradigm. The MindGame is played on a checkerboard-styled game board with 28×18 fields and 12 randomly positioned trees. A "comic character" that is able to move from field to field is placed on this board. Fields with trees constitute potential target stimuli in terms of the oddball paradigm. Starting from the front of the board, the player's task is to move the character from tree to tree along the z-axis, until each tree has been visited. The brain interface for the movement of the character is realized by exploiting the trees as potential target stimuli, in an analogous fashion as the symbols in the symbol matrix of the original P300 Speller Paradigm. One difference, however, is that there are no longer group-wise stimuli highlightings in the form of rows or columns. Instead, one turn of the game consists of the consecutive highlighting of all 12 target fields. Target and background stimuli are coded by different colors, namely red for the target and yellow for non-targets. The player focuses attention on the target such that a red flash will elicit a P300 while a yellow flash will not. Fig. 1 shows the graphical setup of the MindGame. Immediately following each turn[1] the classifier will try to identify the correct target. In the case of a successful recognition the output of the classifier will be translated into a movement of the character, which is modulated gradually. Based on the quality of the detected P300 the character is moved a certain number of steps. The number of steps is not fixed in advance, but is decided according to the "confidence", which can be interpreted as a measure of the quality of the P300. Listing 1 shows the pseudocode for the basic MindGame loop.

Algorithm 1 MindGame: Online classification and game control.

Initialize $k \leftarrow 0$, set $ISI \leftarrow 120$ {k is the subtrial index}
Load pre-trained classifier Φ and PCA matrix $\mathbf{P}$
while $k < 12$ **do**
  Flash all 12 stimuli in random order
  Create subtrial matrix $\mathbf{X}_s$
  Apply PCA matrix: $\hat{\mathbf{X}}_s = \mathbf{X}_s * \mathbf{P}$
  Apply classifier to feature vectors: $y = \Phi(\hat{x}_i^s)$
  if $y > 0$ **then**
    Calculate feedback λ_s
    Move character λ_s steps
    if Target reached **then**
      $k \leftarrow k + 1$ Transform tree
    end if
  end if
end while

Relevant parameters of the MindGame system are mainly the amplitude of the P300, the ISI and the target probability. These parameters have a direct impact on the difficulty of the discrimination task. Longer ISIs are known to allow for larger amplitudes. However, as a tradeoff between large amplitudes and the subtrial duration we chose an ISI of 120 ms. Target probability was set to $p = 0.08$, experimental studies revealed a maximal amplitude around a value $p = 0.1$ (Polich, 1987).

3. Methods

The classification procedure used in the MindGame system relies on supervised learning. We acquired labeled training data using a simple oddball task designed as a two-dimensional image matrix containing 3×4 images of comic characters. The basic task for the classifier is the discrimination between *positive* epochs belonging to a target stimulus, i.e. the $\mathcal{P}^+$ class and *negative* epochs belonging to a background stimulus, i.e. the $\mathcal{P}^-$ class. A training session consisted of 500 subtrials, leading to a dataset containing 500 $\mathcal{P}^+$ epochs and 5500 $\mathcal{P}^-$ epochs. A balanced dataset was used for training, such that 500 epochs were randomly selected from the whole set of $\mathcal{P}^-$ epochs, resulting in a total of 1000 feature vectors. These vectors are comprised of 10 EEG channels with an epoch

[1] The following BCI-specific terminology is common: The time window following each stimulus flash – the base unit for the translation algorithm - is called an *epoch*. The *inter-stimulus interval* (ISI) is the time span between two successive stimulus onsets. The sequence of highlighting all 12 stimuli is a *subtrial*, in the MindGame equal to one turn.

length of 800 ms. Given a sample rate of 256 Hz, this constitutes vectors of the dimension $\lceil 800 \cdot 256/1000 \rceil \cdot 10 = 2050$. Each vector belongs to one stimulus highlighting.

