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REVIEW ARTICLE

Comprehensive review on brain-controlled mobile robots and robotic arms based on electroencephalography signals

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Abstract

There is a significant progress in the development of brain-controlled mobile robots and robotic arms in the recent years. New advances in electroencephalography (EEG) technology have led to the possibility of controlling external devices, such as robots, directly via the brain. The development of brain-controlled robotic devices has allowed people with bodily disabilities to enhance their mobility, individuality, and many types of activity. This paper provides a comprehensive review of EEG signal processing in robot control, including mobile robots and robotic arms, especially based on noninvasive brain computer interface systems. Various filtering approaches, feature extraction techniques, and machine learning algorithms for EEG classification are discussed and summarized. Finally, the conditions of the environments in which robots are used and robot types are also discussed.

Keywords Brain–computer interface (BCI) · Brain-controlled robotic systems · EEG · ERD/ERS · Intelligent system · P300 · SSVEP

1 Introduction

In addition to the use of robots in industry, their use in daily human life, especially as an assistant for people with disabilities, is increasing. Robots can be controlled by a healthy person with the help of an input device, such as a mouse and a keyboard. However, these input interfaces are not practical for people with body disabilities, such as multiple sclerosis (MS) or amyotrophic lateral sclerosis (ALS) patients. In most cases, these patients cannot walk or use their hands and arms, or even speak. Thus, these people cannot easily transmit their thoughts or required actions to robots using these conventional interfaces. The development of brain-controlled robots, which can be controlled directly from the brain, would be very useful in such cases. For this purpose, a brain–computer interface (BCI) system can provide alternative interaction between human brain and external devices such as a robot [1]. BCI systems in general can be classified into two types according to the method of capturing brain signal: invasive and noninvasive [2]. In invasive BCIs, brain signals are captured inside the brain (using electrodes located under the skull), whereas in noninvasive BCIs, signals are captured from locations outside the brain. The signals captured via an invasive BCI are stronger; however, this type requires surgery [3]. For this reason, noninvasive BCIs are preferable in many cases and more easy to use in daily life. This review focuses only on noninvasive BCIs.

Different techniques for reading brain activity exist: electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS). Neurons in the brain communicate with each other via electrical signals, which eventually reach the brain surface. In the EEG technique, brain activity is captured by measuring these electrical signal using electrodes placed in the head scalp [4]. In MEG, a functional neuroimaging technique, brain activity is captured by recording brain magnetic fields using very

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sensitive magnetometers [5]. In the fMRI technique, brain activity is measured through blood oxygenation and flow, which increase in areas that are being used in mental processes. For this technique, equipment of sizeable dimensions and a scanner must be used [6]. In fNIRS, brain activity is measured by identifying variations in the optical properties in brain images using near-infrared light. [7]. Because of the relative low cost and the portability of both EEG and fNIRS equipment, these technologies can be used to gather cerebral information in a real usage scenario. EEG also measures brain activity faster and for a longer duration than other methods. Because of high temporal resolution, EEG is the most frequently employed method in BCI systems [5, 8].

Controlling mobile robots or robotic arms using EEG-based BCI technologies have been the subject of recent research interest. In [9], a discussion of the current developments of BCI systems, including fundamental design aspects for this type of system, was presented. Moreover, in [10, 11], an analysis of brain-controlled mobile robots was presented and a review of the overall systems and key techniques, as well as of the issues regarding the evaluation of these robots, was provided. On a related topic, Janet et al. [12] provided a general overview of the manner in which biocontrol systems can be designed, in particular, using EEG and electromyography (EMG) signals.

This paper presents a review of EEG-based brain-controlled mobile robots and robotic arms. It is organized as follows. Section 2 presents an overview of EEG-based robot control systems, as well as of several EEG feature extraction and classification methods. In Sect. 3, various control systems for mobile robots are discussed, while Sect. 4 addresses robotic arms. Section 5 presents evaluation and most common challenges facing EEG-based robot system. Section 6 provides the main conclusions of this study and the highlights of future research directions.

2 EEG-based robot control

An EEG-based robot control system is a type of system in which robots are governed using EEG signals collected from the human brain. These systems can be divided into three categories according to EEG-based brain signal models: *event-related desynchronization/event-related synchronization* (ERD/ERS), P300 wave, and *steady-state visually evoked potential* (SSVEP). The first category, ERD/ERS-based BCIs, controls the robot using the EEG signals recorded during the performance of mental tasks, e.g., motor imagery (MI), mental arithmetic, and mental rotation [13]. In general, MI is a metal task in which the subject performs mental motoric action without performing actual motoric activity. The mu (8–13 Hz) and beta (14–30 Hz) rhythms of the sensorimotor cortex are very important in the MI analysis [14]. During actual and MI movement of the hands (left and right), the brain activation in the beta band (β-ERD) occurs predominantly over the contralateral right and left motor areas, while the β-ERS is presented *ipsilaterally* [15]. The post-movement ERS related to the action of stopping the motion can be also created over the contralateral motor areas [15]. In general, the brain activity produced by MI is captured from the sensorimotor cortex at EEG electrodes C3, C4, and CZ (according to the international 10–20 system) (see Fig. 2). This type of system may require a training time of many weeks, and the accuracy of such systems is low. Since the accuracy of the ERD/ERS-based BCI strategy is the lowest, the number of command options is also the lowest. However, these systems can be used to generate commands typically every 0.5–4.00 s (see robot applications in Table 1).

