Journal of Neural Engineering

TOPICAL REVIEW

A comprehensive review of EEG-based brain–computer interface paradigms

To cite this article: Reza Abiri *et al* 2019 *J. Neural Eng.* **16** 011001

IOP Publishing
Journal of Neural Engineering
J. Neural Eng. **16** (2019) 011001 (21pp)
https://doi.org/10.1088/1741-2552/aaf12e

Topical Review

A comprehensive review of EEG-based brain–computer interface paradigms

Reza Abiri[1,2], Soheil Borhani[2], Eric W Sellers[3], Yang Jiang[4] and Xiaopeng Zhao[2,5]

[1] Department of Neurology, University of California, San Francisco/Berkeley, CA 94158, United States of America
[2] Department of Mechanical, Aerospace, and Biomedical Engineering, University of Tennessee, Knoxville, TN 37996, United States of America
[3] Department of Psychology, East Tennessee State University, Johnson City, TN 37614, United States of America
[4] Department of Behavioral Science, College of Medicine, University of Kentucky, Lexington, KY 40356, United States of America

E-mail: reza.abiri@ucsf.edu, reza.abiri@berkeley.edu, sborhani@vols.utk.edu, sellers@etsu.edu, yjiang@uky.edu and xzhao9@utk.edu

Received 14 March 2018, revised 12 November 2018
Accepted for publication 15 November 2018
Published 9 January 2019

Abstract

Advances in brain science and computer technology in the past decade have led to exciting developments in brain–computer interface (BCI), thereby making BCI a top research area in applied science. The renaissance of BCI opens new methods of neurorehabilitation for physically disabled people (e.g. paralyzed patients and amputees) and patients with brain injuries (e.g. stroke patients). Recent technological advances such as wireless recording, machine learning analysis, and real-time temporal resolution have increased interest in electroencephalographic (EEG) based BCI approaches. Many BCI studies have focused on decoding EEG signals associated with whole-body kinematics/kinetics, motor imagery, and various senses. Thus, there is a need to understand the various experimental paradigms used in EEG-based BCI systems. Moreover, given that there are many available options, it is essential to choose the most appropriate BCI application to properly manipulate a neuroprosthetic or neurorehabilitation device. The current review evaluates EEG-based BCI paradigms regarding their advantages and disadvantages from a variety of perspectives. For each paradigm, various EEG decoding algorithms and classification methods are evaluated. The applications of these paradigms with targeted patients are summarized. Finally, potential problems with EEG-based BCI systems are discussed, and possible solutions are proposed.

Keywords: brain–computer interface, electroencephalography, BCI paradigm, classification

(Some figures may appear in colour only in the online journal)

[5] Author to whom any correspondence should be addressed. 313 Perkins Hall, University of Tennessee, Knoxville, TN 37996, United States of America.

1. Introduction

The concept of using brain signals to control prosthetic arms was developed in 1971 [1]. Since that time, researchers have been attempting to interpret brain waveforms to establish a more accurate and convenient control over external devices. Later, this research area was termed brain–computer interface (BCI), and its applications spread rapidly [2].

BCI systems utilize recorded brain activity to communicate between the brain and computers to control the environment in a manner that is compatible with the intentions of humans [3]. There are two primary directions in which BCI systems have been applied. The first is studying brain activity to investigate a feedforward pathway used to control the external devices without the aim of rehabilitation [4]. The other dominant direction is closed-loop BCI systems during neurorehabilitation with the feedback loop playing a vital role in recovering the neural plasticity training or regulating brain activities [4].

Brain activity can be recorded through various neuroimaging methods [3, 5]. The methods can be categorized into two groups: invasive and noninvasive. Electrocorticography (ECoG) and electroencephalography (EEG) have become the most common invasive and noninvasive technologies, respectively [3]. ECoG, also known as intracranial EEG, is recorded from the cortical surface. Other invasive technologies record signals from within the brain using single-neuron action potentials (single units), multi-unit activity (MUA), local field potentials (LFPs) [6, 7]. The high quality spatial and temporal characteristics of these signals lead to successful decoding of biomechanic parameters [8–12]. These decoding achievements for upper limb kinematics using invasive electrodes in monkeys and humans have resulted in accurate control of prosthetic devices in 3D space [13–17]. However, the invasive electrodes have significant drawbacks due to the risk of performing surgery and the gradual degradation of the recorded signals. Therefore, noninvasive approaches such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), and EEG have become more widespread in human participants.

Although some noninvasive technologies provide a higher spatial resolution (e.g. fMRI), the EEG has proved to be the most popular method due to direct measures of neural activity, inexpensiveness, and portability for clinical use [3]. EEG measures electrical brain activity caused by the flow of electric currents during synaptic excitations of neuronal dendrites, especially in the cortex, but also in the deep brain structures. The electric signals are recorded by placing electrodes on the scalp [3]. EEG signals have been used to control devices such as wheelchairs [18] and communication aid systems [19]. During the past decade, EEG methods have also become a promising approach in controlling assistive and rehabilitation devices [20]. EEG signals could provide a pathway from the brain to various external devices resulting in brain-controlled assistive devices for disabled people and brain-controlled rehabilitation devices for patients with strokes and other neurological deficits [21–25]. One of the most challenging topics in BCI is finding and analyzing the relationships between recorded brain activity and underlying models of the human body, biomechanics, and cognitive processing. As a result, investigation of relationships between EEG signals and upper limb movement, real and imaginary, has become a fascinating area of research in recent years [26, 27].

To implement an EEG-based BCI system for a particular application, a specific protocol and paradigm has to be chosen for all phases of the experiment. First, the subject performs a particular task (e.g. imagery task, visual task) in order to learn how to modulate their brain activity while EEG signals are recorded from the scalp. Using the recorded EEG as training data, a neural decoder for the paradigm is generated. Afterward, the subject performs the task again and the neural decoder is used for BCI control.

Many EEG-based BCI review papers have been published [18, 23, 24, 28–32]; however, there is a lack of review or guidance in comparing EEG-based BCI paradigms. Here we aim to review the most commonly employed EEG-based BCI paradigms. A guideline on deployed algorithms and classification methods in generating control signals from these paradigms are summarized. Each of these paradigms has their advantages and disadvantages depending on a patient's physical condition and user-friendliness. The current and future potential applications of these paradigms in the manipulation of an external object, rehabilitation, restoration, enhancement, and entertainment are investigated. Finally, present issues and limitations in EEG-based BCI systems are examined, and future possibilities for developing new paradigms are discussed.

2. Motor imagery paradigms

Motor imagery is described as imagining a movement rather than executing a real movement (for more detail on motor imagery see [27]). Previous studies have confirmed that imagination activates areas of the brain that are responsible for generating actual movement [33]. The most common motor imagery paradigms reported in literature are sensorimotor rhythms (SMR) and imagined body kinematics (IBK). In the following sections, the paradigms are described in detail.

2.1. Sensorimotor rhythms (SMR) paradigms

2.1.1. Overview. The sensorimotor rhythms paradigm is one of the most popular motor imagery paradigms (e.g. [34, 35]). In this paradigm, the imagined movement is defined as the imagination of kinesthetic movements of large body parts such as hands, feet, and tongue, which could result in modulations of brain activity [36].

Imagined movement in sensorimotor rhythm paradigms causes event-related desynchronization (ERD) in mu (8–12 Hz) and beta rhythms (18–26 Hz). In contrast, relaxation results in event-related synchronization (ERS), (for an in-depth review see [37]). The ERD and ERS modulations are most prominent in EEG signals acquired from electrode locations C3 and C4 (10/20 international system); these electrode locations are above the sensorimotor cortex. These modulated EEG signals in the aforementioned frequency domains (mu/

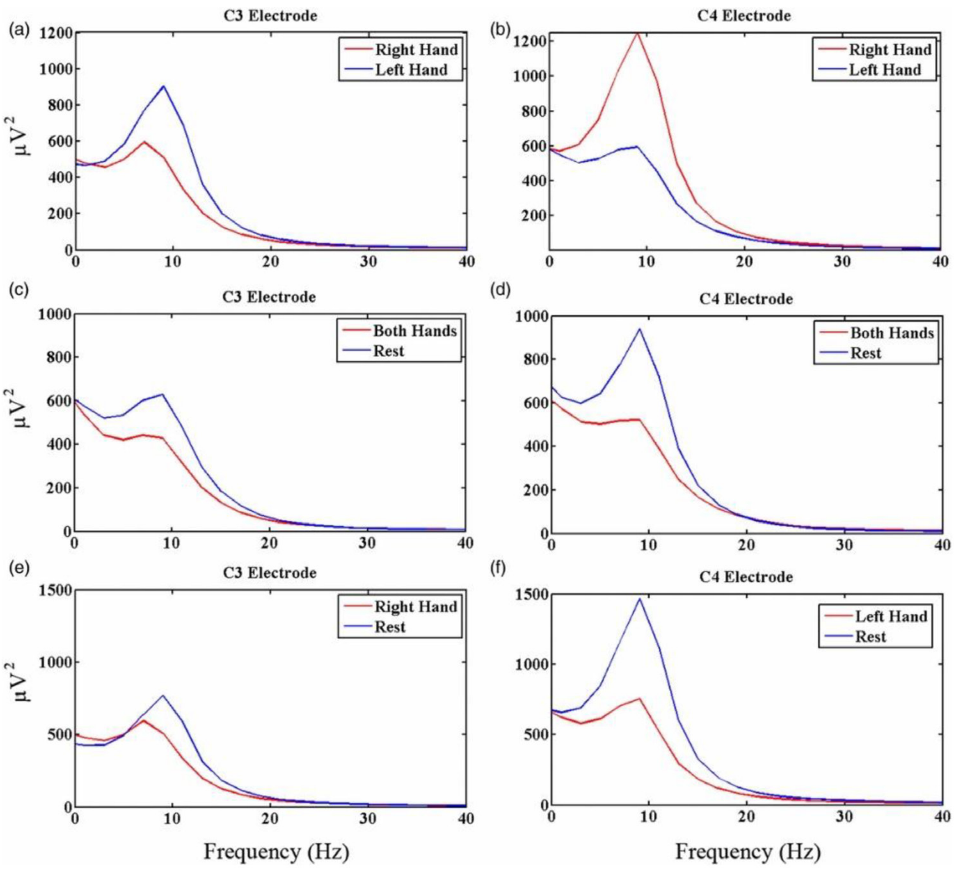

Figure 1. An example of a change in frequency spectra for EEG recorded from C3 and C4. The top row (a) and (b) shows spectral power changes in C3 and C4 electrodes while performing imagined movement of right hand versus left hand. The middle row (c) and (d) shows spectral power change in C3 and C4 electrodes while performing imagined movement of both hands versus rest. The bottom row (e) and (f) shows spectral power change in C3 and C4 electrodes for imagined movement of right hand versus rest and left hand versus rest, respectively. (Reproduced from [39]. © IOP Publishing Ltd. CC BY 3.0.)

beta) can be employed to control prosthetic devices. Wolpaw *et al* [38] controlled a one-dimensional cursor using mu rhythms. Figure 1 shows examples of change in frequency spectra of SMR during imagination of hands.

The main drawback of the SMR paradigm is that the training time for 2D and 3D cursor control can take weeks or months. The training for this system requires subjects to learn how to modulate specific frequency bands of neural activity to move a cursor in different directions to select desired targets.

2.1.2. Analysis and classification methods. SMR paradigms have been employed by many researcher groups. For example, Wolpaw and McFarland introduced the first two-dimensional cursor control strategy [40]. The subjects' task was a center-out cursor task, where the cursor was guided to one of eight targets located around the perimeter of a computer monitor. In this work, each dimension of cursor movement was controlled by a linear equation in which the independent variable was a weighted combination of the amplitudes in a mu or beta rhythm frequency band recorded from the right and left sensorimotor cortices. These changes were generated as the result of right and left-hand imaginary movements.

Bhattacharyya *et al* [41] compared the performance of different classification methods for left/right hand imagery in EEG features. They found that the accuracy of kernelized SVM outperforms the other classifiers. Murguialday *et al* [42] designed a hierarchical linear classification scheme using the peak mu power band to differentiate between relaxation, left-hand movement, and right-hand movement. For movement prediction of the right hand, left hand, tongue, and right foot, Morash *et al* [36] showed that time-frequency features could better depict the non-stationary nature of EEG SMR. Using a parametric modeling approach, they divided time into bins of 256 ms and frequency into bins of 3.9 Hz and applied Naïve Bayesian classification. However, parametric classification methods require *a priori* knowledge of subjects' EEG pattern that is not always applicable for BCI control. Nonetheless, Chen *et al* [43] used a three-layer neural network non-parametric approach, and they investigated an adaptive classifier for controlling an orthotic hand by motor imagery. A summary of previous SMR work is shown in table 1.

2.1.3. Applications and targeted patients' populations. The SMR paradigm has been one of the most promising paradigms used by patients with tetraplegia, spinal cord injury, and amyotrophic lateral sclerosis (ALS). The paradigm was first employed in a one-dimensional computer cursor control task by Wolpaw *et al* [38]. A drawback of the method is a relatively lengthy training period of up to several weeks. Wolpaw and McFarland [44] used mu rhythms from four channels

Table 1. Previous SMR paradigms. DWT: discrete wavelet transform, LMS: least mean square, STFT: short-time Fourier transform, CSP: common spatial pattern, N/A: not applicable.

Reference	Task	Feature	Classification method
[38]	Cursor control in 1D	Mu rhythm (8–12 Hz) amplitude from	N/A
[44]	Cursor control in 2D	FFT + mu rhythm amplitude (7.5–16 Hz)	Linear regression
[45]	Grasping and object manipulation	DWT over 12–14 Hz and 18–22 Hz	LDA
[40]	Cursor control in 2D	Mu (8–12 Hz) and beta (18–26 Hz) rhythm amplitude	Linear regression + LMS to optimize weights
[42]	Control of a prosthetic hand	Peak mu (8–12 Hz) band power	A logistic regression (relaxation and motor imagery) + a logistic regression (right hand and left hand)
[43]	Control of a hand orthosis	STFT over mu band (8–14 Hz)	3-layer feedforward NN classified three classes (right hand, left hand, no imagination)
[46]	Control of a rehabilitation robot	Using CSP algorithm to select features	N/A
[47]	Control of a robotic am	Time-frequency power of EEG over the recorded locations on (10.5, 13.5) Hz frequency range	N/A
[48]	Control of a rehabilitation robot	Time-frequency power in EEG alpha (8, 13) Hz, sigma (14, 18) Hz and beta (18–30) Hz bands over C3, C4, and Cz	LDA

across left and right central sulci to move a cursor in 2D space to targets located in the four corners of a computer monitor. Subsequently, they used the same paradigm with people who had spinal cord injuries to guide the cursor to eight different targets on the sides of a monitor by imagining right and left-hand movement [40]. Finally, they expanded their work and controlled a cursor to hit targets located in three-dimensional space [49]. In all of these studies the subjects learned to modulate their SMR based on imagery of large body parts such as hands and legs.