The classification should be efficient and cause low computational cost for testing and, with regard to a future extension to an online-learning capable system, training. In the presented study we applied Fisher's Linear Discriminant Analysis (FLDA) (Fisher, 1936) for classification. The FLDA requires a matrix inversion of the pooled covariance matrix and thus suffers from nearly singular matrices in very high-dimensional spaces. Consequently, we added an extra dimension reduction step to our method.

Principle component analysis. Calculating PCA on the data acquired during the training session revealed that only 137 to 146 principal components depending on the subject accounted for 99.9% variance. This constitutes a dimension reduction from 2050 to 142 on average. Fig. 2 shows a tempo-spatial plot of the 16 largest principal components (PC) with respect to the eigenvalues of the data covariance matrix as obtained from the training data set of one subject. The first PCs represent specific frequency bands for all electrode locations with higher frequencies found in the later PCs. In later PCs different activation for the electrode sites occurs. This basic pattern is stable across sessions and subjects. Hence, the directions of the basis vectors of the subspace are approximately the same for all data sets recorded under the same experimental conditions. This finding encourages the usage of a pre-computed PCA matrix for online classification. Thus, we calculated the PCA matrix needed for online classification on the training data matrix and stored it for later usage in the game.

Classification. For classifier training, balanced sets were applied, containing 500 epochs of the $\mathcal{P}^+$ and 500 epochs of the $\mathcal{P}^-$ class. Data was bandpass filtered 0.5 to 10 Hz and scaled to an interval of $[-1, 1]$. A five-fold cross-validation was applied to assess the classification accuracies. FLDA has only one parameter, the bias, which was assessed by scanning a total of 400 values; the final bias used later for classification was calculated as the mean of the 5 values obtained from the foldings. In the case of identical covariance matrices the bias can be calculated directly as the mean of the projections of the two class means onto the weight vector. However, the assumption of identical covariance matrices for the two classes in the MindGame system cannot be made. The relation between the duration of one epoch, 800 ms, and the ISI, 120 ms, leads to highly overlapping epochs. All positive epochs start at the onset of the target stimulus, they all contain the P300 waveform in an almost identical temporal course, leading to a small variance of the P300 class, caused mainly by noise in the data and a minor variability in the P300 between subtrials. The negative epochs, in contrast, are subject to large variance, because up to six negative epochs in one subtrial following the target stimulus contain a different part of the P300, while the preceding ones do not contain any P300 at all. These considerations imply that distinct covariance matrices must be assumed and a cross-validation strategy is needed.

Game control. The control mechanism in the game relies on reference values obtained from the training data. These values serve as the basis for the evaluation of the P300. Two reference values are needed for the $\mathcal{P}^+$ class to adjust the stepwidth, the largest projection and the projection of the class mean. They are obtained from the training data during the cross-validation procedure. Within each folding, the projections of the testset data onto the weight vector obtained from the trainset are calculated. From each fold k, the maximal projection $y_k^{\max} = \max_i \left(w^{\mathrm{T}} x_i\right),\ i = 1, \ldots, n$ is obtained, where n is the number of rows in the testset matrix. The reference value is then calculated as the mean of these maximal projections with the class border moved to zero: $y^{ref} = \frac{1}{5}\sum_{k=1}^{5} y_k^{\max} + b$. The second reference is the projection of the mean, μ^+, of all positive epochs, which is calculated on the whole trainset. With these references, a measure for the quality of the P300 is incorporated into the game, determined by an average quality represented by μ^+ and a maximal quality represented by y^{ref}.

In the online MindGame session the data matrix is created after every subtrial. The classification function returns a value for the projection of each feature vector onto the weight vector together with a class label. The value of the target projection is mapped by the translation algorithm onto a stepwidth that will determine the next move of the character in the game. The distance between the class border and the maximal projection y^{ref} is divided into bins, each bin representing a different stepwidth of the character. The basic idea of the control algorithm is to reward projection values larger than the projection of the class mean obtained from the training. Hence, the distance between the class border and the projection of the mean is divided only into two equally sized bins, the first bin containing all projections in the range $0 < y < 0.5 \cdot \mu^+$ and the second bin covers the range $0.5 \cdot \mu^+ \leq y < \mu^+$, given that all projections have been moved such that the class border is zero. The distance between μ^+ and y^{ref} is divided into smaller, also equally sized bins to allow for finely grained steps. The granularity, i.e. the number of bins, is an adjustable parameter in the MindGame.