The second and third categories of systems are the so-called SSVEP-based and P300-based BCIs, respectively. Both categories depend on external stimuli and do not require training [16–19]. SSVEP is a steady-state physical response to outside stimuli, which is periodic [20]. This type of brain activity is generated at the primary visual cortex and can be captured at the occipital EEG electrodes, including Oz, O1, and O2 [21], and also at some surrounding electrodes. On the basis of previous research studies, it had been concluded that the range of SSVEP frequencies is from 1 Hz to 90 Hz with clear resonance phenomena around 10, 20, 40, and 80 Hz [22]. Examples of the repetitive visual stimuli used for evoking SSVEP are square flickers, checkerboards, gratings, and light-emitting diodes (LEDs) [23]. In the case of P300, brain activity is produced when a specific mental action occurs or a specific stimulus acts on the sensory system of the brain. After initiation of the target stimulus, the components of P300 are detected in 300 ms and can be captured in the midline centroparietal regions with electrodes Pz, Fz, Cz, and Oz, and also some surrounding electrodes [24]. A shorter time is required to issue commands using the SSVEP than using the P300 approach, although SSVEP presents a lower accuracy. Several studies related to EEG-based BCI systems have been reported in the literature, focusing especially on SSVEP [25–27], P300 [28], and ERD/EDS [29, 33] signals. Besides the three control signals mentioned so far, there is also another control signal which is slow cortical potentials (SCPs). SCPs are slow voltage shifts in the EEG that last one to several seconds. SCPs are based on brain signals with a frequency less than 1 Hz [34]. According to our best knowledge, we did not find implementation of this type of control signal in this field (mobile robots and robotic arms) in the literature. This review focuses on the first three control signals. Table 1 presents a comparison of these three main types of EEG signals and the main references in robots. Table 1 presents a comparison of these three main types of EEG signals and the main references in robots.

Table 1 Comparison of SSVEP, P300, and ERD/ERS with examples in robots

Category	Stimulus	Number of choices	Accuracy	Producing command time	Training time	References
ERD/ERS	No	Low	(60–70%)	0.5–4 s	Needed for many weeks	[29–33, 35–61]
SSVEP	Yes	High	(80–90%)	2–4 s	Not needed	[25–27, 62–69, 71–76]
P300	Yes	High	(90%)	10–20 s	Not needed	[28, 69, 77–81]

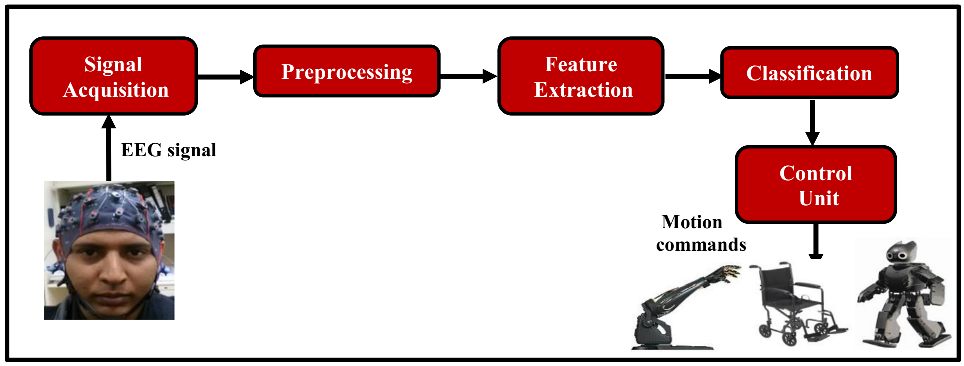


Fig. 1 Block diagram of an EEG-based brain-controlled robotics system

Recent developments in signal processing and machine learning methods have allowed computer systems to perform more sophisticated tasks, including the analysis of EEG signals. EEG signals are usually decomposed into different EEG sub-bands: delta (<4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz). A generic block diagram of the EEG-based brain-controlled robotics system is shown in Fig. 1. As shown in the figure, the system consists of five basic stages: signal acquisition, preprocessing, feature extraction, classification, and the control unit phase [82]. In the signal acquisition stage, the brain signals are recorded by means of specific electrodes and then sent to the preprocessing stage for signal enhancement and noise reduction. In the feature extraction stage, the discriminative characteristics of the enhanced signal are generated, and the size of the data sent to the classification stage is decreased. Finally, in the classification and control unit stages, the produced features are translated into commands and then sent to the device to be controlled [9]. The following subsections discuss these five stages in more detail.

2.1 Signal acquisition

As mentioned above, two methods of EEG signal acquisition exist: invasive and noninvasive. We focus on the noninvasive method on which all examples of EEG-based brain-controlled robotics are based. In this method, raw electrical signals are recorded through sensors (electrodes) located on the scalp according to the international 10–20 system. In this standard system, the distance between adjacent pair of electrodes is either 10% or 20% of the scalp diameter, as shown in Fig. 2 [83]. The electrodes should be stable, low cost, and present low contact impedance. The most widely used electrodes are made of silver/silver chloride (Ag/AgCl). However, gel is required to improve the conductivity between these wet electrodes and the scalp, as described, for instance, in [29, 33, 58, 84]. Dry electrodes, for instance those produced by Emotiv Systems Inc. [85–87] or NeuroSky Inc. [62, 88, 89], can be employed to avoid the time consumption of the application of wet electrodes. Various recording and data acquisition devices exist, which vary in shape, electrode number, etc. The devices most frequently used to capture EEG signals are Epoc, produced by Emotiv Systems Inc., and gUSBamp and g.HIamp, produced by g.tec medical engineering. Emotiv Systems Inc. provides a device with 14 dry electrodes, whereas g.tec's device has 256 electrodes to improve the spatial resolution of the acquired signals. Other types of EEG signal recording devices and electrodes are shown in Table 2, together with examples of EEG-based brain-controlled robotics.