Applications other than cursor control have also been employed using SMR. Guger *et al* [50] used SMR to open and close a prosthetic hand with imagined right or left-hand movement. Pfurtscheller *et al* [51] employed foot imagery to restore hand grasp in a patient with tetraplegia. Muller-Putz *et al* [45] developed an EEG-based SMR system using imagined foot and hand movements to help a paralyzed patient do simple tasks such as grasping a cylinder and moving an object by controlling a functional electrical stimulation (FES) device. Sun *et al* [52] and Roy *et al* [53] used motor imagery to control an artificial upper limb. Murguialday *et al* [42] also used an SMR design to open and close a prosthetic hand. In recent years, SMR control signals have been applied to control objects such as quadcopters [39], virtual helicopters [54], and robotic manipulators [20, 47, 55]. SMR is also employed in rehabilitation robots [46, 48] and hand orthosis [43]. The paradigm has also been tested with healthy and stroke patients [56–61].

2.2. Imagined body kinematics paradigms

2.2.1. Overview. Efforts to extract motor imagery commands from EEG signals has been progressing for years [49]. However, the time-consuming process of training and model calibration limits the efficacy of BCI utilization for many potential users. Furthermore, the first critique in controlling prosthetics for amputees via SMR is the lack of natural and intuitive control [62]. In other words, SMR lacks the ability of direct extraction of kinematic parameters. Although the technique can distinguish motor activities corresponding to large body parts, the decoded motor information does not contain magnitude or direction of kinematics parameters (e.g. position, velocity, or acceleration).

Imagined body kinematics (IBK) is a motor imagery paradigm that originated from invasive BCI technology [9, 10]. However, noninvasive work has noted that the information for this paradigm is extracted from low-frequency SMR signals (less than 2 Hz) [34]. IBK is classified as an independent paradigm from SMR because the training protocols and analysis methods are fundamentally different from SMR paradigms. In IBK, the subject is asked to imagine the continuous movement of only one body part in multi-dimensional space. The recorded signals are then decoded in the time domain. This paradigm is sometimes referred to as a natural imaginary movement. In noninvasive devices, Bradberry *et al* [63] investigated 2D cursor control with a natural imaginary movement paradigm and analyzed the data in time-domain frequencies of less than 1 Hz. Their subjects were instructed to use the natural imaginary movement of the right-hand index finger, thereby reducing training time to a level similar to invasive devices [10, 16].

In addition to Bradberry *et al*'s work in noninvasive EEG technology, Ofner *et al* [64] studied the continuous and natural imaginary movements of the right hand in a 2D plane. They estimated the imagined continuous velocities from EEG signals. Kim *et al* [65] decoded the three-dimensional trajectory of imagined right-hand movement in space and also examined the effects of eye movements on linear and nonlinear decoding models. Andres *et al* [66] conducted a similar study in 2D space using linear models. Gu *et al* [67] decoded two types of imaginary movements of the right wrist at two different speeds and later [68] considered the imagined speed of wrist movements in paralyzed ALS patients. Others have studied the imaginary movement of the shoulder, elbow, wrist, and finger [69–71]. Although most of this recent work could be classified as decoding of IBK, their application for BCI is limited and is still under investigation.

2.2.2. Analysis and classification methods. A number of seminal works have suggested that the low-frequency components of EEG signals (<2 Hz) located over motor cortex carry kinematic information [63–65, 67–69, 72, 73]. Although many studies have shown kinematic data is present in low frequencies, Gu *et al* [67] were the first to use this information for classification. They decoded wrist rotation and extension at fast and slow speeds. They found that discrete imagined movement is encoded in the movement-related cortical potential (MRCP). In their study, EEG signals were low-pass filtered at 2 Hz and the negative slope 2 s before the movement onset known as Bereitschaftspotential (BP) was examined. The BP has two parts, the NS1 (Negative Slope of early BP) and the NS2 (steeper Negative Slope of late BP). The NS1, NS2, and the mu (8–12 Hz) and beta rhythms (18–26 Hz) constituted the feature space in their study. In another study, Yuan *et al* [74] decoded seven different hand clenching speeds using spatial-temporal characteristics of alpha (8–12 Hz) and beta (18–26 Hz) bands. To translate multiple discrete speeds of hand imagery they developed multiple linear regression models and smoothed the output with a low-pass 1 Hz filter. Although they found a correlation between higher frequency bands and the speed of imagery, they did not successfully find movement trajectory information. Bradberry *et al* [63] conducted a prominent study on IBK; they were able to extract two-dimensional hand imagery [63] and actual three-dimensional hand movement trajectory [72] using low-frequency EEG signals (<1 Hz). A linear decoding model with first-order temporal differences of EEG data was developed, and they successfully modeled continuous cursor velocity, which was correlated with the defined trajectory. They also showed that EEG data from 100 ms before movement imagination onset is correlated with the movement. The linear model was as follows:

$$x[t] - x[t-1] = a_x + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nkx} S_n[t-k].$$

The same equation was used for horizontal and vertical velocities. In this equation $x[t] - x[t-1]$ is cursor velocity along one axis, N is the number of EEG channels, L is the number of time lags, $S_n[t-k]$ is the temporal lagged version of EEG at EEG channel n at time lag k, and a and b are the weights that result from the linear regression.

Using partial least squares (PLS) regression, Ofner and Müller-Putz [73] were able to reduce EEG artifacts And also eliminate highly correlated variables. They were also able to identify relationships between latent predictors and desired response variables. By using different electrode locations and different time lags as latent variables, the algorithm captured the user's source space contribution to the latent variables. Finally, Kim *et al* [65] explored a nonlinear decoding model called kernel ridge regression (KRR). They showed that KRR algorithm significantly reduced eye movement contamination, which is common in linear models. Andres *et al* [66] and Kim *et al* [65] examined the role of eye movement in the linear decoding of IBK. By comparing the decoding performance with and without EOG contaminated brain signals, they found that eye movement plays a significant role in IBK tasks. Additionally, in contrast to a report published by Korik *et al* [75] and Kim *et al* [65] confirmed that the SMR bands do not contain kinematic parameter information.

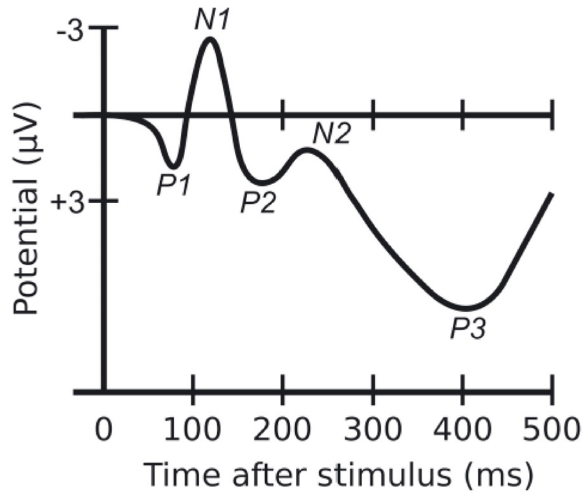

Figure 2. ERP components after the onset of a visual stimulus. Reproduced from [92]. CC BY 3.0.

2.2.3. Applications and targeted patient population. The IBK paradigm is new to noninvasive devices. Thus far, it has been applied to a limited number of applications. The reason for this is likely due to the poor decoding of EEG signals [76]. Abiri *et al* employed natural imagery movements of one hand to control different gestures of a social robot [77, 78] and to manipulate a robotic arm [79]. Gu *et al* [68] employed the imagined speed of wrist movements in paralyzed ALS patients. It was shown that employing natural IBK paradigms can dramatically reduce the training times. A generic model which can be operated with zero-training is also a promising future development. Abiri *et al* [80, 81] used the IBK in a zero-training BCI paradigm to control a quadcopter in 2D space.

3. External stimulation paradigms

Brain activity can be affected by external stimulations such as flicking LEDs and sounds. The altered EEG activity can be collected and decoded to control real or virtual objects or external prosthetics. This is the basic principle for external stimulation paradigms. External stimulation can be visual [82, 83], auditory [83, 84], or somatosensory [85]. The following sections discuss the most common external stimulation paradigms employed by BCI researchers.

3.1. Visual P300 paradigms

3.1.1. Overview. One of the most popular paradigms in EEG-based BCI systems is visual P300 (for review see [86, 87]). Farwell and Donchin pioneered the use of the visual

Table 2. A summary of studies with P300 paradigm.

Reference	Task	Feature	Classification method
[88]	6 × 6 row/column (RC) speller	Data from Pz, channel were extracted, and band-pass filtered (0.02, 35) Hz and downsampled to 50 Hz	SWLDA
[95]	Control a virtual ball in 2D	Data from Cz, Pz, Oz, and Fz channels were extracted, and ICA was applied to extract features	A three-layer ANN
[96, 102]	6 × 6 row/column (RC) speller	Moving average and decimation with factor of 12	SWLDA
[97]	Computer cursor control in 2D	Low-pass filter with cut-off frequency of 34 Hz and decimation to 128 Hz	Continuous wavelet transform (CWT) and genetic algorithm (GA)
[103]	Control of a humanoid robot	Band-pass filter (0.5, 30) Hz and downsampling to 100 Hz	SVM
[104]	Single character (SC) speller	Band-pass filter (0.5, 30) Hz and downsampling to 60 Hz	LDA
[106]	Region-based (RB) speller	C1, C2, Cz, Pz, and Fz channels were used	Averaged Mexican-hat wavelet coefficients used as feature set
[107]	8 × 9 checkerboard (CB) speller	Cz, Pz, PO7, and PO8 channels were used	SWLDA
[2, 109]	Single character (SC) speller	Scaling data samples into (−1, 1) and downsampling to 32 Hz	Bayesian linear discriminant analysis (BLDA) and Fisher's linear discriminant analysis (FLDA)
[110]	Target selection in 3D space	Channel selection and downsampling to16 Hz	SWLDA

P300-BCI in 1988 [88] by creating what is now referred to as the P300 Speller. The P300 is one of the most studied event-related potentials (ERP). An ERP is derived by averaging EEG signals of a specific event type. The P300 component is elicited in response to infrequently presented events using what is known as an 'oddball paradigm'. The P300 is a positive peak in the ERP ranging from 5 to 10 microvolts in size and a latency between 220 to 500 ms posterior to the event onset (see figure 2). This ERP is defined as an averaged increase in the amplitude of time series of brain signals which is most significant at midline locations (Pz, Cz, and Fz in the 10/20 international system). When inter-stimulus intervals are less than 250–300 ms [89], the definition of P300 becomes debatable because the P300 response and the presentation of subsequent stimuli overlap in time. For example, with very short inter-stimulus intervals, like 125 ms, 3 to 5 stimuli are delivered in the range 0–500 ms from the onset of first stimulus. Likely, the P300 elicited in this paradigm is the sum of the P300 and other components that are elicited by other stimuli that are presented prior to and after any given stimulus presentation.

The most important advantages of the visual P300 BCI are that most subjects can use it with very high accuracy and it can be calibrated in minutes. Therefore, the user can easily and quickly use the system to control devices. Disadvantages of this paradigm include fatigue from the high level of attention and visual focus required to use the system [90], and the inability for people with visual impairments to use the system [91].

3.1.2. Analysis and classification methods. A summary of previous studies using P300 is shown in table 2. The P300 was initially reported by Sutton *et al* [93] in 1967. The P300 speller was initially introduced by Farwell and Donchin [88] within a row/column paradigm (RCP) comprised of a 6 × 6 matrix of letters and numbers. Since collecting subject's overt behavioral response is not necessary for this paradigm, it can be used as a motor-free means of communication for severely disabled patients. Additionally, P300 shares very similar inter-subject characteristics which help to diminish the subjects' training time [94]. However, the subject is required to maintain attention throughout the experiment. The P300 amplitude is subjective to a number of elements such as the probability of target appearance, the inter-trial duration, difficulty of the experiment, attentional state of the participant and the habitual effects [92]. Faster P300 responses are indicative of better cognitive performance in attentional and immediate memory task [92]. Latency jitter can make it difficult to extract the P300 deflection; thus, presenting multiple trials and averaging the EEG response is required to increase the signal-to-noise ratio and, thereby, improve decoding accuracy. However, when more trials are presented the rate of communication is slower, which leads to a speed/accuracy trade-off.

In [88, 94], the authors addressed the relationship between the number of trials and decoding accuracy using stepwise discriminant analysis (SWDA) and reported that more trials significantly improved performance. Piccione *et al* [95] extract P300 by using the fuzzy method to combine decomposed components of ICA over EEG. Krusienski *et al* [96] compared various classification techniques including Pearson's correlation method (PCM); Fisher linear discriminant (FLD); stepwise linear discriminant analysis (SWLDA); and, linear and nonlinear support vector machines (SVMs). They illustrated that FLD and SWLDA performed significantly better than other classification methods. Moreover, their analysis indicated that the P300 was stable across sessions and subjects.

Citi *et al* [97] introduced a 2D cursor control P300-based BCI. They were able to extract an analog control signal with a single-trial approach using a genetic algorithm. Also, there are other single-trial classification approaches using P300 signals [98–101]. Most of the early P300 Speller research had focused on EEG locations along the midline (e.g. Fz, Cz, and Pz). In [102] information from posterior locations such as PO7, PO8, and Oz were added to an SWLDA classifier. They showed that adding additional electrode locations significantly improved the discriminability of data samples. Bell *et al* [103] increased the information transfer rate (ITR) to 24 bits min^{-1} for a four-choice classification problem relying on the fact that P300 has a robust response to multiple trials. They elicited P300-based control analyzing only five trials of P300 responses with 95% accuracy using SVMs. Edlinger *et al* [104] and Chen *et al* [105] applied the paradigm in a virtual environment (VE) as an actuator for a smart building scenario and to control a virtual hand, respectively. By dividing the screen into seven different regions Fazel-Rezai and Abhari [106] were able to reduce distraction caused by adjacent items and, at the same time, were able to lower the stimulus probability. These changes resulted in larger P300 amplitudes, which resulted in higher detection accuracy and higher ITR [92].

An innovative checkerboard paradigm (CBP) was introduced in [107]. The CBP showed significantly higher mean accuracy than the row-column paradigm (RCP) (i.e. 92% compared to 77%) and mean ITR was increased to 23 bits min^{-1} from 17 bits min^{-1}. The CBP is able to avoid stimulus adjacency-distraction error addressed in [106] and also increases P300 detection accuracy by lowering the probability of target-occurrence. In [108], a language model to enhance typing speed was utilized. They examined P300 BCI paradigms including single-character presentation (SCP), RCP, and they also tested a rapid serial visual presentation (RSVP) paradigm. They applied PCA over a band-pass (1.5–42) Hz filtered EEG to extract a one-dimensional feature vector from multiple locations over frontal, central, and parietal regions.