Experimental setup. The MindGame implementation was evaluated in an experimental series with 11 subjects, 9 male, 2 female, aged 24–39 years. 10 electrodes were applied to the scalp according to the international 10–20 system at the locations Fz, Cz, Pz, Oz, C3, C4, P3, P4, PO7 and PO8 and referenced to both ear lobes. The data was sampled at 256 Hz using the EEG amplifier *Mindset24* by *Nolan Computer Systems LLC*. The subjects completed the training session and the MindGame session consecutively in one experimental block. The MindGame session consisted of 4 rounds of the game, each round having a variable length, i.e. a variable number of subtrials, depending on the subject's performance.

4. Results

Offline classifier evaluation. The performance of the classifier was estimated from the cross-validation of all 11 training data sets. Data sets were preprocessed with PCA and classified with FLDA as described in the previous section. Table 1 lists the overall means for all subjects. For comparison, a Quadratic Discriminant Analysis (QDA) which can by itself cope with unequal covariance matrices was also tested. Data preprocessing was computed in the same fashion as in the previous case. Obviously, the accuracies obtained with a quadratic discriminant stay clearly below those achieved with linear separation mean accuracy 0.735 ± 0.027 in case of QDA with PCA versus 0.849 ± 0.030 for FLDA with PCA). The pitfall with QDA seems to be an overfitting effect on the training data leading to worse generalization capabilities on the test data. Apparently, the general properties of the class distributions are best represented with a linear class border.

Online gaming. A mean single-trial classification rate of 0.659 was achieved, considering all four rounds of the MindGame from all subjects. Compared with the prior probability of $p = 0.08$, this is a value clearly beyond chance. A mean classification rate of this scale is actually very high for an online operated BCI. Fig. 3a shows the

Table 1
Mean results from the linear and the quadratic classifier. Results are averages over 11 subjects and 5 foldings from cross-validation.

	FLDA + PCA	QDA + PCA
Accuracy	0.849 ± 0.030	0.735 ± 0.027
Sensitivity	0.855 ± 0.029	0.649 ± 0.045