2.2 Preprocessing

Since brain pulses are very small, they must be amplified before digitization. Furthermore, raw EEG signals may contain noise having different sources: electric or electromagnetic fields (e.g., the power line, the sensing and digitalization process, or other devices), and so on. A preprocessing step is therefore required for cleaning the signals. Frequency domain filtering and spatial filtering are the main preprocessing methods applied in BCIs. For frequency domain filtering, bandpass filters and notch filters are commonly used in EEG

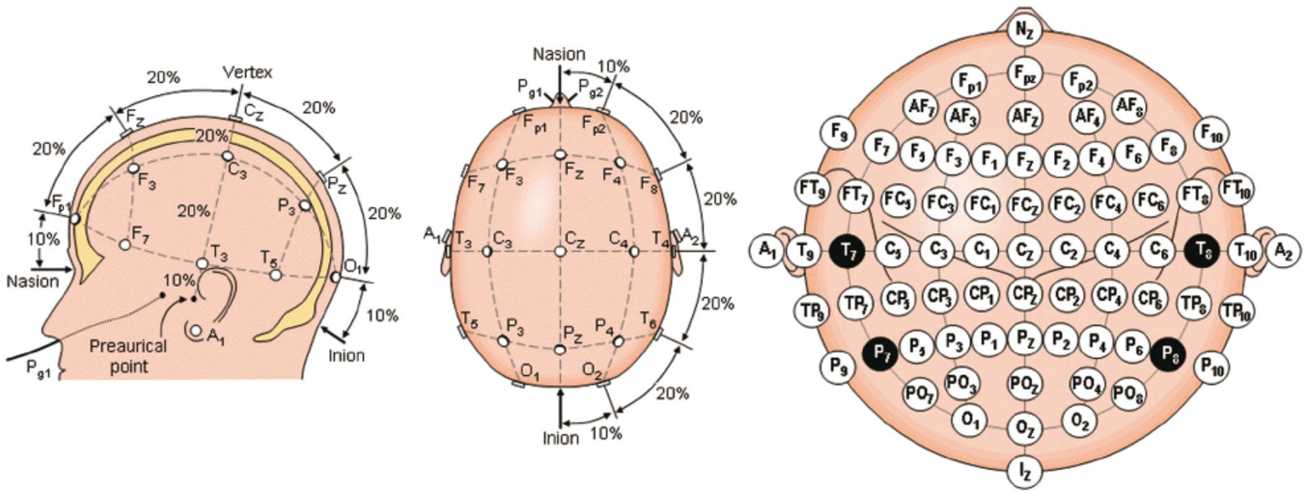


Fig. 2 10–20 international system [83]

preprocessing. In general, bandpass filtering methods are used for removing noise and artifacts from the EEG signal (for instance, see [33, 36, 48, 49, 90]), whereas notch filters should be used to remove the noise generated by the power line [15] (for instance, see references [28, 33, 82, 93]). Discrete wavelet transform (DWT) may also be employed for time–frequency domain filtering, as described in [94, 105]. Wavelet transform (WT) analyzes the characteristics of the signal in the time and frequency domain by decomposing the signal into several functions by a single function to generate shifting and detailing.

Another method for preprocessing is using spatial filter. Spatial filter is able to increase signal-to-noise ratio (SNR) of the brain signal [106]. This is achieved by processing the brain signal data of multiple channels; for instance, see [59, 82, 101]. A simple spatial filtering method is Laplacian filtering, in which a signal from an important channel is multiplied by a factor; all the signals from surrounding channels are then subtracted from it. Common average reference (CAR) is an additional spatial filtering method in which the average value of all the channels is subtracted from an important channel to render the EEG recording nearly reference-free. A common spatial filter (CSP) algorithm may be employed to produce a set of peak variance spatial filters for the discrimination of two classes and to reduce the number of channels used. Other types of spatial filtering may be employed, including autocorrelation (AC), canonical correlation analysis (CCA), independent component analysis (ICA), minimum energy combination (MEC), and principal component analysis (PCA). The blind source separation (BSS) method was also used, as described in [29, 33]. Table 3 lists some of the preprocessing methods of different EEG paradigms and their application in robots. Most of these preprocessing methods are very useful to increase the robustness of the system. However, if these methods are not designed properly in the BCI system, they might remove also the useful information in the EEG signal. Also, every method has advantages and disadvantages comparing with other. For example, Laplacian filter is very simple and easy to use but is not very robust. In other hand, more advanced filtering method such as common spatial filter (CSP) is more robust but need a greater number of EEG channels. Moreover, although CSP does not require a priori selection of specific bands and knowledge of these bands, its performance is greatly affected by the position of the EEG electrodes. Reference [107] has discussed in more detail about advantages and disadvantages for several EEG preprocessing methods.