3.1.3. Applications of visual P300 and targeted patient population.

The most common application of visual P300 has been in developing prosthetic keyboards to provide a pathway of communication for disabled patients. Usually, speller devices in BCI consist of a matrix of letters, numbers, and symbols [94]. The rows and columns of this matrix are flashed in sequence, and the subject has to focus attention on the intended character. The intended character is then determined by the speller based on its row and column. These devices use a statistical model based on the P300 ERP to identify the correct symbol during flashing. The main advantage of P300 spellers has been their usefulness to people with ALS [92, 111, 112] and brainstem stroke [113]. P300 has also been investigated as a way for a subject to control some specific tasks in the environment [114]. It has also been used to control a humanoid robot [103], and to navigate a wheelchair [110, 115]. This paradigm was also employed to control a computer cursor in 2D space [97] by paralyzed patients [95]. Additionally, it has been used to control a virtual hand [105] in a virtual reality smart apartment [104].

3.2. Steady state visual evoked potential paradigms

3.2.1. Overview.

The steady state visual evoked potential (SSVEP) is another popular visual component used in BCI [116, 117]. SSVEP is also called photic driving since the generators of this response are located in visual cortex. Rather than either motor execution or imagined motor action, subjects have to shift gaze and as well as their attention to flickering stimuli, which requires highly accurate eye control.

In the SSVEP paradigm, a constant frequency flickering stimulus on the central retina results in an EEG pattern consistent with the flickering rate. The frequencies of stimulation can be varied from low (1–3.5 Hz) to high frequency (75–100 Hz) [118]. The stimulus can be produced using a light-emitting diode (LED) or a cathode ray tube (CRT). Multiple flickering targets with distinct flickering frequencies are typically presented to the user. There is a strong correlation between flicker frequency and the observed frequency of the EEG. The user's intended target is determined by matching the pattern of EEG activity to the command associated with the particular frequency.

There are advantages associated with the SSVEP paradigm. Because the stimuli are exogenous, it is a no-training paradigm that can be used by many subjects. The stimuli flash at many different frequencies, thereby resulting in many commands and more degrees of freedom to control prosthetic devices. In addition, the SSVEP frequencies can be more reliably classified than event-related potentials. However, the use of flickering stimuli could lead to fatigue for the subject, mainly when using low flickering frequency [119–122]. This paradigm is also not well suited for people with visual impairments due to the required gaze shifts during use. However, Min *et al* [123] have recently proposed a new SSVEP paradigm that uses a grid-shaped line array. They suggested that this novel presentation is gaze-independent. There are also steady-state somatosensory evoked potentials (SSSEP) [124] and hybrid SSSEP and P300 applications [125].

3.2.2. SSVEP analysis and classification methods.

As opposed to transient VEP which is used to measure the travel time of a visual stimulus from the eye to the occipital cortex [117], SSVEP depicts a stable characteristic of the spectral content of EEG signals. Among various EEG paradigms, SSVEP is less vulnerable to artifacts and has higher ITR. BCIs based on P300 or SMR paradigms reach ITR of 4–60 bits min^{-1}, SSVEP-based BCIs yield ITR of 100 bits min^{-1} and higher. Since information in SSVEP paradigms is located in narrow-band frequency ranges, a narrow-band band-pass filter is typically part of the signal preprocessing of SSVEP. However, the amplitude and phase characteristics of SSVEP depend on the intensity and frequency of the stimulus.

Herrmann [118] investigated the correlation between frequency of stimulus presentation and the firing rates of neurons. The results exhibited resonance phenomena at 40 Hz, subharmonics at 10 Hz and 20 Hz, and weaker intensity integer multiples of the stimulus (e.g. 80 Hz). Muller-Putz and Pfurtscheller [126] applied SSVEP in a hand prosthesis using four-class classification with LED flicker at 6, 7, 8 and 13 Hz. Harmonic sums at each of the stimulation frequency yielded

Table 3. An overview of SSVEP paradigms.

Reference	Task	Feature	Classification method
[132]	Spelling using a multi-level selection criterion	(6–10) Hz over O_z, A1 and grounded by A2	Bayesian model enhanced by language entropy model
[133]	Lower limb exoskeleton	(9–17) Hz with eight electrodes over occipital and parietal lobes referenced by FCz and grounded by Fpz	CCA and kNN
[135]	Checkerboard as visual stimuli	(6–10) Hz over O_z, O_1, and O_2	Maximum likelihood
[123]	Spelling using a grid-shaped flicking structure	(5–10) over 3 electrodes of occipital lobe	CCA and rLDA
[136]	Navigation in two-dimensional computer game	15, 30, 45 Hz and their 90° phase shift over occipital and parietal lobes	CCA
[131]	Spelling characters	(7–70) Hz with nine electrodes over parietal and occipital lobe	CCA
[126]	Control of an electrical prosthesis	(6–13) Hz with four electrodes over occipital lobe	Maximum likelihood
[129]	A brain-to-brain motion control system	(6–13) Hz with four electrodes over occipital lobe	LDA
[130]	Spelling	(7–10) Hz with eight electrodes over occipital lobe	MEC

the feature set for classification of SSVEP. They achieved online accuracy between 44% and 88%. A drawback of the SSVEP paradigm is that low-frequency stimulation can lead to fatigue or epileptic seizure. Therefore, a high-frequency flicker (60–100 Hz) is preferred [127]. Bryan *et al* [128] used an estimated signal's power spectrum generated by the fast Fourier transform (FFT) as an input to control a humanoid robot with a single electrode (Oz). Li and Zhang [129] applied an LDA classifier and an optimization algorithm to improve SSVEP online accuracy. A minimum energy combination (MEC) was utilized in [130] to detect principle and harmonic frequencies in spatially filtered signals. They also conducted an extensive study including 61 subjects in order to investigate the scope of applicability of SSVEP-based BCIs. In addition to performance, they examined a number of covariates including age, gender, and level of tiredness. Chen *et al* [131] examined the correlation coefficients between stimulus frequency and subject's EEG frequency using canonical correlation analysis (CCA). Considering accuracy and ITR simultaneously, they determined a user-specific optimal stimulation duration and phase interval. In a text input application, Chen *et al* [132] attempted to enhance ITR by employing entropy coding algorithms such as Huffman coding. An advantage of the SSVEP paradigm is that it is less susceptible to motion artifacts. Thus, it is a suitable choice for a mobile subject. Pfurtscheller *et al* [133], showed that a gait-assistance exoskeleton could be accurately controlled. They evaluated online and offline performance of CCA and k nearest neighbors (kNN) classifiers.

Most studies conducted with the SSVEP paradigm are based on decoding bottom-up visual information. Thus, these systems are gaze-shift dependent. Min *et al* [123] examined a top-down visual condition within the paradigm. The results in the top-down condition showed a different pattern over the occipital lobe than the pattern produced by the bottom-up condition. Moreover, a randomly-shuffled LDA (rLDA) classifier performed more accurately in the top-down condition than the more commonly used CCA classifier. An overview of previous SSVEP studies with accuracy and ITR is shown in table 3.

Bio-inspired intelligent information processing techniques can also help to understand the human perceptual systems and to incorporate the biological models and features of human perceptual systems into the bioinspired information processing techniques to process the physiological signals for BCI. For instance, entropy can be used to measure the dynamic complexity of EEG signals. Cao *et al* [134] proposed using inherent fuzzy entropy for the improvement of EEG complexity evaluation, which can apply to SSVEP.

3.2.3. SSVEP applications and targeted patients population. Due to a large number of discrete control commands and high reliability of SSVEP, the paradigm has been studied by many BCI researchers. Recently, a high-speed SSVEP speller was used to enable the subject to choose among 40 characters including letters of English alphabet, numbers, and some symbols [131]. In addition, an user-dependent SSVEP based on determining the prominent key-parameter for each user was developed by [130] to spell only one phrase. According to the appearance frequency of letters, a multilevel SSVEP-based BCI was designed in [132] to type text. Bryan *et al* [128] used SSVEP signals to control a humanoid robot. Other applications include an electrical prosthesis [126], an orthosis [137], and a lower limb exoskeleton [133]. Recently [135] demonstrated the feasibility of an SSVEP paradigm in locked-in syndrome. SSVEPs have even been used to allow a cockroach to navigate the desired path [129] and to navigate in a two-dimensional BCI game [136].

4. Error-related potential

4.1. Overview

The error-related potential (ErrP) recently been used as an ERP component that can be used to correct BCI errors [138].

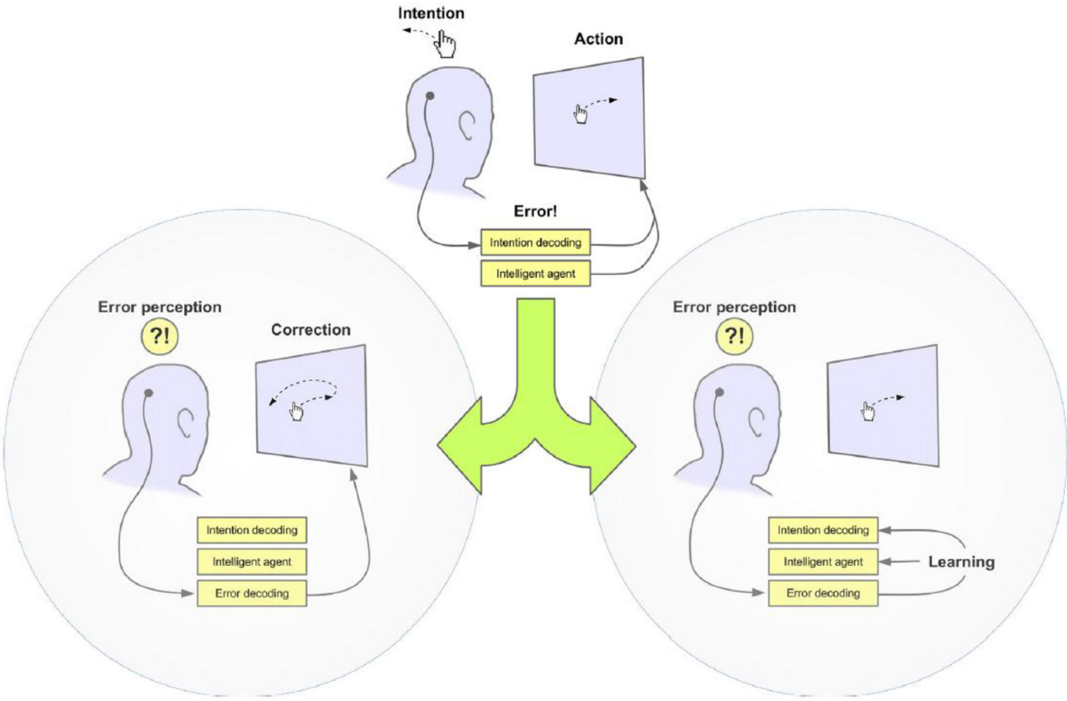

Figure 3. A schematic of how an ErrP paradigm can be used in a BCI system (Reproduced from [138]. CC BY 4.0.). (Left) Detecting the existence of error and correct the last movement. (Right) Using ErrP in a learning process to update a BCI classifier.

The ErrP occurs when there is a mismatch between a subject's intention to perform a given task and the response provided by the BCI. For example, assume a user wishes to move a cursor from the middle of a monitor to the left side of the monitor. If the cursor erroneously moves to the right, an error-related potential will be generated. The ErrP is mostly pronounced at frontal and central lobes and has a latency of 200–700 ms. Figure 3 shows a schematic of how an ErrP is generated and how it can be used to teach an intelligent agent to control a BCI. The paradigm no longer relies on an average number of trials like in P300, but it uses a short window in a single trial basis. Ferrez and Millan [139] decoded errors followed the occurrence of miss recognition of user intent by the BCI system. Subsequently, Chavarriaga and Millan [140] utilized the ErrP to control an external autonomous device within the concept of shared autonomy. The shared autonomy describes the situation where the user has only a supervisory control over the action of a system upon which he/she has no control. Consistent with the previous reports, they reported an ERP response located over the medial-frontal cortex with a negative amplitude around 260 ms after an error was detected by the subject. Moreover, the amplitude of the ERP is inversely [140] modulated by the frequency of the autonomous system error.

A real-time and closed-loop BCI system can be regarded as a control problem. The ErrP can be used to adjust the input control signals to the device. While in a traditional control system, the adjustment is performed by the using linear or nonlinear controllers, in a BCI system where the brain plays the role of controller, the adjustment can be automatically performed by the power of brain signals (for more information see review [141]). Finding a suitable controller in a traditional control system has become a solvable problem; however, understanding brain-controlled signals and translating them into logical and stable commands for usage in an external device remains challenging. This investigation is further discussed in a study by Artusi *et al* [142].

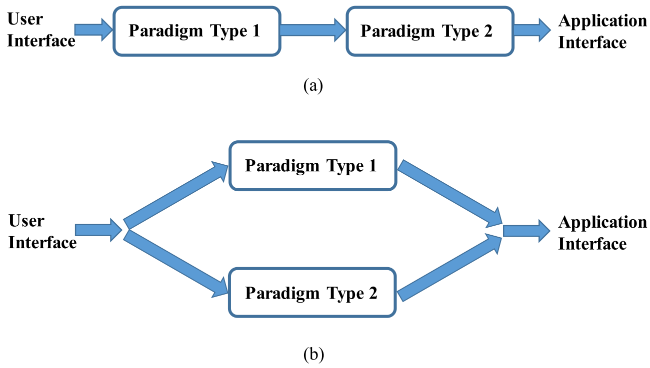

Figure 4. A schematic of two employed structures in hybrid BCI systems; (a) sequential form, (b) simultaneous form.

The process of using ErrP in a closed-loop BCI system could be considered as analogous to 'learn from your mistake'. In contrast to a traditional control system, in which error signal can be sensed in milliseconds, the brain does not produce an ErrP until 200 ms–700 ms after the subject receives feedback [139, 142]. The feedback is the relevant event whose onset engages the brain circuits to process error-related information. The delay and non-stationarity of the signal slows the system and makes real-time implementation difficult. Additionally, since the ErrP does not contain any information about direction or magnitude, there is still the challenge of how to adjust command signals based on detected ErrP in a

Table 4. An overview of previously published BCI hybrid paradigms.

Reference	Task	Feature	Classification method
[160]	Control rehabilitation robotic devices	Sequential P300 and SSVEP	Matched filter, FFT
[161]	2D cursor control	Simultaneous mu/beta rhythm and P300	SVM
[137]	Control an orthosis	Sequential ERS and SSVEP	FLDA
[170]	Control an artificial upper limb with 2 (degree of freedom) DoF	Simultaneous motor imagery and SSVEP	CCA, FLDA
[163]	2D cursor control	Simultaneous ERD and SSVEP	LDA
[166]	Quadcopter flight control	Sequential motor imagery and eye tracking	SVM
[162]	2D cursor control	Simultaneous SSVEP and P300	RBF SVM, FLDA
[164]	Robotic grasp control	Sequential SSVEP and mu rhythm	CCA, STFT
[171]	Robotic control	Sequential EOG and ERP	LDA
[172]	Quadcopter flight control	Simultaneous EEG and NIRS	LDA
[165]	Neurofeedback training	Simultaneous motor imagery and SSVEP	CCA, CSP+FFT

multi-degree-of-freedom control system. Thus, most BCI systems are designed using pre-learned algorithms to perform a task in a closed-loop BCI [140, 143]. Recently, Iturrate *et al* [144] developed a BCI system using the ErrP to autonomously complete a task after a training time of several minutes. In their task, a brain-controlled robotic arm learned how to reach a specific target based on a pre-learned algorithm using ErrP paradigm.