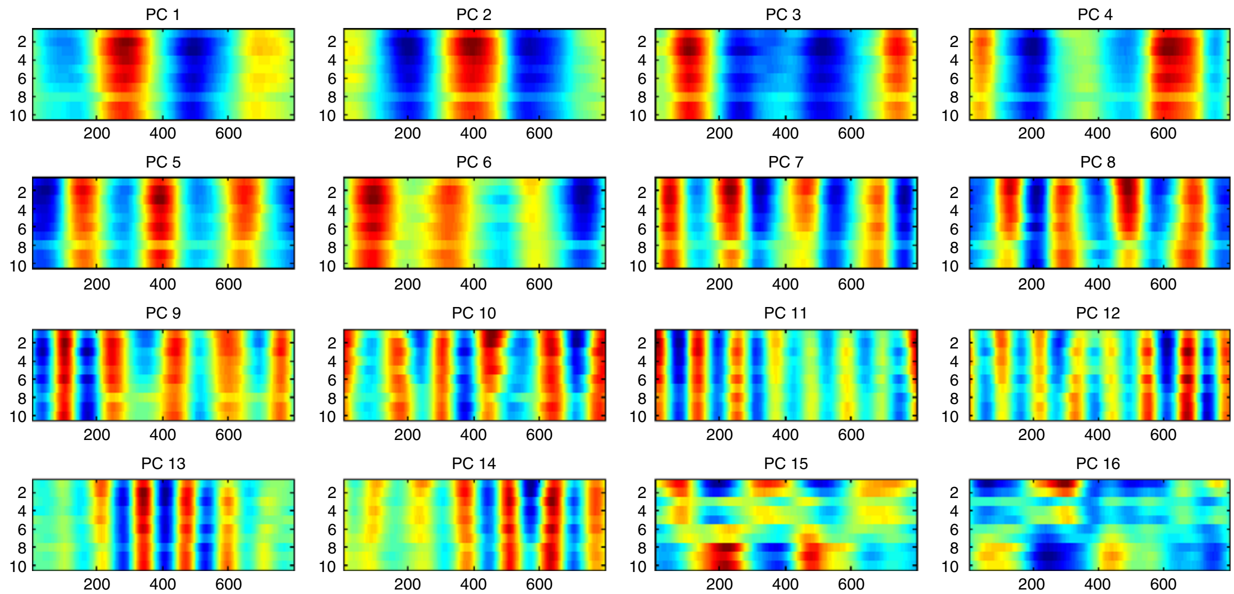

Fig. 2. The first 16 principle components (PC) representing the 16 largest eigenvalues of the covariance matrix calculated from data of subject 6. Apparently, the PCs reflect mainly activity in certain frequency bands with increasing frequency towards higher PCs. The labels on the *y*-axes refer to different electrode locations in the order: Fz, Cz, Pz, C3, C4, P3, P4, PO7, PO8, Oz. The *x*-axes show the time of one epoch in ms.

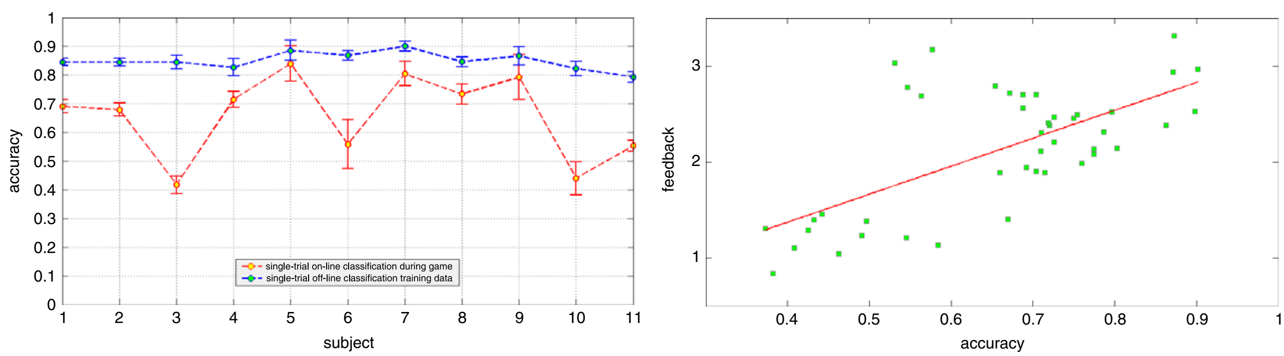

Fig. 3. (a) Comparison of the mean classification results obtained in offline classifier training (blue line) and the mean classification results obtained in online classification during the game session. (b) Relation between classification accuracy and feedback. Large steps resp. projections correlate with high classification rates.

single-trial accuracies as obtained during the online operation of the MindGame system for all subjects. For comparison, the offline accuracies obtained from the training sets are also plotted.

Usually, P300-based BCIs rely on averaging across several subtrials, using either a static or a dynamic number of subtrials. The classification of one target is then calculated as the average of the subtrials. In the work of Lenhardt et al. (2008), where a dynamic subtrial limitation algorithm was used, an accuracy of 0.6 could not be achieved before the third subtrial. In the MindGame approach all classifications are computed purely on single-trial level. However, given a standard deviation of 0.146, the results expose a very high variance among subjects which is typical for online operated BCIs. A combination of the stepwidth and the single-trial classification rate determined the duration of each round of the game. Classification rate is plotted against the stepwidth in Fig. 3b. The number of subtrials the subjects accomplished before reaching the goal of the game varied between a minimum of 47 subtrials for subject 5 in the 4th round up to 149 subtrial for subject 10 in round 2. We were interested if the subjects' performance would improve in the game where active feedback was constantly given, compared to the performance in the training session without feedback. The critical boundary or reference value for defining improvement was the projection of the mean vector of the positive epochs onto the weight vector as obtained from the training data. This boundary corresponds to a feedback stepwidth of 3. Hence, it was desired to achieve a mean performance above this boundary. An overall mean of 3.23 steps was achieved, the means over all subjects for the particular rounds also exceeded the boundary of 3 steps, though in the second round only marginal. Thus, with the interactive MindGame paradigm classification results that are equal or even superior to a passive standard oddball paradigm can be achieved.