2.3 Feature extraction methods

The goal of feature extraction is to transform the preprocessed signal into a feature vector by highlighting its important feature (i.e., eliminates redundant data from the feature vector) [36]. However, not all feature extraction methods produce the desired result. It is therefore important to choose the appropriate method to achieve this goal. Many promising techniques are available for extracting features from EEG signals, including Fourier transform (FT), WT, common spatial pattern (CSP), and the logarithmic band power method. In FT methods, mainly the power spectrum density is analyzed. The Fourier transform types include fast Fourier transform (FFT) and discrete Fourier transform (DFT). FFT is frequently used in practical applications because of its simplicity and short computation time as compared to DFT. It has been concluded that the frequency components of EEG signals vary as a function of time (i.e., the signal is nonstationary) [108]. For this reason, WT, which supports a flexible time–frequency resolution, is preferable to FT and thus frequently used to analyze EEG signals. A common spatial filter is also frequently used in EEG anal-

Table 2 Examples in robots of signal acquisition

Category	Authors	Electrodes / electrodes number (ground: G, reference: R, left earlobe: A1, right earlobe: A2)	Sampling rate	Company
ERD/ERS	Tanaka et al. [36]	C3, C4, P3, P4, O1, O2, Fz, F8, T3, T4, T5,T6, Fz, A (G)	1024 Hz	–
	Leeb et al. [30]	Cz and Fz (G)	250 Hz	g.tec
	Galan et al. [42]	64 electrodes	512 Hz	–
	Choi et al. [29, 33]	C3, C4, Cz, FC3, FC4, Fpz (G), A (R)	256 Hz	g.tec
	Tsui et al. [48, 90]	C1, C2, C3, C4, Cz, A (G)	250 Hz	g.tec
	Barbosa et al. [37]	F3, Fz, F4, C3, Cz, C4, P3, P4	1000 Hz	DAQ
	Dand. et al. [91]	27 elec. including C1, C2, C3, C4, C5, Cz, A (R)	256 Hz	g.tec
	Chae et al. [84]	32 elec. including C3, C4, Cz, Fpz (G), A (R)	250 Hz	Compumedics
	Kilicarslan et al. [92]	64 elec. including FCz (R), AFz (G)	100 Hz	Brain Products
	Song et al. [93]	C1, C2, C3, C4, C5, C6, CP3, CP4, FC3, FC4, A1, A2	256 Hz	Thought Tech.
	Varona-Moya et al. [59]	C3, C4, Cz, F3, F4, T7, T8, P3, P4, Fpz (G)	200 Hz	Brain Products
	Lee et al. [56]	16 elec. including C3, C4, Cz, Fpz (G), A (R)	512 Hz	USBAmp, g.tec
	Ron-Angevin et al [60]	10 electrodes, AFz (G), Fz (R)	200 Hz	g.tec
	Gao et al. [94]	FC5, FC6, A1&A2 (R)	128 Hz	Emotiv Epoc
	Aljalal et al. [58]	64 electrodes including C3, C4, Cz, A1, A2 (G), Fz (R)	250 Hz	g.tec
SSVEP	Müller-Putz et al. [95]	5 electrodes including Fz (G)	256 Hz	g.tec
	Prueckl et al. [26, 63]	O1, O2, Oz, POz, PO3, PO4, PO7, PO8, Fpz (G), A (R)	256 Hz	g.tec
	Dasgupta et al. [25]	8 electrodes including O1, O2	256 Hz	g.tec
	Ortner et al. [27]	O1, O2, Oz, POz, PO3, PO4, PO7, PO8, Fpz (G), A (R)	256 Hz	g.tec
	Pfurtscheller et al. [96]	O1, A2 (G)	256 Hz	gBSamp, g.tec
	Ortner et al. [97]	O1, O2, Oz, POz, PO3, PO4, PO7, PO8, Fpz (G), A (R)	256 Hz	g.tec
	Horki et al. [98]	21 electrodes, A1 (R), A2 (G)	250 Hz	g.BSamp, g.tec
	Choi et al. [99]	O1, O2, AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8	128 Hz	Emotiv Epoc
	Chu et al. [100]	O1, O2, AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8	128 Hz	Emotiv Epoc
	Zhao et al. [69]	Oz	1000 Hz	Cerebus™
	Gao et al. [94]	O1, O2, AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8	128 Hz	Emotiv Epoc
	Chen et al. [75]	O1, O2, Oz, P3, Pz, P4, PO3, PO4, T5, T6, (G: FPz, Fz), Cz (R)	250 Hz	–
	Shao et al. [76]	32 elec. including O1, O2, P7, P8	500 Hz	Brain Products
P300	Pires et al. [28]	Fz, Cz, C3, C4, CPz, Pz, P3, P4, PO7, PO8, POz, Oz, AFz(G)	256 Hz	gUSBamp,g.tec
	Iturrate et al. [77]	16 elec. including FP1, FP2, C3, C4, Cz, Oz, FPz (G), A1 (R)	256 Hz	gUSBamp,g.tec
	Escolano et al. [78]	FP1, FP2, F3, F4,T7, T8, C3, C2, C4, CP3, CP4, P3, P2, P4 Oz	256 Hz	gUSBamp,g.tec
	Escolano et al. [79, 101]	24 elec. including FP1, FP2, F3,T7, T8, C3,C4,Fz (R), A1 (R)	256 Hz	gUSBamp,g.tec
	Panicker et al. [102]	Cz, C1, C2, Pz, P1, P2, Oz, O1, O2	256 Hz	ANT-Neuro
	Choi et al. [99]	AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2	128 Hz	Emotiv Epoc
	Zhao et al. [69]	Pz, Fz,, Cz	1000 Hz	Cerebus™
	Li et al. [103]	32 electrodes, AFz (G), A1 & A2 (R)	1000 Hz	Cerebus™
	Zhang et al. [104]	30 electrodes including Fz, FCz, Cz, CPz, Pz, Oz	250 Hz	Compumedics
	Wang et al. [105]	30 electrodes including Fz, FCz, Cz, CPz, Pz, Oz	256 Hz	Compumedics

yses because of its ability to provide a set of spatial filters for decreasing the variance of one class while increasing it for the other class and thus reducing the number of channels used to represent the EEG signals [109]. Logarithmic band power is a method frequently used in EEG analysis for estimating the power of EEG signals. The advantage of this method is its simplicity (i.e., it involves only squaring, averaging, and logarithm operations), which renders its use preferable in real-time applications. In our previous study [58], we combined the logarithmic band power method with CSP to redistribute the features of two classes to achieve easy classification. Several nonlinear methods exist for analyzing EEG signals, such as the largest Lyapunov exponent (LLE), fractal dimension (FD), and several entropy functions.