4.2. ErrP analysis and classification methods

One approach to extracting the ErrP is to detect the discrepancy of the observed action and the translated action in the BCI platform. Ferrez and Millan [139] found an interaction between the subject and the BCI system. They observed positive peaks at 200 ms and 450 ms after feedback and negative peaks 250 ms and 450 ms after feedback. They also observed that ErrP amplitude is higher as the error rate decreases. Chavarriaga and Millan [140] investigated the consequences of the subject monitoring an external agent that the subject does not have control over. They used a cursor movement paradigm and estimated the posterior probability of moving the cursor in the wrong direction as P_{err} by classifying the EEG signal using a Gaussian classifier. They found that electrode locations FCz and Cz were most closely correlated to the ErrP response.

Itturate *et al* [145] designed a study where a subject observed a virtual robot performing a reaching task. The subject was instructed to judge the robot motion based on prior information of the correct path. The averaged EEG waveforms at each electrode location were calculated, and the results showed a significant difference between the correct and incorrect operation of the robot. On error trials, a sharp positive peak at approximately 300 ms was observed and was followed by a negative peak at approximately 400 ms. The averaged EEG waveforms were derived in two steps: First, bipolar channels in the medial and posterior regions within the range (150–700 ms) were selected, offset components were removed, a bandpass filter of 0.5–10 Hz was applied, and the result was down-sampled to 64 Hz; Second, they applied a Functional Decision Tree in their AdaBoost classification algorithm to the resulting feature vector. Ten-Fold cross-validation suggested that the resulting averaged EEG waveforms distinguished between correct and incorrect motion of a robot.

4.3. ErrP applications and targeted patients

The use of ErrP in BCI systems was initially investigated by Ferrez and Millan [139]. Chavarriaga and Millan [140] employed the ErrP to allow a user to control and correct the behavior of an external autonomous system. In their approach, the user watched and maintained supervisory control over the autonomous system in order to correct behavior of a system without any direct or continuous control.

ErrP has been employed for robot reinforcement learning [145], 1D cursor control [139, 140, 146–150], and 2D cursor control [144, 151]. Iturrate *et al* [143] used ErrP with shared control for a 2D reaching task. ErrP has also been used in BMI systems to control artificial [152] and robotic arms [149, 153], and it has been used to teach a robotic BMI system how to reach a particular target in a 2D plane [144].

The ErrP can provide additional information to improve closed-loop BCI systems. It is likely that, in the future, the ErrP will allow a user to observe and spontaneously make the desired change in a BCI system without the need for directly performing a control task [154, 155].

5. Hybrid paradigms

5.1. Overview

A hybrid paradigm refers to a combination of two or more physiological measures in which at least one is EEG (for review see [156–158]). The other physiological measures could be other bio-signals such as heart rate (ECG), eye movements (EOG) or hemodynamic signal recorded by fNIRS [159]. In hybrid paradigms, sequential or simultaneous processing structures can be used to output control commands to the BCI system [157]. Figure 4 shows a schematic of each system. In the simultaneous processing configuration, bio-signals

Table 5. Less common EEG-based BCI paradigms.

References	Paradigm description
[174–179]	*Overt (Covert) attention paradigm:* the EEG signals are generated through overt (eye movement) or covert (eye fixation) attention on movements of a cursor on a screen
[180–187, 200–204]	*Discrete movement intention paradigm:* using recorded EEG signals, intention of subject is decoded prior to performing a task. It is a popular paradigm in rehabilitative robotics
[83, 84, 188–190, 205–207]	*Auditory paradigm:* the origin of EEG signals is related to an external sound stimulus. The potential future application could be for aural prostheses
[208]	*Olfactory paradigm:* smelling/remembering an odor could cause distinguishable changes in EEG signals
[209–211]	*Real movement paradigm:* EEG signals are recorded (used for control) while subject is performing real movement
[85, 124, 191–194, 212, 213]	Somatosensory (tactile) paradigm: tactile sensors are used to stimulate parts of body (in different frequency) while the EEG signals are recorded for classification and generating control commands
[154, 155]	*Passive paradigm:* passive EEG signals without the purpose of voluntary control, such as the user's intentions, situational interpretations, and emotional states, are utilized as a complementary BCI
[214]	*Non-motor mental imagery paradigm:* EEG signals origin from non-motor imaginary tasks such as math calculation
[19, 215–218]	*Slow cortical potentials paradigm:* low frequency EEG signals recorded from prefrontal cortex are modulated through a long training time of a cognitive task while receiving neurofeedback, as well
[219–221]	*Observation-based paradigm:* EEG signals are collected while the subject observes different actions performed by an external device (such as prosthetic hand)
[222–224]	*Eye-movement paradigm:* EEG signals are recorded while the subject is instructed to have eye movement to different directions. Discrete classes are extracted from EEG signals for controlling external objects
[195–199]	*Reflexive Semantic Conditioning Paradigm:* the EEG signals is modulated by presenting various statements. The paradigm is primarily used for communication in ALS and CLIS populations

concurrently enter two (or more) parallel decoding systems while in a sequential setting one decoding paradigm acts as a gating function for another decoding system. Visual P300, SSVEP, and SMR paradigms are the most prevalent paradigms in the development of hybrid BCI systems [82, 116].

In recent BCI studies, combining various mentioned paradigms or combining a BCI paradigm with another interface has shown to enhanced BCI performance. For example, Luth *et al* [160] paired P300 and SSVEP in controlling an assistive robotic arm. In a 2D cursor task, Li *et al* [161] used Mu and Beta rhythms for controlling horizontal movement and P300 for vertical movement. Bi *et al* [162] also used a combination of SSVEP and P300. The SSVEP paradigm was used to extract directional information (clockwise/counterclockwise), and the P300 was used to decode the speed of the cursor. To minimize false positive rates of the user's resting state, Pfurtscheller *et al* [137] introduced a hybrid BCI that combined of event-related synchronization (ERS) and SSVEP collected from an EEG channel located above motor cortex and another electrode located above visual cortex. Allison *et al* [163] developed a 2D cursor control BCI incorporating SSVEP for decoding horizontal and event-related desynchronization (ERD) for vertical movements.

5.2. Analysis and classification methods

Duan *et al* [164] developed a hybrid BCI platform to control a robot to execute the grasp motion using SSVEP, Mu rhythm, and feet motor imagery. A comparison between a single-paradigm versus hybrid neurofeedback real-time BCI consisting of motor imagery and SSVEP were reported by Yu *et al* [165]. They used the Common Spatial Pattern (CSP) method to extract maximally different mu and beta band powers for distinct classes of motor imagery and utilized the CCA to decode flickering frequency. Hyung Kim *et al* [166] combined EEG and eye tracking for controlling a quadcopter. They discriminated two mental states of intentional concentration and non-concentration using EEG signals. They applied CSP to filter EEG and then utilized the Autoregressive (AR) model to estimate the spectral power of EEG from 11 Hz to 19 Hz. The classification between two states of the model was performed by SVM, and it worked as a gating function to switch on the quadcopter. Afterwards, eye tracker was exploited to control the direction of the drone. Kim *et al* [167] utilized the same BCI platform in a pointing and selection task. A summary of previous studies on hybrid BCI is shown in table 4. Further information in regard to hybrid BCIs can be seen in recent review articles [116, 156–158, 168, 169].

5.3. Applications and targeted patients population

Hybrid paradigms have been developed and applied to many BCI applications. Some studies have used a combination of two EEG signals to control virtual objects and prosthetic devices. For example, Bi *et al* [162] used P300 and SSVEP paradigms to control a 2D computer cursor. Allison *et al* [163] used SMR and SSVEP paradigms to control a computer cursor in 2D space. Li *et al* [161] used SMR and P300 paradigms to control a 2D computer cursor. Horik *et al* [170] combined SMR and SSVEP to control a 2-DOF artificial upper limb. Also using SMR and SSVEP, Duan *et al* [164] controlled a humanoid robot to perform simple tasks. Pfurtscheller *et al* [137] evaluated the feasibility of orthosis control using a combination of SSVEP and motor imagery paradigms. Yu *et al*

[165] also used a combination of SSEVP and motor imagery to enhance training performance for a motor imagery paradigm. Luth *et al* [160] employed a hybrid P300 and SSVEP for a low-level application of a semi-autonomous robotic rehabilitation system.

In other hybrid BCI systems, EEG is combined with other bio-signals such as EOG. For example, Kim *et al* [167] and Malechka *et al* [173] developed wearable hybrid BCI systems using EEG and an eye-tracking device. Kim *et al* [166] employed their system with a motor imagery paradigm to control a quadcopter in three-dimensional space. Ma *et al* [171] developed a novel hybrid BCI using eye movements and the P300 ERP to control devices such as mobile robots and humanoid robots. Other studies have combined EEG paradigms with other neuroimaging techniques (e.g. fNIRS) for communication purposes in ALS and monitoring of patients vigilance state [159] and to control external devices such as quadcopters [172].

6. Other paradigms

In addition to the most common BCI paradigms detailed above, other paradigms have been examined in a limited number of studies. Table 5 shows a number of previously generated EEG-based BCI paradigms and a brief description of each system. Among the paradigms shown in table 5, the 'covert and overt attention', 'discrete movement intention' and 'auditory paradigm' paradigms have shown promise as BCI devices.

6.1. Covert and overt attention paradigm

Hunt and Kingstone [174] were among the first to use a covert attention BCI paradigm. They discovered the existence of a dissociation between voluntary shifts in overt and covert attention. In a covert attention paradigm, the subject is instructed to look at a centrally located fixation point. The subject's task is to follow another point (e.g. cursor) without overt eye movement. In contrast to covert attention, an overt attention task the subject is instructed to use overt eye movements while they attend to a moving object. Both of these approaches depend on visual attention, and the EEG signals are typically recorded from the posterior cortex. Additional studies using this paradigm were performed by Kelly *et al* [175, 176]. In [176], they investigated Parieto-occipital alpha band (8–14 Hz) EEG activity in a covert attention paradigm to classify the spatial attention to the right and left. Later, they confirmed the existence of distinct patterns in overt and covert attention during preparatory processes [175]. Tonin and colleagues [177, 178] used a covert attention paradigm in a 2-class classification problem (i.e. attention to right corner target of a monitor versus attention to left corner target of a monitor) to control a BCI system in online mode and provide feedback to the subject by showing the result of classification. Additionally, Treder *et al* [179] employed a covert attention paradigm for a two-dimensional BCI control to covertly choose a target among six targets which are equally distributed around a circle on a screen.

6.2. Discrete movement intention paradigm

In the movement intention paradigm, EEG signals collected before movement onset are used to detect the intended movement of a BCI user and manipulate the environment accordingly. In these studies, the subject may or may not be able to physically execute an actual movement. However, their EEG signals can confirm the intention of movement before movement occurs [180]. In some studies, the terminology 'attempted' [181] or 'planned' [182] movement is used to describe the intention of movement. This paradigm can be primarily and fruitfully used in motor rehabilitation. By using the movement intention paradigm in robotic rehabilitation, a patient's intentions can initiate the movement of a robot. Frisoli *et al* [183] used a gaze-dependent variation of this paradigm for upper limb rehabilitation. EEG signals were used to adjust jerk, acceleration, and speed of the exoskeleton. As a means of therapy for post-stroke patients, Muralidharan *et al* [181] successfully extracted intention from EEG signals to open or close a paretic left/right hand. A similar study by Lew *et al* [184] was performed using two able-bodied subjects and two post-stroke patients with an overall success rate of 80% in detection of movement. Investigation of EEG signals for the intention of the right-hand and left-hand movements was performed by Bai *et al* [185]. Bai *et al* [180] predicted wrist extension movements in seven healthy subjects. Zhou *et al* [186] classified the information from EEG signals during the moment in which the subjects (four healthy, two stroke) intended to perform shoulder abduction or elbow flexion movements. Also, EEG data were analyzed for a chronic stroke patient before the onset of hand movement toward a target [187].

6.3. Auditory paradigm

Auditory paradigms have also been investigated by a number of BCI researchers [83]. Brain signals can be modulated either by using an intention-driven (endogenous) BCI or stimulus-driven (exogenous) BCI depending on the paradigm. For example, auditory P300 [188] considered as an exogenous stimulation is used to evoke auditory steady-state responses (ASSR) [189]. ASSR is an auditory evoked potential in response to rapid auditory stimuli; Picton *et al* [189] showed that the ASSR maximum amplitude is recorded from the vertex of the scalp. Sellers and Donchin [188] compared P300 auditory and visual paradigms in patients with ALS. Although they showed proof of principle with the auditory P300 BCI, performance was significantly better in the visual condition. Nijboer *et al* [84] also validated the feasibility of an auditory-based BCI by comparing with visual-based BCI. Ferracuti *et al* [190] used a novel paradigm where five classes of auditory stimuli were presented in five different locations of space.

6.4. Somatosensory (tactile) paradigm

In recent years, the usage of a somatosensory paradigms for patients with visual impairment has become popular. In this paradigm, vibrotactile sensors are located in pre-determined parts of body while stimulations happen at different frequencies [191]. The stimulations of these sensors will be reflected on EEG signals recorded from the scalp. Muller-Putz *et al* [124] investigated the usability of the steady-state somatosensory evoked potential paradigm. Other researchers employed tactile P300 paradigms in their BCI systems [192]. Imagined tactile paradigms were also investigated by Yao *et al* [85]. The somatosensory paradigm was utilized in assisting patients with locked-in syndrome [193, 194].

6.5. Reflexive semantic conditioning paradigm

BCIs for communication purposes have been developed since the late eighties; however, it remains a great challenge to provide reliable results for people with severe motor disabilities, such as completely locked-in syndrome (CLIS). A paradigm named 'reflexive semantic conditioning' (based on Pavlov theory) was developed and tested in healthy participants as well as in people with diagnosis of ALS. The main goal of the paradigm is to deal with communication problems in CLIS and ALS patients [195–199].