5. Conclusion

Brain–Computer Interfaces (BCIs) were originally developed as communication devices for severely paralyzed patients. Within the scope of the presented study we developed a BCI based on the P300 event-related potential as a device for *game control*, where signals from the brain replace the common control devices like mice or joysticks. Thus, the game is controlled without any motor actions. The current approaches in BCI research targeting the field of multimedia control utilize several different EEG components, but none of them the P300. While game and multimedia control with a BCI is inherently a challenging field, it potentially also opens the door for interesting applications in a clinical context. The proposed system implements a gradual control mechanism for a game where the gradual decisions are derived from the output of the FLDA classifier. Following the hypothesis that the P300 potential is a marker of attention, the MindGame could in the future serve as a neurofeedback system allowing for training attention. Showing true neurofeedback effects requires long-term studies with multiple subjects and multiple sessions and is beyond the scope of this work. However, we believe that the insight gained can guide further development of similar or more challenging games. An appealing setting for future research is the development of games which can be played competitively by two or more players and thus allowing for a competition in terms of cognitive performance.

Acknowledgement

Andrea Finke gratefully acknowledges the financial support from Honda Research Institute Europe for the project ''A Brain-Robot Interface for Controlling ASIMO''.

References

Bell, C. J., Shenoy, P., Chalodhorn, R., & Rao, R. P. N. (2008). Control of a humanoid robot by a noninvasive brain–computer interface in humans. *Journal of Neural Engineering*, *5*, 214–220.

Datta, A., Cusack, R., Hawkins, K., Heutink, J., Rorden, C., Robertson, I. H., & Manly, T. (2007). The P300 as a marker of waning attention and error propensity. *Computational Intelligence and Neuroscience*, *2007*.

Dornhege, G., del R Millán, J., Hinterberger, T., McFarland, D., & Müller, K.-R. (2007). *Toward brain–computer interfacing*. MIT Press.

Duncan-Johnson, C., & Donchin, E. (1977). On quantifying surprise: The variation of event-related potentials with subjective probability. *Psychophysiology*, *14*, 456–467.

Farwell, L., & Donchin, E. (1988). Talking off the top of your head: Towards a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and clinical Neurophysiology*, *70*, 510–523.

Fisher, R. (1936). The use of multiple measurements in taxonomic problems. *Annals of Eugenics*, *7*, 179–188.

Lenhardt, A., Kaper, M., & Ritter, H. (2008). An adaptive P300-based online brain–computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *16*, 121–130.

Polich, J. (1987). Task difficulty, probability, and inter-stimulus interval as determinants of P300 from auditory stimuli. *Electroencephalography and Clinical Neurophysiology*, *68*, 311–320.

Polich, J. (2003). *Detection of change: Event-related potential and fMRI findings*. Boston: Kluwer Academic Press, (Chapter 5).

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*, 2128–2148.

Serby, H., Yom-Tov, E., & Inbar, G. F. (2005). An improved P300-based Brain-Computer Interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *13*, 89–98.

Wolpaw, J. R. (2007). Brain–computer interfaces as new brain output pathways. *Journal of Physiology*, *579*, 613–619.

Wolpaw, J. R., Birbaumer, N., McFarland,, Dennis, J., Pfurtscheller, G., & Vaughan, T. (2002). Brain–computer interfaces for communication and control. *Clinical Neurophysiology*, *113*, 767–791.