Table 3 Methods of EEG preprocessing and their application in robots

Category	Authors	Methods
ERD/ERS	Tanaka et al. [36]	0.53–30 Hz bandpass filter, BSS
	Leeb et al. [30]	0.5–30 Hz bandpass filter
	Galan et al. [42]	1 Hz high-pass filter, CAR
	Choi et al. [29, 33]	8-order, 35 &59 Hz low pass filters, 0.16 Hz high-pass filter,
	Barbosa et al. [37]	8–30 Hz bandpass filter, 50 Hz notch filter, BSS
	Tsui et al. [90]	11–14 Hz, 15–25 Hz & 15–30 Hz bandpass filters
	Dand. et al. [91]	0.1–100 Hz bandpass filter
	Chae et al. [84]	1–100 Hz bandpass filter, 55–56 Hz notch filter, Laplacian filter
	Kilicarslan et al. [92]	2-order bandpass Butterworth filter, notch filter
	Song et al. [93]	4-order Butterworth IIR filter, 50 Hz notch filter, Laplacian filter
	Varona-Moya et al. [59]	Several bandpass filters, Laplacian filter
	Lee et al. [56]	14–19 Hz filtering, CAR filtering
	Ron-Angevin et al [60]	5-order, 5–17 Hz Butterworth filter, Laplacian filter
	Aljalal et al. [58]	5-order, 0.5–100 Hz, 8–34 Hz Butterworth filter, 60 Hz notch filter
SSVEP	Müller-Putz et al. [95]	3–60 Hz bandpass filter, CAR filtering
	Prueckl et al. [26, 63]	0.5–60 Hz bandpass filter, 50 Hz notch filter, Laplacian filter
	Dasgupta et al. [25]	0.5–60 Hz bandpass filter, 50 Hz notch filter, 2 s segmentation
	Ortner et al. [27]	0.5–100 Hz bandpass filter, 50 Hz notch filter
	Ortner et al. [97]	0.5–30 Hz bandpass filter, 50 Hz notch filter
	Choi et al. [99]	5-order, 4–50 Hz Butterworth bandpass filter
	Chu et al. [100]	5-order, 2 Hz cutoff Butterworth filter, 50 Hz notch filter, CSP
	Zhao et al. [69]	3–30 Hz bandpass filter, notch filter
	Gao et al. [94]	Discrete wavelet transform (DWT)
	Chen et al. [75]	Removing linear trends, notch filter
	Shao et al. [76]	Band pass filtering using WT
P300	Pires et al. [28]	4-order, 7 Hz low pass filter, 50 Hz notch filter, normalization
	Iturrate et al. [77]	0.5–30 Hz bandpass filter, notch filter
	Escolano et al. [79, 101]	0.5–30 Hz bandpass filter, notch filter
	Panicker et al. [102]	3-order, 0.5–12 Hz Butterworth bandpass filter
	Choi et al. [99]	1–20 Hz bandpass filter, down samples, spatial filter
	Zhao et al. [69]	0.5–26 Hz bandpass filter, removing signal drift, down samples
	Li et al. [103]	1–10 Hz bandpass filter
	Zhang et al. [104]	0.5–100 Hz bandpass filter
	Wang et al. [105]	0.5–32 Hz Butterworth bandpass filter, DWT

Nonlinear methods can be used to measure the complexity, regularity, and statistic quantification of EEG signals. We also proposed a method that combines features from different feature extraction methods. However, a combination of too many features may lead to redundancy, overfitting, and an increase in the processing time. To avoid features with redundant information, a feature selection or dimensionality reduction method, such as the t test and analysis of variance, may be needed before the classification step [36]. Table 4 summarizes the existing feature extraction methods for EEG signals and their application in robots.

2.4 Classifications methods

After the feature extraction process, a classifier or multiple classifiers should be implemented to classify the signal. Various machine learning methods are available for EEG data classification, including linear and nonlinear classifiers. In linear classifiers, unlike in nonlinear classifiers, it is not necessary to adjust many parameters, and thus, this type of classifier is more robust and less prone to overfitting. However, there are some applications, especially those that are complex or involve large data sets, in which nonlinear classifiers produce better results, [114]. The most widely