7. Current issues and future considerations

In recent years, BCI research has made significant progress in neurorehabilitation and assistive device technology. Each of the methodologies presented in this review has promise as brain-controlled external prosthetic devices for spinal cord injury patients and other with severe communication disorders such as ALS, LIS, and multiple sclerosis (MS). No doubt, there is a strong possibility that BCI systems will be commercialized shortly. In fact, a limited number of commercial devices are already available. Some programs such as the BNCI Horizon 2020 project [225] has established a future roadmap for BCI systems. Nevertheless, there are critical limitations, challenges, and issues related to BCI paradigms and platforms that should be addressed and considered by the BCI community. It is a common practice in the BCI literature to report the results of a study in term of classification accuracy. Few publications address issues such as reliability of the platforms. Also, it is often not clear what are the behavioral, cognitive, sensory, and motor functional outcomes in a BCI study. To further advance BCI research for practical applications, we believe these important issues should be addressed in future work.

7.1. Training time and fatigue

One of the most significant challenges in BCI is the training required for a subject to become proficient with the system. Most paradigms have lengthy training times, which can cause fatigue in subjects. Although there are examples of long-term use of stimulus-based BCI such as [112, 226], overall external stimulus paradigms such as P300-based systems may cause fatigue over extended periods of use. Moreover, subject-dependency and even inter-session variability can make it necessary for BCI researchers to collect calibration data at the beginning of each session. To mitigate this problem, some recent studies have used methods such as transfer learning to develop a zero training/generic BCI model that generalizes to most subjects [81, 227–230].

7.2. Signal processing and novel decoders

Many different decoding methods, signal processing algorithms [231], and classification algorithms [30] have been recently investigated. Nevertheless, the information extracted from EEG signals does not have a high enough signal-to-noise ratio to control a system such as a neuroprosthetic arm with multiple degrees of freedom. More robust, accurate, and fast online algorithms are required to be able to control a multi-DOF system. In recent years, some researchers have suggested that source localization of EEG [232] and active data selection [233] can improve classification performance. Other researchers have suggested the use of advanced machine learning and deep learning methods [234–237], which have potential to extract additional features that can improve classification. Furthermore, other researchers have proposed adaptive classifiers and decoders in order to compensate for the non-stationary nature of EEG signals [238]. Meanwhile, a particular standardization system is essential to evaluate the performance of decoding algorithms in specific applications and BCI systems [239].

7.3. From shared control to supervisory control in closed-loop BCIs

A closed-loop BCI is considered to be a co-adaptive and mutual learning system where the human and computer learn from each other, while adaptation in mathematical algorithms and neural circuits also occurs. Millan [240] described the closed-loop BCI system as a 'two-learner system'. The terms 'shared control' and 'hybrid control' were also used to describe the contributions of both human and machine in performing the control task [20, 55, 143, 241–243]. The shared BCI system includes both high-level and low-level control systems. High-level control commands are generated by the brain and traditional control systems are responsible for low-level control tasks. Interestingly, in high-level control, there is always a tradeoff between the natural way of control and subject fatigue. The ideal BCI system with mutual interaction can be described as a supervisory control system in which the subject is the leader with minimum involvement (in high-level control), and the BCI system serves as an intelligent system (in low-level control) [140, 244]. By cognitive monitoring, the user can act as a supervisor of the external autonomous system instead of continuously interacting with control commands.

The definition of a closed-loop control system is currently a controversial issue [141, 245]. In reality, in an EEG-based BCI, some types of artificial sensory feedback, except visual feedback [246], should be considered to provide the subject with the highest feeling of control in a closed-loop form. In contrast, invasively controlled prosthetic arms include the sense of touch, which increases the perception of a closed-loop control system [247]. In EEG-based BCI platforms, various feedback mechanisms have been investigated, including brain stimulation [35], reaction force [248], and somatosensory stimulation [42].

7.4. Development of new EEG technologies

Since scalp EEG is categorized as low-cost and affordable technology among brain monitoring technologies, it has the potential to be commercialized for general public [3]. There are studies to determine alertness/drowsiness from brain dynamics while evaluating behavioral changes with applications to drowsy driving. Having a portable EEG headset helps understand the brain dynamics underlying integration of perceptual functions of the brain in different scenarios. Some studies evaluate behavioral changes in response to auditory signals in a driving environment and find correlations between brainwaves and other sensory inputs such as haptic feedback. As part of development for this technology many researchers have investigated the development of wearable and wireless EEG headsets [173, 249]. Dry EEG sensors have also developed [250–253]. These sensors do not require skin preparation or gel applications that are required of conventional wet sensors. The development of these new EEG headsets could facilitate the application of BCIs beyond current levels. For example, a forehead EEG-based BCI can be used as a sleep management system that can assess sleep quality. The device could also be used as a depression treatment screening system that could evaluate and predict the efficacy of rapid antidepressant agents. Nevertheless, there are still limitations to dry electrode technology. For example, the sensors are uncomfortable to the scalp and they are very sensitive to muscle and movement artifacts. In addition, current dry headsets recording quality typically degrades after approximately 1 h.

7.5. Neurofeedback and the future paradigms

One future direction of BCI is its application in neurofeedback [254]. Neurofeedback, a type of biofeedback, is the process of self-regulating brainwaves to improve various aspects of cognitive control. In some cases, neurofeedback-based BCIs could potentially replace medications, thereby reducing the negative side effects of medication. For example, this technology could help to alleviate cognitive and pathological neural diseases, such as migraine headaches. A headache detection and management system can notify migraine patients' imminent migraine headaches days in advance while offering a treatment in neurofeedback form. Neurofeedback-based BCIs could also be developed to assist the treatment of people with addiction, obesity, autism, and asthma [255]. New EEG paradigms can also be developed to facilitate cognitive control [256] and interaction with the environment [154, 155]. For instance, ErrP can be used as a useful mechanism to enhance neurofeedback since it allows a user to observe and spontaneously make the desired change in a BCI system without the need to directly perform a control task. Moreover, new cognitive models of neurofeedback can be developed for neuro-rehabilitation of cognitive deficits, such as ADHD, anxiety, epilepsy, Alzheimer's disease, traumatic brain injury, and post-traumatic stress disorder [257–263].

8. Conclusions

Currently, there is a high level of interest in non-invasive BCI technology. Many variables have facilitated the popularity of these systems. Because of wireless recording, low-cost amplifiers, higher temporal resolution, and advanced signal analysis methodology, the systems are more accessible to researchers in many scientific domains. As described in this review, a critical aspect of employing a BCI system is to match the appropriate control signal with the desired application. It is essential to choose the most reliable, accurate, and convenient paradigm to manipulate a neuroprosthetic device or implement a specific neurorehabilitation program. The current review has evaluated several EEG-based BCI paradigms in terms of their advantages and disadvantages from a variety of perspectives. Each paradigm was described and presented in terms of the control signals, various EEG decoding algorithms, and classification methods, and target populations of each paradigm were summarized. Finally, potential problems with EEG-based BCI systems were discussed, and possible solutions were proposed.

Acknowledgments

The authors are grateful to Dr Jose Millan for his insightful comments to an early draft of this manuscript. The assistance of Megan Pitz to the manuscript is also appreciated. This work was partially supported by NeuroNET at UTK.

Author contributions

R A and S B contributed equally and have shared first authorship. E S and Y J revised the paper and contributed with insightful comments. X Z was involved in all aspects of the study.

Competing financial interests

The authors declare no competing financial interests.

ORCID iDs

Reza Abiri https://orcid.org/0000-0001-8975-8210
Soheil Borhani https://orcid.org/0000-0002-4887-1417
Yang Jiang https://orcid.org/0000-0003-4589-0097
Xiaopeng Zhao https://orcid.org/0000-0003-1207-5379

References

[1] Nirenberg L M, Hanley J and Stear E B 1971 A new approach to prosthetic control: EEG motor signal tracking with

an adaptively designed phase-locked loop *IEEE Trans. Biomed. Eng.* **BME-18** 389–98
[2] Wolpaw J R, Birbaumer N, McFarland D J, Pfurtscheller G and Vaughan T M 2002 Brain–computer interfaces for communication and control *Clin. Neurophysiol.* **113** 767–91
[3] Nicolas-Alonso L F and Gomez-Gil J 2012 Brain computer interfaces, a review *Sensors* **12** 1211–79
[4] Lebedev M A and Nicolelis M A 2017 Brain–machine interfaces: from basic science to neuroprostheses and neurorehabilitation *Physiol. Rev.* **97** 767–837
[5] Ramadan R A and Vasilakos A V 2017 Brain computer interface: control signals review *Neurocomputing* **223** 26–44
[6] Waldert S, Pistohl T, Braun C, Ball T, Aertsen A and Mehring C 2009 A review on directional information in neural signals for brain–machine interfaces *J. Physiol.* **103** 244–54
[7] Slutzky M W and Flint R D 2017 Physiological properties of brain–machine interface input signals *J. Neurophysiol.* **118** 1329–43
[8] Moran D W and Schwartz A B 1999 Motor cortical representation of speed and direction during reaching *J. Neurophysiol.* **82** 2676–92
[9] Hochberg L R *et al* 2006 Neuronal ensemble control of prosthetic devices by a human with tetraplegia *Nature* **442** 164–71
[10] Kim S-P, Simeral J D, Hochberg L R, Donoghue J P and Black M J 2008 Neural control of computer cursor velocity by decoding motor cortical spiking activity in humans with tetraplegia *J. Neural Eng.* **5** 455
[11] Mulliken G H, Musallam S and Andersen R A 2008 Decoding trajectories from posterior parietal cortex ensembles *J. Neurosci.* **28** 12913–26
[12] Hauschild M, Mulliken G H, Fineman I, Loeb G E and Andersen R A 2012 Cognitive signals for brain–machine interfaces in posterior parietal cortex include continuous 3D trajectory commands *Proc. Natl Acad. Sci.* **109** 17075–80
[13] Hochberg L R *et al* 2012 Reach and grasp by people with tetraplegia using a neurally controlled robotic arm *Nature* **485** 372–5
[14] Kim S-P, Simeral J D, Hochberg L R, Donoghue J P, Friehs G M and Black M J 2011 Point-and-click cursor control with an intracortical neural interface system by humans with tetraplegia *IEEE Trans. Neural Syst. Rehabil. Eng.* **19** 193–203
[15] Vogel J *et al* 2015 An assistive decision-and-control architecture for force-sensitive hand–arm systems driven by human–machine interfaces *Int. J. Robot. Res.* **34** 763–80
[16] Taylor D M, Tillery S I H and Schwartz A B 2002 Direct cortical control of 3D neuroprosthetic devices *Science* **296** 1829–32
[17] Velliste M, Perel S, Spalding M C, Whitford A S and Schwartz A B 2008 Cortical control of a prosthetic arm for self-feeding *Nature* **453** 1098–101
[18] Bi L, Fan X-A and Liu Y 2013 EEG-based brain-controlled mobile robots: a survey *IEEE Trans. Hum. Mach. Syst.* **43** 161–76
[19] Birbaumer N *et al* 1999 A spelling device for the paralysed *Nature* **398** 297–8
[20] Meng J, Zhang S, Bekyo A, Olsoe J, Baxter B and He B 2016 Noninvasive electroencephalogram based control of a robotic arm for reach and grasp tasks *Sci. Rep.* **6** 38565
[21] Daly J J and Wolpaw J R 2008 Brain–computer interfaces in neurological rehabilitation *Lancet Neurol.* **7** 1032–43
[22] Birbaumer N and Cohen L G 2007 Brain–computer interfaces: communication and restoration of movement in paralysis *J. Physiol.* **579** 621–36
[23] Machado S, Almada L F and Annavarapu R N 2013 Progress and prospects in EEG-based brain–computer interface: clinical applications in neurorehabilitation *J. Rehabil. Robot.* **1** 28–41 (https://synergypublishers.com/jms/index.php/jrr/article/view/17/57)
[24] Moghimi S, Kushki A, Marie Guerguerian A and Chau T 2012 A review of EEG-based brain–computer interfaces as access pathways for individuals with severe disabilities *Assist. Technol.* **25** 99–110
[25] Birbaumer N 2006 Breaking the silence: brain–computer interfaces (BCI) for communication and motor control *Psychophysiology* **43** 517–32
[26] Contreras-Vidal J L, Presacco A, Agashe H and Paek A 2012 Restoration of whole body movement: toward a noninvasive brain–machine interface system *IEEE Pulse* **3** 34–7
[27] Mulder T 2007 Motor imagery and action observation: cognitive tools for rehabilitation *J. Neural Transm.* **114** 1265–78
[28] Vaughan T M, Wolpaw J R and Donchin E 1996 EEG-based communication: prospects and problems *IEEE Trans. Rehabil. Eng.* **4** 425–30
[29] Hwang H-J, Kim S, Choi S and Im C-H 2013 EEG-based brain–computer interfaces: a thorough literature survey *Int. J. Hum. Comput. Interact.* **29** 814–26
[30] Lotte F, Congedo M, Lécuyer A, Lamarche F and Arnaldi B 2007 A review of classification algorithms for EEG-based brain–computer interfaces *J. Neural Eng.* **4** R1
[31] Pfurtscheller G, Graimann B and Neuper C 2006 EEG-based brain–computer interface system *Encyclopedia of Biomedical Engineering* 1st edn vol 2 (New Jersey: John Wiley & Sons) pp 1156–66
[32] Machado S *et al* 2010 EEG-based brain–computer interfaces: an overview of basic concepts and clinical applications in neurorehabilitation *Rev. Neurosci.* **21** 451–68
[33] Pfurtscheller G and Neuper C 1997 Motor imagery activates primary sensorimotor area in humans *Neurosci. Lett.* **239** 65–8
[34] Yuan H and He B 2014 Brain–computer interfaces using sensorimotor rhythms: current state and future perspectives *IEEE Trans. Biomed. Eng.* **61** 1425–35
[35] He B, Baxter B, Edelman B J, Cline C C and Wenjing W Y 2015 Noninvasive brain–computer interfaces based on sensorimotor rhythms *Proc. IEEE* **103** 907–25
[36] Morash V, Bai O, Furlani S, Lin P and Hallett M 2008 Classifying EEG signals preceding right hand, left hand, tongue, and right foot movements and motor imageries *Clin. Neurophysiol.* **119** 2570–8
[37] Pfurtscheller G and Da Silva F L 1999 Event-related EEG/MEG synchronization and desynchronization: basic principles *Clin. Neurophysiol.* **110** 1842–57
[38] Wolpaw J R, McFarland D J, Neat G W and Forneris C A 1991 An EEG-based brain–computer interface for cursor control *Electroencephalogr. Clin. Neurophysiol.* **78** 252–9
[39] LaFleur K, Cassady K, Doud A, Shades K, Rogin E and He B 2013 Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain–computer interface *J. Neural Eng.* **10** 046003
[40] Wolpaw J R and McFarland D J 2004 Control of a two-dimensional movement signal by a noninvasive brain–computer interface in humans *Proc. Natl Acad. Sci. USA* **101** 17849–54
[41] Bhattacharyya S, Khasnobish A, Konar A, Tibarewala D N and Nagar A K 2011 Performance analysis of left/right hand movement classification from EEG signal by intelligent algorithms *2011 IEEE Symp. on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB)* pp 1–8
[42] Murguialday A R *et al* 2007 Brain–computer interface for a prosthetic hand using local machine control and haptic feedback *IEEE 10th Int. Conf. on Rehabilitation Robotics, 2007 (ICORR 2007)* pp 609–13