Table 4 Methods of EEG feature extraction and their application in robots

Category	Feature extraction methods	References
ERD/ERS	Fast Fourier transform (FFT)	[59, 108]
	Discrete wavelet transform (DWT)	[37, 93, 106]
	Logarithmic band power	[30, 48, 49, 58, 90]
	Common spatial pattern (CSP)	[29, 33, 58, 93]
	Common spatial frequency subspace decomposition (CSFSD)	[33]
	Linear discriminant analysis (LDA)	[32, 109]
	Autoregressive model (AR)	[84, 109, 110]
	Principal component analysis (PCA)	[108]
	Estimating power spectral density (PSD)	[56, 59, 60]
	Others	[59, 111, 113]
SSVEP	Fast Fourier transform	[69]
	Welch periodogram with FFT	[88]
	Minimum energy approach (ME) with FFT	[65, 89]
	Ensemble empirical mode decomposition	[64]
	Canonical Correlation Analysis (CCA)	[65, 75, 76]
P300	Principal component analysis (PCA)	[113]

used methods for addressing the classification problem in brain-controlled mobile robots include linear discriminant analysis (LDA), support vector machine (SVM), artificial neural network (ANN), k-nearest neighbor (KNN), and fuzzy classifiers. LDA is a well-known binary classification method based on mean vectors and covariance matrices of feature vectors for individual classes. It uses a hyperplane to distinguish between classes, minimizing the variance within a class and maximizing the variance between classes [115]. An LDA classifier is preferred because of its satisfactory performance and low computational cost and because it does not require extensive pretraining. However, because of its linearity, LDA may yield poor results when handling large nonlinear EEG data. This problem can be avoided by employing a suitable kernel function [116]. SVM methods also distinguish classes by building a linear optimal hyperplane. For a given set of training data, an SVM builds a model or hyperplane that separates the patterns belonging to the different classes by the widest possible margin [117]. When handling a nonlinear classification problem, SVMs use a kernel trick to transform the original data (or feature) to another space to facilitate the solution of the classification problem. LDA and SVM were originally two-class classifiers. However, they may also be employed to classify multiclass problems. This can be achieved by either modifying the method or using the "One Versus the Rest" strategy. In the latter method, each class is separated from all other classes. For example, Chae et al. [84] employed an adapted LDA method, QDA, to classify three mental tasks (involving the left hand, right hand, and foot). In addition to LDA and SVMs, ANNs are widely used as multiclass classifiers in the BCI field. An ANN is an information processing system that simulates the process of human cognition. It involves several interconnected computational neural units. To produce the desired mapping, an ANN must be trained to adjust the weights and biases of the connections. Among several neural networks, the multilayer perceptron (MLP) is the method most widely used for classification. The kernel of this feedforward artificial method is the backpropagation (BP) algorithm, which includes output layers, hidden layers, and input layers. The practical situation in question determines the number of hidden layers. In the training process, the feature vectors should be applied to the input of the network to adjust its variable parameters and the weights and biases. Thus, the relationship between the patterns of the inputs and outputs is captured. An ANN classifier is rarely applied in SSVEP and P300. However, it shows a satisfactory performance when applied in ERD/ERS and provides a good accuracy level. In addition to the methods that have just been discussed, also fuzzy systems can be used to distinguish between different patterns. These systems are able to discover patterns in data that are usually difficult to detect. Fuzzy systems depend on the tolerance of imprecision and uncertainty, to accomplish tractable and robust solutions for classification [12]. In some applications, the neural network is combined with fuzzy systems (ANFIS) to obtain a new classifier as in [120]. Like other classifiers, KNN can classify between two or more patterns. The principle underlying the algorithm of this classifier is that features that represent different patterns will form different clusters in the features space, while similar or convergent patterns will form similar clusters. In order to distinguish a test feature vector, KNN considers k metric distances between the test samples features and those of the nearest patterns. These metric distances represent a measure of the matches between the test feature vector and the feature vectors of each pattern [9]. More details on this classifier can be found in [9, 121]. It is worth noting that KNN is used rarely in BCI applications, because this classifier is highly sensitive to the dimension of the feature vector [122]. In addition, several other classifiers can be used to classify EEG signals. Table 5 summarizes the existing methods for EEG classification and some examples in robots.

Table 5 Methods of EEG classification and their application in robots

Category	Classification methods	References
ERD/ERS	Artificial neural network (ANN)	[37, 45, 51, 53, 54, 56, 85, 108, 118, 119]
	Adaptive neural fuzzy network (ANFN)	[45, 120]
	Linear discriminant analysis (LDA)	[32, 39, 40, 47–50, 52, 58, 59, 90, 96, 101, 123–130]
	Quadratic discriminant analysis (QDA)	[84]
	Mahalanobis linear distance (MLD)	[91]
	Linear classifier (simple threshold)	[30, 94, 131]
	Statistical classifier	[35, 38, 42–44, 132]
	Support vector machine (SVM)	[25, 29, 33, 41, 55, 57, 93, 133–136]
	Recursive training (Euclidean distance)	[36]
	k-Nearest neighbor (kNN)	[110]
	Random forests (RF)	[56]
SSVEP	Artificial neural network (ANN)	–
	Linear discriminant analysis (LDA)	[26, 27, 62, 100, 113]
	Statistical classifier	–
	Support vector machine (SVM)	[25]
	Fuzzy logic	[65]
	PSD-based HSD	[95–97]
	Linear classifier (simple threshold)	[75, 76, 94]
P300	Artificial neural network (ANN)	–
	Linear discriminant analysis (LDA)	[77–80, 113]
	Statistical classifier	[28, 137, 138]
	Support vector machine (SVM)	[123–126, 134, 139, 140]
	Linear classifier (simple threshold)	[141]

2.5 Control unit

After the classification process, the control unit translates the obtained categories into motion commands and then submits them to a robot or an assistive device, such as a wheelchair, robotic arm, or computer. Mobile robots are required to perform certain actions, including stop, turn to the left, turn to the right, and walk forward. A robotic arm is required to perform functions such as grasp (fingers opening/closing), rotate wrist (left/right), drop, and lift. We discuss the commands and the types of motions for both mobile robots and robotics arms, together with some published examples, in the next sections.

2.6 Software libraries

The processing of EEG signals, such as filtering, feature extraction, and classification, can be implemented using software. An open-source software system used for BCI research is called BCI2000. This software suite has been widely employed for data acquisition, stimulus presentation, and brain monitoring applications [142]. Several authors employed BCI2000 in their studies, such as those reported in [77, 79, 101, 143], to perform the tasks mentioned above. A second open-source software, called OpenViBE [144], is a software platform that can be employed as a generic real-time EEG acquisition, processing, and visualization system, as described in [69, 102, 145]. In addition, EEGLAB is a MATLAB toolbox that is capable of processing EEG data and other electrophysiological signals. ICA, time–frequency analysis, artifact rejection, several modes of data visualization, and other tasks can be implemented using this toolbox; for instance, see [146]. In addition, other software programs such as MATLAB [30, 147] or LabVIEW [93, 148] have been used for the implementation of brain-controlled robots.

3 Mobile robot control

In this paper, the term mobile robot refers to a wheelchair, humanoid robot, simulated or virtual robot, or any robot that can be navigated in two dimensions. The main goal of brain-controlled robot design is to enable a subject to control a mobile robot to reach a target safely and accurately through brain signals. The BCI is the core technology used to attain this goal. There are additional techniques that can be used in conjunction with a BCI to achieve this goal, such as robot intelligence techniques and hybrid control. Some tasks allow a mobile robot to be navigated efficiently, including peripheral sensing, localization, route planning, and collision avoidance. These may be achieved by using robot intelligence techniques. A combination of two (or more) BCI systems may be employed to achieve hybrid control to perform a certain task through allowing control to be shared between the BCI and an intelligent controller [77].

3.1 ERD/ERS-based approaches

In this section, we present a review of some examples of EEG-controlled mobile robots for which the ERD/ERS approach is implemented. As mentioned above, an ERD/ERS-based BCI controls the robot using the EEG signals recorded dur-

Table 6 Summary of ERD/ERS BCI-based mobile robot control examples

Author(s)	No. of Elec.	Features extraction	Classification	Mental tasks/Actions	Robot type	Performance
Tanaka et al. [36]	13	FFT	Recursive training (nearest neighbor)	Left thinking right thinking	Wheelchair	Success rate 80%
Choi et al. [29, 33]	5	CSP and CSFSD	SVMs	Left: imagining clenching the left hand Right: imagining squeezing the right hand. Forward: imagining walking with both feet **Stop**: EMG	Wheelchair	Success rate 90–95%
Leeb et al. [30]	1	Logarithmic band power	Simple threshold	Foot movement imagination	Simulated robot and virtual environment	Accuracy 90%
Barbosa et al. [37]	8	DWT	MLPNN	—-	Toruo mobile robot	Classification rate 65%, successful command rate was 91%
Tsui et al. [48] [49] [90]	5	Logarithmic band power	Two LDAs	Left thinking Right thinking	Simulated robot and virtual environment	Accuracy 75% (without online training) and 85% (with online training)
Dand. et al. [101]	27	—-	MLD	Left, right, go/stop	Virtual environment using BCI2VR	Success rate 87.55%
Chae et al. [50]	32	AR & FDA	LDA & QDA	3 mental tasks (left, right, and forward) mapped onto motion commands	Nao humanoid robot	Accuracy 75%
Song et al. [93]	10	Wavelet CSP	SVM	2 mental tasks (left and right) mapped onto motion commands	BrookStone Rover 2.0	NA
Varona-Moya et al. [59]	9	Estimating PSD	LDA	2 mental states (right-hand MI and mental relaxation)	Wheelchair	NA
Lee et al. [56]	16	Estimating PSD	RF	Move: imagine moving both hands. Relax: imagine relaxing both hands	Lower-limb exoskeleton	NA
Ron-Angevin, Ricardo et al [60]	10	Estimating PSD	LDA	2 mental tasks (right-hand motor imagery or mental idle state)	Wheelchair	Accuracy above 83%
Aljalal et al. [58]	64	CSP + Logarithmic band power	LDA	2 mental tasks (left and right hand) mapped onto four motion commands	Simulated robot	Successful command rate of 80%