[43] Chen C-W, Lin C-C K and Ju M-S 2009 Hand orthosis controlled using brain–computer interface *J. Med. Biol. Eng.* **29** 234–41 (http://www.jmbe.org.tw/files/425/public/425-1546-1-PB.pdf)
[44] Wolpaw J R and McFarland D J 1994 Multichannel EEG-based brain–computer communication *Electroencephalogr. Clin. Neurophysiol.* **90** 444–9
[45] Muller-Putz G R, Scherer R, Pfurtscheller G and Rupp R 2005 EEG-based neuroprosthesis control: a step towards clinical practice *Neurosci. Lett.* **382** 169–74
[46] Ang K K *et al* 2009 A clinical study of motor imagery-based brain–computer interface for upper limb robotic rehabilitation *Engineering in Medicine and Biology Society, 2009 (EMBC 2009). Annual Int. Conf. of the IEEE* (IEEE) pp 5981–4
[47] Baxter B S, Decker A and He B 2013 Noninvasive control of a robotic arm in multiple dimensions using scalp electroencephalogram *2013 6th Int. IEEE/EMBS Conf. on Neural Engineering (NER)* (IEEE) pp 45–7
[48] Sarac M, Koyas E, Erdogan A, Cetin M and Patoglu V 2013 Brain computer interface based robotic rehabilitation with online modification of task speed *IEEE Int. Conf. on Rehabilitation Robotics* vol 2013 p 6650423
[49] McFarland D J, Sarnacki W A and Wolpaw J R 2010 Electroencephalographic (EEG) control of three-dimensional movement *J. Neural Eng.* **7** 036007
[50] Guger C, Harkam W, Hertnaes C and Pfurtscheller G 1999 Prosthetic control by an EEG-based brain–computer interface (BCI) *Proc. AAATE 5th European Conf. for the Advancement of Assistive Technology* pp 3–6 (https://pdfs.semanticscholar.org/c864/6a15245732a8f91fb74294562b99d19628df.pdf)
[51] Pfurtscheller G, Müller G R, Pfurtscheller J, Gerner H J and Rupp R 2003 'Thought'—control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia *Neurosci. Lett.* **351** 33–6
[52] Sun A, Fan B and Jia C 2011 Motor imagery EEG-based online control system for upper artificial limb *2011 Int. Conf. on Transportation, Mechanical, and Electrical Engineering (TMEE)* pp 1646–9
[53] Roy R, Konar A, Tibarewala D N and Janarthanan R 2012 EEG driven model predictive position control of an artificial limb using neural net *2012 3rd Int. Conf. on Computing Communication & Networking Technologies (ICCCNT)* pp 1–9
[54] Doud A J, Lucas J P, Pisansky M T and He B 2011 Continuous three-dimensional control of a virtual helicopter using a motor imagery based brain–computer interface *PloS One* **6** e26322
[55] Li T, Hong J, Zhang J and Guo F 2014 Brain–machine interface control of a manipulator using small-world neural network and shared control strategy *J. Neurosci. Methods* **224** 26–38
[56] Fok S *et al* 2011 An EEG-based brain computer interface for rehabilitation and restoration of hand control following stroke using ipsilateral cortical physiology *Int. Conf. IEEE Eng. Med. Biol. Soc.* vol 2011 pp 6277–80
[57] Wang C *et al* 2009 A feasibility study of non-invasive motor-imagery BCI-based robotic rehabilitation for Stroke patients *4th Int. IEEE/EMBS Conf. on Neural Engineering, 2009 (NER'09)* (IEEE) pp 271–4
[58] Buch E *et al* 2008 Think to move: a neuromagnetic brain–computer interface (BCI) system for chronic stroke *Stroke* **39** 910–7
[59] Ramos-Murguialday A *et al* 2012 Proprioceptive feedback and brain computer interface (BCI) based neuroprostheses *PloS One* **7** e47048
[60] Ramos-Murguialday A *et al* 2013 Brain–machine interface in chronic stroke rehabilitation: a controlled study *Ann. Neurol.* **74** 100–8
[61] Kaiser V, Daly I, Pichiorri F, Mattia D, Müller-Putz G R and Neuper C 2012 Relationship between electrical brain responses to motor imagery and motor impairment in stroke *Stroke* **43** 2735–40
[62] Pereira J, Ofner P, Schwarz A, Sburlea A I and Müller-Putz G R 2017 EEG neural correlates of goal-directed movement intention *NeuroImage* **149** 129–40
[63] Bradberry T J, Gentili R J and Contreras-Vidal J L 2011 Fast attainment of computer cursor control with noninvasively acquired brain signals *J. Neural Eng.* **8** 036010
[64] Ofner P and Müller-Putz G R 2014 EEG-based classification of imagined arm trajectories *Replace, Repair, Restore, Relieve—Bridging Clinical and Engineering Solutions in Neurorehabilitation* (Berlin: Springer) pp 611–20
[65] Kim J-H, Biessmann F and Lee S-W 2014 Decoding three-dimensional trajectory of executed and imagined arm movements from electroencephalogram signals *IEEE Trans. Neural Syst. Rehabil. Eng.* **23** 867–76
[66] Úbeda A, Azorín J M, Chavarriaga R and Millán J D. R 2016 Evaluating decoding performance of upper limb imagined trajectories during center-out reaching tasks *2016 IEEE Int. Conf. on Systems, Man, and Cybernetics (SMC)* (IEEE) pp 000252–7
[67] Gu Y, Dremstrup K and Farina D 2009 Single-trial discrimination of type and speed of wrist movements from EEG recordings *Clin. Neurophysiol.* **120** 1596–600
[68] Gu Y, Farina D, Murguialday A R, Dremstrup K, Montoya P and Birbaumer N 2009 Offline identification of imagined speed of wrist movements in paralyzed ALS patients from single-trial EEG *Frontiers Neurosci.* **3** 62
[69] Vuckovic A and Sepulveda F 2008 Delta band contribution in cue based single trial classification of real and imaginary wrist movements *Med. Biol. Eng. Comput.* **46** 529–39
[70] Chakraborti T *et al* 2011 Implementation of EEG based control of remote robotic systems *2011 Int. Conf. on Recent Trends in Information Systems (ReTIS)* (IEEE) pp 203–8
[71] Mohamed A K, Marwala T and John L R 2011 Single-trial EEG discrimination between wrist and finger movement imagery and execution in a sensorimotor BCI *Int. Conf. IEEE Eng. Med. Biol. Soc.* vol 2011 pp 6289–93
[72] Bradberry T J, Gentili R J and Contreras-Vidal J L 2010 Reconstructing three-dimensional hand movements from noninvasive electroencephalographic signals *J. Neurosci.* **30** 3432–7
[73] Ofner P and Müller-Putz G R 2015 Using a noninvasive decoding method to classify rhythmic movement imaginations of the arm in two planes *IEEE Trans. Biomed. Eng.* **62** 972–81
[74] Yuan H, Perdoni C and He B 2010 Relationship between speed and EEG activity during imagined and executed hand movements *J. Neural Eng.* **7** 26001
[75] Korik A, Sosnik R, Siddique N and Coyle D 2016 Imagined 3D hand movement trajectory decoding from sensorimotor EEG rhythms *2016 IEEE Int. Conf. on Systems, Man, and Cybernetics (SMC)* (IEEE) pp 004591–6
[76] Abiri R, Heise G, Schwartz F and Zhao X 2015 EEG-based control of a unidimensional computer cursor using imagined body kinematics *Biomedical Engineering Society Annual Meeting (BMES 2015)* (https://hal.archives-ouvertes.fr/hal-01574279/document)
[77] Abiri R, Zhao X, Heise G, Jiang Y and Abiri F 2017 Brain computer interface for gesture control of a social robot: an offline study *2017 Iranian Conf. on Electrical Engineering (ICEE)* (IEEE) pp 113–7
[78] Abiri R, Borhani S, Zhao X and Jiang Y 2017 Real-time brain machine interaction via social robot gesture control *ASME 2017 Dynamic Systems and Control Conf.* (American Society of Mechanical Engineers) p V001T37A002

[79] Abiri R, Kilmarx J, Borhani S, Zhao X and Jiang Y 2017 A brain–machine interface for a sequence movement control of a robotic arm *Society for Neuroscience (SfN 2017)* (https://hal.archives-ouvertes.fr/hal-01741342/document)
[80] Abiri R, Kilmarx J, Raji M and Zhao X 2016 Planar control of a quadcopter using a zero-training brain machine interface platform *Biomedical Engineering Society Annual Meeting (BMES 2016)* (https://hal.archives-ouvertes.fr/hal-01574290/document)
[81] Borhani S, Abiri R, Zhao X and Jiang Y 2017 A transfer learning approach towards zero-training BCI for EEG-based two dimensional cursor control *Society for Neuroscience (SfN 2017)* (https://hal.archives-ouvertes.fr/hal-01640834/document)
[82] Kapgate D and Kalbande D 2015 A review on visual brain computer interface *Advancements of Medical Electronics* (Berlin: Springer) pp 193–206
[83] Gao S, Wang Y, Gao X and Hong B 2008 Visual and auditory brain–computer interfaces *IEEE Trans. Biomed. Eng.* **61** 1436–47
[84] Nijboer F *et al* 2008 An auditory brain–computer interface (BCI) *J. Neurosci. Methods* **167** 43–50
[85] Yao L, Sheng X, Zhang D, Jiang N, Farina D and Zhu X 2017 A BCI system based on somatosensory attentional orientation *IEEE Trans. Neural Syst. Rehabil. Eng.* **25** 81–90
[86] Fabiani M, Gratton G, Karis D and Donchin E 1987 Definition, identification, and reliability of measurement of the P300 component of the event-related brain potential *Adv. Psychophysiol.* **2** 78 (https://scholarcommons.usf.edu/psy_facpub/286/)
[87] Polich J 2007 Updating P300: an integrative theory of P3a and P3b *Clin. Neurophysiol.* **118** 2128–48
[88] 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
[89] Halder S *et al* 2013 Prediction of P300 BCI aptitude in severe motor impairment *PloS One* **8** e76148
[90] Fazel-Rezai R, Allison B Z, Guger C, Sellers E W, Kleih S C and Kübler A 2012 P300 brain computer interface: current challenges and emerging trends *Frontiers Neuroeng.* **5** 14
[91] McCane L M *et al* 2014 Brain–computer interface (BCI) evaluation in people with amyotrophic lateral sclerosis *Amyotroph. Lateral Scler. Frontotemporal Degener.* **15** 207–15
[92] Cipresso P *et al* 2012 The use of P300-based BCIs in amyotrophic lateral sclerosis: from augmentative and alternative communication to cognitive assessment *Brain Behav.* **2** 479–98
[93] Sutton S, Tueting P, Zubin J and John E R 1967 Information delivery and the sensory evoked potential *Science* **155** 1436–9
[94] 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
[95] Piccione F *et al* 2006 P300-based brain computer interface: reliability and performance in healthy and paralysed participants *Clin. Neurophysiol.* **117** 531–7
[96] Krusienski D J *et al* 2006 A comparison of classification techniques for the P300 Speller *J. Neural Eng.* **3** 299
[97] Citi L, Poli R, Cinel C and Sepulveda F 2008 P300-based BCI mouse with genetically-optimized analogue control *IEEE Trans. Neural Syst. Rehabil. Eng.* **16** 51–61
[98] Silvoni S *et al* 2009 P300-based brain–computer interface communication: evaluation and follow-up in amyotrophic lateral sclerosis *Frontiers Neurosci.* **3** 60
[99] Marchetti M, Piccione F, Silvoni S and Priftis K 2012 Exogenous and endogenous orienting of visuospatial attention in P300-guided brain computer interfaces: a pilot study on healthy participants *Clin. Neurophysiol.* **123** 774–9
[100] Marchetti M, Piccione F, Silvoni S, Gamberini L and Priftis K 2013 Covert visuospatial attention orienting in a brain–computer interface for amyotrophic lateral sclerosis patients *Neurorehabil. Neural Repair* **27** 430–8
[101] Silvoni S, Cavinato M, Volpato C, Ruf C A, Birbaumer N and Piccione F 2013 Amyotrophic lateral sclerosis progression and stability of brain–computer interface communication *Amyotroph. Lateral Scler. Frontotemporal Degener.* **14** 390–6
[102] 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
[103] Bell C J, Shenoy P, Chalodhorn R and Rao R P 2008 Control of a humanoid robot by a noninvasive brain–computer interface in humans *J. Neural Eng.* **5** 214
[104] Edlinger G, Holzner C, Groenegress C, Guger C and Slater M 2009 Goal-oriented control with brain–computer interface *Int. Conf. on Foundations of Augmented Cognition* (Springer) pp 732–40
[105] Chen W-D *et al* 2010 A P300 based online brain–computer interface system for virtual hand control *J. Zhejiang Univ. Sci.* C **11** 587–97
[106] Fazel-Rezai R and Abhari K 2009 A region-based P300 speller for brain–computer interface *Can. J. Electr. Comput. Eng.* **34** 81–5
[107] Townsend G *et al* 2010 A novel P300-based brain–computer interface stimulus presentation paradigm: moving beyond rows and columns *Clin. Neurophysiol.* **121** 1109–20
[108] Moghadamfalahi M, Orhan U, Akcakaya M, Nezamfar H, Fried-Oken M and Erdogmus D 2015 Language-model assisted brain computer interface for typing: a comparison of matrix and rapid serial visual presentation *IEEE Trans. Neural Syst. Rehabil. Eng.* **23** 910–20
[109] 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
[110] Iturrate I, Antelis J M, Kubler A and Minguez J 2009 A noninvasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation *IEEE Trans. Robot.* **25** 614–27
[111] Nijboer F *et al* 2008 A P300-based brain–computer interface for people with amyotrophic lateral sclerosis *Clin. Neurophysiol.* **119** 1909–16
[112] 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
[113] Sellers E W, Ryan D B and Hauser C K 2014 Noninvasive brain–computer interface enables communication after brainstem stroke *Sci. Transl. Med.* **6** 257re7
[114] Aydin E A, Bay Ö F and Güler I 2016 Implementation of an embedded web server application for wireless control of brain computer interface based home environments *J. Med. Syst.* **40** 1–10
[115] He S *et al* 2017 A P300-based threshold-free brain switch and its application in wheelchair control *IEEE Trans. Neural Syst. Rehabil. Eng.* **25** 715–25
[116] Amiri S, Rabbi A, Azinfar L and Fazel-Rezai R 2013 A review of P300, SSVEP, and hybrid P300/SSVEP brain–computer interface systems *Brain–Computer Interface Systems—Recent Progress and Future Prospects* (Rijeka: InTech) Ch 10
[117] Vialatte F-B, Maurice M, Dauwels J and Cichocki A 2010 Steady-state visually evoked potentials: focus on essential paradigms and future perspectives *Prog. Neurobiol.* **90** 418–38

[118] Herrmann C S 2001 Human EEG responses to 1–100 Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena *Exp. Brain Res.* **137** 346–53
[119] Chang M H, Baek H J, Lee S M and Park K S 2014 An amplitude-modulated visual stimulation for reducing eye fatigue in SSVEP-based brain–computer interfaces *Clin. Neurophysiol.* **125** 1380–91
[120] Molina G G and Mihajlovic V 2010 Spatial filters to detect steady-state visual evoked potentials elicited by high frequency stimulation: BCI application *Biomed. Tech.* **55** 173–82
[121] Müller S M T, Diez P F, Bastos-Filho T F, Sarcinelli-Filho M, Mut V and Laciar E 2011 SSVEP-BCI implementation for 37–40 Hz frequency range *Engineering in Medicine and Biology Society, EMBC, 2011 Annual Int. Conf. IEEE* (IEEE) pp 6352–5
[122] Volosyak I, Valbuena D, Luth T, Malechka T and Graser A 2011 BCI demographics II: how many (and what kinds of) people can use a high-frequency SSVEP BCI? *IEEE Trans. Neural Syst. Rehabil. Eng.* **19** 232–9
[123] Min B-K, Dähne S, Ahn M-H, Noh Y-K and Müller K-R 2016 Decoding of top-down cognitive processing for SSVEP-controlled BMI *Sci. Rep.* **6** 36267
[124] Muller-Putz G R, Scherer R, Neuper C and Pfurtscheller G 2006 Steady-state somatosensory evoked potentials: suitable brain signals for brain–computer interfaces? *IEEE Trans. Neural Syst. Rehabil. Eng.* **14** 30–7
[125] Pokorny C, Breitwieser C and Müller-Putz G R 2016 The role of transient target stimuli in a steady-state somatosensory evoked potential-based brain–computer interface setup *Frontiers Neurosci.* **10** 152
[126] Muller-Putz G R and Pfurtscheller G 2008 Control of an electrical prosthesis with an SSVEP-based BCI *IEEE Trans. Biomed. Eng.* **55** 361–4
[127] Liu Q, Chen K, Ai Q and Xie S Q 2013 Review: recent development of signal processing algorithms for SSVEP-based brain computer interfaces *J. Med. Biol. Eng.* **34** 299–309
[128] Bryan M *et al* 2011 An adaptive brain–computer interface for humanoid robot control *2011 11th IEEE-RAS Int. Conf. on Humanoid Robots (Humanoids)* (IEEE) pp 199–204
[129] Li G and Zhang D 2016 Brain–computer interface controlled cyborg: establishing a functional information transfer pathway from human brain to cockroach brain *PloS One* **11** e0150667
[130] Gembler F, Stawicki P and Volosyak I 2015 Autonomous parameter adjustment for SSVEP-based BCIs with a novel BCI wizard *Frontiers Neurosci.* **9** 474
[131] Chen X, Wang Y, Nakanishi M, Gao X, Jung T-P and Gao S 2015 High-speed spelling with a noninvasive brain–computer interface *Proc. Natl Acad. Sci.* **112** E6058–67
[132] Chen Y-J, Chen S-C, Zaeni I A, Wu C-M, Tickle A J and Chen P-J 2015 The SSVEP-based BCI text input system using entropy encoding algorithm *Math. Probl. Eng.* **2015** 234260
[133] Kwak N-S, Müller K-R and Lee S-W 2015 A lower limb exoskeleton control system based on steady state visual evoked potentials *J. Neural Eng.* **12** 056009
[134] Cao Z and Lin C-T 2018 Inherent fuzzy entropy for the improvement of EEG complexity evaluation *IEEE Trans. Fuzzy Syst.* **26** 1032–5
[135] Hwang H J *et al* 2017 Clinical feasibility of brain–computer interface based on steady-state visual evoked potential in patients with locked-in syndrome: case studies *Psychophysiology* **54** 444–51
[136] Chen J, Zhang D, Engel A K, Gong Q and Maye A 2017 Application of a single-flicker online SSVEP BCI for spatial navigation *PloS One* **12** e0178385
[137] Pfurtscheller G, Solis-Escalante T, Ortner R, Linortner P and Muller-Putz G R 2010 Self-paced operation of an SSVEP-based orthosis with and without an imagery-based 'brain switch': a feasibility study towards a hybrid BCI *IEEE Trans. Neural Syst. Rehabil. Eng.* **18** 409–14
[138] Chavarriaga R, Sobolewski A and Millán J D R 2014 Errare machinale est: the use of error-related potentials in brain–machine interfaces *Frontiers Neurosci.* **8** 208
[139] Ferrez P W and Millán J D R 2008 Error-related EEG potentials generated during simulated brain–computer interaction *IEEE Trans. Biomed. Eng.* **55** 923–9
[140] Chavarriaga R and Millán J D R 2010 Learning from EEG error-related potentials in noninvasive brain–computer interfaces *IEEE Trans. Neural Syst. Rehabil. Eng.* **18** 381–8
[141] Wright J, Macefield V G, van Schaik A and Tapson J C 2016 A review of control strategies in closed-loop neuroprosthetic systems *Frontiers Neurosci.* **10** 312
[142] Artusi X, Niazi I K, Lucas M-F and Farina D 2011 Performance of a simulated adaptive BCI based on experimental classification of movement-related and error potentials *IEEE J. Emerg. Sel. Top. Circuits Syst.* **1** 480–8
[143] Iturrate I, Montesano L and Minguez J 2013 Shared-control brain–computer interface for a two dimensional reaching task using EEG error-related potentials *2013 35th Annual Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)* (IEEE) pp 5258–62
[144] Iturrate I, Chavarriaga R, Montesano L, Minguez J and Millán J D R 2015 Teaching brain–machine interfaces as an alternative paradigm to neuroprosthetics control *Sci. Rep.* **5** 13893
[145] Iturrate I, Montesano L and Minguez J 2010 Robot reinforcement learning using EEG-based reward signals *2010 IEEE Int. Conf. on Robotics and Automation (ICRA)* (IEEE) pp 4822–9
[146] Tsoneva T, Bieger J and Garcia-Molina G 2010 Towards error-free interaction *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* (IEEE) pp 5799–802
[147] Goel M K, Chavarriaga R and Millán J D R 2011 Cortical current density versus surface EEG for event-related potential-based brain–computer interface *2011 5th Int. IEEE/EMBS Conf. on Neural Engineering (NER)* (IEEE) pp 430–3
[148] Zhang H, Chavarriaga R, Goel M K, Gheorghe L and Millán J D R 2012 Improved recognition of error related potentials through the use of brain connectivity features *2012 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* (IEEE) pp 6740–3
[149] Iturrate I, Chavarriaga R, Montesano L, Minguez J and Millán J D R 2012 Latency correction of error potentials between different experiments reduces calibration time for single-trial classification *2012 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* (IEEE) pp 3288–91
[150] Iturrate I, Montesano L and Minguez J 2013 Task-dependent signal variations in EEG error-related potentials for brain–computer interfaces *J. Neural Eng.* **10** 026024
[151] Omedes J, Iturrate I, Chavarriaga R and Montesano L 2015 Asynchronous decoding of error potentials during the monitoring of a reaching task *2015 IEEE Int. Conf. on Systems, Man, and Cybernetics (SMC)* (IEEE) pp 3116–21
[152] Kreilinger A, Neuper C and Müller-Putz G R 2012 Error potential detection during continuous movement of an artificial arm controlled by brain–computer interface *Med. Biol. Eng. Comput.* **50** 223–30
[153] Omedes J, Iturrate I, Montesano L and Minguez J 2013 Using frequency-domain features for the generalization of EEG error-related potentials among different tasks *2013 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)* (IEEE) pp 5263–6

[154] George L and Lécuye A 2010 An overview of research on 'passive' brain–computer interfaces for implicit human–computer interaction *Int. Conf. on Applied Bionics and Biomechanics ICABB 2010-Workshop W1 'Brain–Computer Interfacing and Virtual Reality'* (https://hal.inria.fr/inria-00537211/document)
[155] Zander T O and Kothe C 2011 Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general *J. Neural Eng.* **8** 025005
[156] Amiri S, Fazel-Rezai R and Asadpour V 2013 A review of hybrid brain–computer interface systems *Adv. Hum. Comput. Interact.* **2013** 187024
[157] Pfurtscheller G *et al* 2010 The hybrid BCI *Frontiers Neurosci.* **4** 3
[158] Banville H and Falk T 2016 Recent advances and open challenges in hybrid brain–computer interfacing: a technological review of non-invasive human research *Brain Comput. Interfaces* **3** 9–46
[159] Chaudhary U, Xia B, Silvoni S, Cohen L G and Birbaumer N 2017 Brain–computer interface–based communication in the completely locked-in state *PLoS Biol.* **15** e1002593
[160] Luth T, Ojdanic D, Friman O, Prenzel O and Graser A 2007 Low level control in a semi-autonomous rehabilitation robotic system via a brain–computer interface *IEEE 10th Int. Conf. on Rehabilitation Robotics, 2007 (ICORR 2007)* (IEEE) pp 721–8
[161] Li Y *et al* 2010 An EEG-based BCI system for 2D cursor control by combining mu/beta rhythm and P300 potential *IEEE Trans. Biomed. Eng.* **57** 2495–505
[162] Bi L, Lian J, Jie K, Lai R and Liu Y 2014 A speed and direction-based cursor control system with P300 and SSVEP *Biomed. Signal Process. Control* **14** 126–33
[163] Allison B Z, Brunner C, Altstätter C, Wagner I C, Grissmann S and Neuper C 2012 A hybrid ERD/SSVEP BCI for continuous simultaneous two dimensional cursor control *J. Neurosci. Methods* **209** 299–307
[164] Duan F, Lin D, Li W and Zhang Z 2015 Design of a multimodal EEG-based hybrid BCI system with visual servo module *IEEE Trans. Auton. Mental Dev.* **7** 332–41
[165] Yu T *et al* 2015 Enhanced motor imagery training using a hybrid BCI with feedback *IEEE Trans. Biomed. Eng.* **62** 1706–17
[166] Hyung Kim B, Kim M and Joevaluated S 2014 Quadcopter flight control using a low-cost hybrid interface with EEG-based classification and eye tracking *Comput. Biol. Med.* **51** 82–92
[167] Kim M, Kim B H and Jo S 2015 Quantitative evaluation of a low-cost noninvasive hybrid interface based on EEG and eye movement *IEEE Trans. Neural Syst. Rehabil. Eng.* **23** 159–68
[168] Hong K-S and Khan M J 2017 Hybrid brain–computer interface techniques for improved classification accuracy and increased number of commands: a review *Frontiers Neurorobot.* **11** 35
[169] Choi I, Rhiu I, Lee Y, Yun M H and Nam C S 2017 A systematic review of hybrid brain–computer interfaces: taxonomy and usability perspectives *PloS One* **12** e0176674
[170] Horki P, Solis-Escalante T, Neuper C and Müller-Putz G 2011 Combined motor imagery and SSVEP based BCI control of a 2 DoF artificial upper limb *Med. Biol. Eng. Comput.* **49** 567–77
[171] Ma J, Zhang Y, Cichocki A and Matsuno F 2015 A novel EOG/EEG hybrid human–machine interface adopting eye movements and ERPs: application to robot control *IEEE Trans. Biomed. Eng.* **62** 876–89
[172] Khan M J, Hong K-S, Naseer N and Bhutta M R 2015 Hybrid EEG-NIRS based BCI for quadcopter control *2015 54th Annual Conf. Society of Instrument and Control Engineers of Japan (SICE)* (IEEE) pp 1177–82
[173] Malechka T, Tetzel T, Krebs U, Feuser D and Graeser A 2015 sBCI-headset—wearable and modular device for hybrid brain–computer interface *Micromachines* **6** 291–311
[174] Hunt A R and Kingstone A 2003 Covert and overt voluntary attention: linked or independent? *Cogn. Brain Res.* **18** 102–5
[175] Kelly S P, Foxe J J, Newman G and Edelman J A 2010 Prepare for conflict: EEG correlates of the anticipation of target competition during overt and covert shifts of visual attention *Eur. J. Neurosci.* **31** 1690–700
[176] Kelly S, Lalor E, Reilly R and Foxe J 2005 Independent brain computer interface control using visual spatial attention-dependent modulations of parieto-occipital alpha *2nd Int. IEEE EMBS Conf. on Neural Engineering, 2005, Conf. Proc.* (IEEE) pp 667–70
[177] Tonin L, Leeb R and Millán J D R 2012 Time-dependent approach for single trial classification of covert visuospatial attention *J. Neural Eng.* **9** 045011
[178] Tonin L, Leeb R, Sobolewski A and Millán J D R 2013 An online EEG BCI based on covert visuospatial attention in absence of exogenous stimulation *J. Neural Eng.* **10** 056007
[179] Treder M S, Bahramisharif A, Schmidt N M, van Gerven M A and Blankertz B 2011 Brain–computer interfacing using modulations of alpha activity induced by covert shifts of attention *J. Neuroeng. Rehabil.* **8** 24
[180] Bai O *et al* 2011 Prediction of human voluntary movement before it occurs *Clin. Neurophysiol.* **122** 364–72
[181] Muralidharan A, Chae J and Taylor D 2011 Extracting attempted hand movements from EEGs in people with complete hand paralysis following stroke *Frontiers Neurosci.* **5** 39
[182] Yang L, Leung H, Plank M, Snider J and Poizner H 2015 EEG activity during movement planning encodes upcoming peak speed and acceleration and improves the accuracy in predicting hand kinematics *IEEE J. Biomed. Health Inform.* **19** 22–8
[183] Frisoli A *et al* 2012 A new gaze-BCI-driven control of an upper limb exoskeleton for rehabilitation in real-world tasks *IEEE Trans. Syst. Man Cybern.* C **42** 1169–79
[184] Lew E, Chavarriaga R, Silvoni S and Millán J D R 2012 Detection of self-paced reaching movement intention from EEG signals *Frontiers Neuroeng.* **5** 13
[185] Bai O, Lin P, Vorbach S, Li J, Furlani S and Hallett M 2007 Exploration of computational methods for classification of movement intention during human voluntary movement from single trial EEG *Clin. Neurophysiol.* **118** 2637–55
[186] Zhou J, Yao J, Deng J and Dewald J P 2009 EEG-based classification for elbow versus shoulder torque intentions involving stroke subjects *Comput. Biol. Med.* **39** 443–52
[187] Ibáñez J *et al* 2014 Detection of the onset of upper-limb movements based on the combined analysis of changes in the sensorimotor rhythms and slow cortical potentials *J. Neural Eng.* **11** 056009
[188] Sellers E W and Donchin E 2006 A P300-based brain–computer interface: initial tests by ALS patients *Clin. Neurophysiol.* **117** 538–48
[189] Picton T W, John M S, Dimitrijevic A and Purcell D 2003 Human auditory steady-state responses: respuestas auditivas de estado estable en humanos *Int. J. Audiol.* **42** 177–219
[190] Ferracuti F, Freddi A, Iarlori S, Longhi S and Peretti P 2013 Auditory paradigm for a P300 BCI system using spatial hearing *2013 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems* (IEEE) pp 871–6
[191] Hamada K, Mori H, Shinoda H and Rutkowski T M 2014 Airborne ultrasonic tactile display brain–computer interface paradigm (arXiv:1404.4184)

[192] Brouwer A-M and Van Erp J B 2010 A tactile P300 brain–computer interface *Frontiers Neurosci.* **4** 19
[193] Guger C *et al* 2017 Complete locked-in and locked-in patients: command following assessment and communication with vibro-tactile P300 and motor imagery brain–computer interface tools *Frontiers Neurosci.* **11** 251
[194] Lugo Z R *et al* 2014 A vibrotactile P300-based brain–computer interface for consciousness detection and communication *Clin. EEG Neurosci.* **45** 14–21
[195] Furdea A *et al* 2012 A new (semantic) reflexive brain–computer interface: in search for a suitable classifier *J. Neurosci. Methods* **203** 233–40
[196] Ruf C A *et al* 2013 Semantic classical conditioning and brain–computer interface control: encoding of affirmative and negative thinking *Frontiers Neurosci.* **7** 23
[197] Birbaumer N, Piccione F, Silvoni S and Wildgruber M 2012 Ideomotor silence: the case of complete paralysis and brain–computer interfaces (BCI) *Psychol. Res.* **76** 183–91
[198] Gallegos-Ayala G, Furdea A, Takano K, Ruf C A, Flor H and Birbaumer N 2014 Brain communication in a completely locked-in patient using bedside near-infrared spectroscopy *Neurology* **82** 1930–2
[199] Chaudhary U, Birbaumer N and Ramos-Murguialday A 2016 Brain–computer interfaces for communication and rehabilitation *Nat. Rev. Neurol.* **12** 513
[200] Wang Y and Makeig S 2009 Predicting intended movement direction using EEG from human posterior parietal cortex *Foundations of Augmented Cognition: Neuroergonomics and Operational Neuroscience* (Berlin: Springer) pp 437–46
[201] Hammon P S, Makeig S, Poizner H, Todorov E and de Sa V R 2008 Predicting reaching targets from human EEG *IEEE Signal Process. Mag.* **25** 69–77
[202] Muralidharan A, Chae J and Taylor D M 2011 Early detection of hand movements from electroencephalograms for stroke therapy applications *J. Neural Eng.* **8** 046003
[203] Bhagat N A *et al* 2014 Detecting movement intent from scalp EEG in a novel upper limb robotic rehabilitation system for stroke *36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)* pp 4127–30
[204] Xu R, Jiang N, Lin C, Mrachacz-Kersting N, Dremstrup K and Farina D 2014 Enhanced low-latency detection of motor intention from EEG for closed-loop brain–computer interface applications *IEEE Trans. Biomed. Eng.* **61** 288–96
[205] Halder S *et al* 2013 Prediction of auditory and visual P300 brain–computer interface aptitude *PloS One* **8** e53513
[206] Käthner I, Ruf C A, Pasqualotto E, Braun C, Birbaumer N and Halder S 2013 A portable auditory P300 brain–computer interface with directional cues *Clin. Neurophysiol.* **124** 327–38
[207] Klobassa D S *et al* 2009 Toward a high-throughput auditory P300-based brain–computer interface *Clin. Neurophysiol.* **120** 1252–61
[208] Placidi G, Avola D, Petracca A, Sgallari F and Spezialetti M 2015 Basis for the implementation of an EEG-based single-trial binary brain computer interface through the disgust produced by remembering unpleasant odors *Neurocomputing* **160** 308–18
[209] Kim Y J *et al* 2015 A study on a robot arm driven by three-dimensional trajectories predicted from non-invasive neural signals *Biomed. Eng.* **14** 81
[210] Úbeda A, Hortal E, Alarcón J, Salazar-Varas R, Sánchez A and Azorín J M 2015 Online detection of horizontal hand movements from low frequency EEG components *2015 7th Int. IEEE/EMBS Conf. on Neural Engineering (NER)* (IEEE) pp 214–7
[211] Kiguchi K, Lalitharatne T D and Hayashi Y 2013 Estimation of forearm supination/pronation motion based on EEG signals to control an artificial arm *J. Adv. Mech. Des. Syst. Manuf.* **7** 74–81
[212] Breitwieser C, Pokorny C, Neuper C and Muller-Putz G R 2011 Somatosensory evoked potentials elicited by stimulating two fingers from one hand—usable for BCI? *2011 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* vol 2011 pp 6373–6
[213] van der Waal M, Severens M, Geuze J and Desain P 2012 Introducing the tactile speller: an ERP-based brain–computer interface for communication *J. Neural Eng.* **9** 045002
[214] Hortal E *et al* 2015 SVM-based brain–machine interface for controlling a robot arm through four mental tasks *Neurocomputing* **151** 116–21
[215] Birbaumer N 1997 Slow cortical potentials: their origin, meaning, and clinical use *Brain and Behavior: Past, Present and Future* (Netherlands: Tilburg University Press) pp 25–39
[216] Birbaumer N *et al* 2000 The thought translation device (TTD) for completely paralyzed patients *IEEE Trans. Rehabil. Eng.* **8** 190–3
[217] Kübler A, Kotchoubey B, Kaiser J, Wolpaw J R and Birbaumer N 2001 Brain–computer communication: unlocking the locked in *Psychol. Bull.* **127** 358
[218] Hinterberger T, Houtkooper J M and Kotchoubey B 2004 Effects of feedback control on slow cortical potentials and random events *Parapsychological Association Convention* Vienna, Austria pp 39–50
[219] Tkach D, Reimer J and Hatsopoulos N G 2008 Observation-based learning for brain–machine interfaces *Curr. Opin. Neurobiol.* **18** 589–94
[220] Agashe H and Contreras-Vidal J L 2014 Observation-based training for neuroprosthetic control of grasping by amputees *36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)* (IEEE) pp 3989–92
[221] Agashe H A and Contreras-Vidal J L 2013 Observation-based calibration of brain–machine interfaces for grasping *2013 6th Int. IEEE/EMBS Conf. on Neural Engineering (NER)* (IEEE) pp 1–4
[222] Belkacem A N, Hirose H, Yoshimura N, Shin D and Koike Y 2013 Classification of four eye directions from EEG signals for eye-movement-based communication systems *J. Med. Biol. Eng.* **34** 581–8 (http://www.jmbe.org.tw/files/2633/public/2633-6619-1-PB.pdf)
[223] Ramli R, Arof H, Ibrahim F, Idris M Y I and Khairuddin A 2015 Classification of eyelid position and eyeball movement using EEG signals *Malaysian J. Comput. Sci.* **28** 28–45 (https://jice.um.edu.my/index.php/MJCS/article/view/6853)
[224] Belkacem A N *et al* 2015 Real-time control of a video game using eye movements and two temporal EEG sensors *Comput. Intell. Neurosci.* **2015** 653639
[225] Brunner C *et al* 2015 BNCI Horizon 2020: towards a roadmap for the BCI community *Brain Comput. Interfaces* **2** 1–10
[226] Holz E M, Botrel L, Kaufmann T and Kübler A 2015 Long-term independent brain–computer interface home use improves quality of life of a patient in the locked-in state: a case study *Arch. Phys. Med. Rehabil.* **96** S16–26
[227] Wang P, Lu J, Zhang B and Tang Z 2015 A review on transfer learning for brain–computer interface classification *2015 5th Int. Conf. on Information Science and Technology (ICIST)* (IEEE) pp 315–22
[228] Jayaram V, Alamgir M, Altun Y, Scholkopf B and Grosse-Wentrup M 2016 Transfer learning in brain–computer interfaces *IEEE Comput. Intell. Mag.* **11** 20–31

[229] Lotte F 2015 Signal processing approaches to minimize or suppress calibration time in oscillatory activity-based brain–computer interfaces *Proc. IEEE* **103** 871–90

[230] Waytowich N R, Faller J, Garcia J O, Vettel J M and Sajda P 2016 Unsupervised adaptive transfer learning for steady-state visual evoked potential brain–computer interfaces *2016 IEEE Int. Conf. on Systems, Man, and Cybernetics (SMC)* (IEEE) pp 004135–40

[231] Bashashati A, Fatourechi M, Ward R K and Birch G E 2007 A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals *J. Neural Eng.* **4** R32–57

[232] Edelman B J, Baxter B and He B 2016 EEG source imaging enhances the decoding of complex right-hand motor imagery tasks *IEEE Trans. Biomed. Eng.* **63** 4–14

[233] Tomida N, Tanaka T, Ono S, Yamagishi M and Higashi H 2015 Active data selection for motor imagery EEG classification *IEEE Trans. Biomed. Eng.* **62** 458–67

[234] Längkvist M, Karlsson L and Loutfi A 2014 A review of unsupervised feature learning and deep learning for time-series modeling *Pattern Recognit. Lett.* **42** 11–24

[235] Schmidhuber J 2015 Deep learning in neural networks: an overview *Neural Netw.* **61** 85–117

[236] Sturm I, Lapuschkin S, Samek W and Müller K-R 2016 Interpretable deep neural networks for single-trial EEG classification *J. Neurosci. Methods* **274** 141–5

[237] Marblestone A H, Wayne G and Kording K P 2016 Toward an integration of deep learning and neuroscience *Frontiers Comput. Neurosci.* **10** 94

[238] Perdikis S, Leeb R and Millán J D R 2016 Context-aware adaptive spelling in motor imagery BCI *J. Neural Eng.* **13** 036018

[239] Dal Seno B, Matteucci M and Mainardi L T 2010 The utility metric: a novel method to assess the overall performance of discrete brain–computer interfaces *IEEE Trans. on Neural Syst. Rehabil. Eng.* **18** 20–8

[240] Millán J D R 2015 Brain–machine interfaces: the perception-action closed loop: a two-learner system *IEEE Syst. Man Cybern. Mag.* **1** 6–8

[241] Fifer M S *et al* 2014 Simultaneous neural control of simple reaching and grasping with the modular prosthetic limb using intracranial EEG *IEEE Trans. Neural Syst. Rehabil. Eng.* **22** 695–705

[242] McMullen D P *et al* 2014 Demonstration of a semi-autonomous hybrid brain–machine interface using human intracranial EEG, eye tracking, and computer vision to control a robotic upper limb prosthetic *IEEE Trans. Neural Syst. Rehabil. Eng.* **22** 784–96

[243] Leeb R, Chavarriaga R, Perdikis S, Iturrate I and Millán J D R 2015 Moving brain-controlled devices outside the lab: principles and applications *Recent Progress in Brain and Cognitive Engineering* (Berlin: Springer) pp 73–94

[244] Vidaurre C, Klauer C, Schauer T, Ramos-Murguialday A and Müller K-R 2016 EEG-based BCI for the linear control of an upper-limb neuroprosthesis *Med. Eng. Phys.* **38** 1195–204

[245] Cunningham J P, Nuyujukian P, Gilja V, Chestek C A, Ryu S I and Shenoy K V 2011 A closed-loop human simulator for investigating the role of feedback control in brain–machine interfaces *J. Neurophysiol.* **105** 1932–49

[246] Dadarlat M C, O'doherty J E and Sabes P N 2015 A learning-based approach to artificial sensory feedback leads to optimal integration *Nat. Neurosci.* **18** 138–44

[247] Flesher S N *et al* 2016 Intracortical microstimulation of human somatosensory cortex *Sci. Transl. Med.* **8** 361ra141

[248] Broccard F D *et al* 2014 Closed-loop brain–machine–body interfaces for noninvasive rehabilitation of movement disorders *Ann. Biomed. Eng.* **42** 1573–93

[249] Suresh S, Liu Y and Yeow R C-H 2015 Development of a wearable electroencephalographic device for anxiety monitoring *J. Med. Devices* **9** 030917

[250] Saab J, Battes B and Grosse-Wentrup M 2011 Simultaneous EEG recordings with dry and wet electrodes in motor-imagery *5th Int. Brain–Computer Interface Conf. (BCI 2011)* (https://www.is.mpg.de/publications/saabbg2011)

[251] Zander T O *et al* 2011 A dry EEG-system for scientific research and brain–computer interfaces *Frontiers Neurosci.* **5** 53

[252] Mullen T R *et al* 2015 Real-time neuroimaging and cognitive monitoring using wearable dry EEG *IEEE Trans. Biomed. Eng.* **62** 2553–67

[253] Chen Y *et al* 2016 A high-security EEG-based login system with RSVP stimuli and dry electrodes *IEEE Trans. Inf. Forensic. Secur.* **11** 2635–47

[254] Ordikhani-Seyedlar M, Lebedev M A, Sorensen H B and Puthusserypady S 2016 Neurofeedback therapy for enhancing visual attention: state-of-the-art and challenges *Frontiers Neurosci.* **10** 352

[255] Wyckoff S and Birbaumer N 2014 Neurofeedback and brain–computer interfaces *The Handbook of Behavioral Medicine* (New Jersey: Wiley-Blackwell) pp 275–312

[256] Abiri R, McBride J, Zhao X and Jiang Y 2015 A real-time brainwave based neuro-feedback system for cognitive enhancement *ASME 2015 Dynamic Systems and Control Conf. (Columbus, OH)* pp V001T16A005

[257] Steiner N J, Frenette E C, Rene K M, Brennan R T and Perrin E C 2014 In-school neurofeedback training for ADHD: sustained improvements from a randomized control trial *Pediatrics* **133** 483–92

[258] Steiner N J, Frenette E C, Rene K M, Brennan R T and Perrin E C 2014 Neurofeedback and cognitive attention training for children with attention-deficit hyperactivity disorder in schools *J. Dev. Behav. Pediatr.* **35** 18–27

[259] Abiri R, Zhao X and Jiang Y 2016 A real time EEG-based neurofeedback platform for attention training *Biomedical Engineering Society Annual Meeting (BMES 2016)* (https://hal.archives-ouvertes.fr/hal-01574291/document)

[260] Jiang Y, Abiri R and Zhao X 2017 Tuning up the old brain with new tricks: attention training via neurofeedback *Frontiers Aging Neurosci.* **9** 52

[261] Bassett D S and Khambhati A N 2017 A network engineering perspective on probing and perturbing cognition with neurofeedback *Ann. New York Acad. Sci.* **1396** 126–43

[262] Abiri R, Zhao X and Jiang Y 2016 Controlling gestures of a social robot in a brain machine interface platform *6th Int. Brain–Computer Interface Meeting (2016 BCI)* p 122 (https://hal.archives-ouvertes.fr/hal-01599271/document)

[263] Abiri R, Borhani S, Zhao X and Jiang Y 2017 Real-time neurofeedback for attention training: brainwave-based brain computer interface *Organization for Human Brain Mapping (OHBM 2017)*