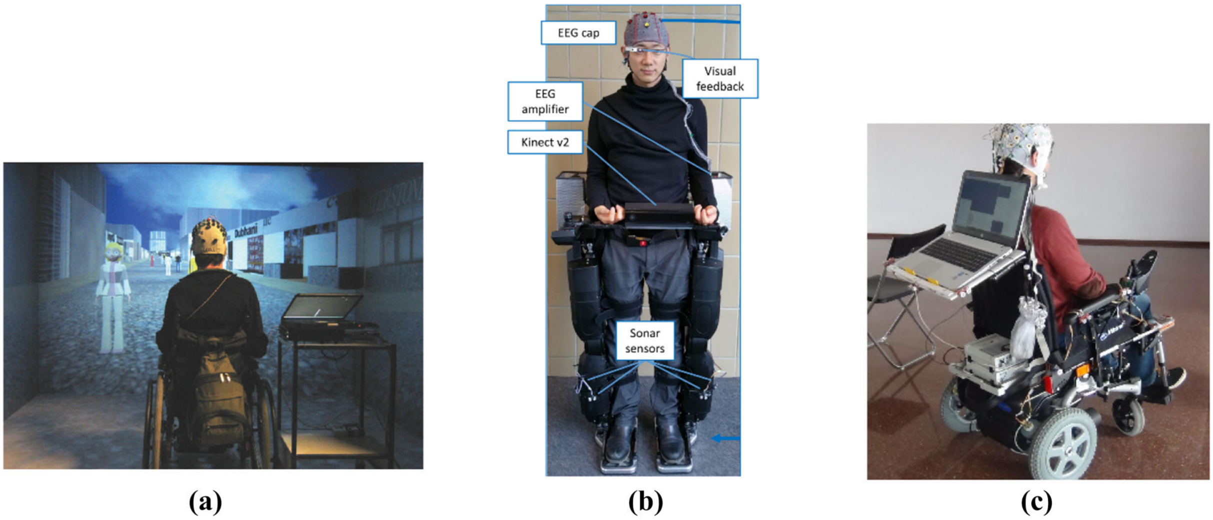


Fig. 3 Examples of the brain-controlled mobile robots using ERD/ERS: **a** from [30], **b** from [56], and **c** from [59]

ing the performance of mental tasks, e.g., during MI, mental arithmetic, and mental rotation. Table 6 summarizes previous works on robot controls based on ERD/ERS approach. Figure 3 shows several selected examples of mobile robot from the previous works ([30, 56, 59]). These examples are briefly presented, and their signal acquisition, preprocessing, feature extraction, and classification methods, as well as their output commands, are analyzed. Because it would be very long to discuss in detail about EEG analysis for each work, we summarized them in Table 6 and we will focus on the important finding for each work in the text. Millán et al. [35] built the first brain-controlled mobile robot in a virtual environment (VE). They employed several mental tasks, e.g., relaxation, imaginary movement of the left and right hand, and cube rotation. They found that mental control was a competitive alternative to manual control for the same predefined task, showing a performance ratio of 0.74.

Tanaka et al. [36] presented an investigation of an EEG-based control implemented in an electric wheelchair. The evaluation criterion was defined by the following statement: "The electric wheelchair is able to reach the target when the number of wrong direction decisions is ≤ 1 and the number of correct direction decisions is 3." After 20 control trials using 6 subjects, the mean success rate achieved was about 80%. Leeb et al. [30] developed an asynchronous BCI that was able to control a wheelchair in a VE. In their study, a participant in a wheelchair was placed in a street VE together with 15 avatars. The objective was "to go" from one point to another until the end of the street was reached. The subject was able to complete this experimental trial well with an accuracy level of up to 90%, on average. Tsui et al. [48, 49] proposed an additional asynchronous online training BCI system. In their studies, a simulated robot was used. The average accuracy of two subjects without online training was 75%, while that of subjects with online training was 85%.

Choi et al. [29, 33] developed a noninvasive BCI for controlling a motorized wheelchair. Three healthy men were trained by means of visual feedback provided every 0.125 s in order to reduce the training duration and improve their performance. To evaluate this method, experiments on controlling bars and avoiding obstacles were conducted. Furthermore, the results obtained using the feedback training method were compared with those obtained in an imaginary movement experiment without any visual feedback in which two different subjects participated. In the bar control experiment, two subjects obtained a success rate of 95.00%, while the third achieved a success rate of 91.66%. In the obstacle avoidance experiments, all three subjects obtained a success rate of 90%, as much, and took almost same time to complete the task as when a joystick control was used. A synchronous operant conditioning BCI was developed by Barbosa et al. [37] for the control of a mobile robot; the evaluation criterion used was: "The occurrence of each class is evaluated after 5 trials, if a class reaches an occurrence rate of at least 50%, then it is selected and translated to a motion." The classification rate was 65%, while the successful command rate was 91%. Dandan et al. [91] proposed a practical approach for a BCI-based virtual wheelchair control system in 2D. In the BCI2VR program, the simulated scenario size was set to 20 m^2 and the speed of the wheelchair to 0.4 m/s, with a rotational speed of 27 s per 360 degrees. Using these settings, the mean time to reach a target located 10 m from the subject was 58.6 s (5.9 s/m) using MI and 51.52 s (5.2 s/m) using physical movement. The average success rate for reaching a target was at least 87.55%. The objective of Chae et al.'s study was to develop an asynchronous EEG-based BCI system for humanoid robot navigation. Five healthy male subjects were recruited for this study, and two classifiers were trained offline until an accuracy level of at least 75% was accomplished. The speed of the robot was 3.3 cm/s, with a rotational speed of 48 s per 360 degrees. The system was developed with the aim of optimizing the BCI and navigation performance. In their study, Kilicarslan et al. [92] examined online control of Rex (a hands-free, self-supporting, independently controlled, robotic mobility device) by a paraplegic user using EEG signals to deliver go forward and stop action commands. Three subjects participated in the study conducted by Varona-Moya et al. [59]. The research team examined the possibility of controlling a robotic wheelchair by using a BCI. They concluded that, according to the results obtained, the BCI system is an effective option for controlling a wheelchair. Lee et al. [56] controlled a powered lower-limb exoskeleton using the ERD-based EEG strategy. They developed a binary decoder that was able to discriminate two mental tasks, move and rest, which was employed in a cascaded manner to control the exoskeleton in three directions. Ron-Angevin et al. [60] developed a brain-controlled wheelchair based on the discrimination of only two mental tasks. The control signals used were sensorimotor rhythms modulated through a right-hand MI task or mental idle state. The peculiarity of the control system was that it was based on a serial auditory interface that provided the user with four navigation commands. In their study, nine subjects controlled a wheelchair and achieved a medium accuracy level above 0.83.

We have also recently presented a study that focused on a synchronous control system with an MI-based BCI for robot navigation. In our paper [58], we proposed a new feature extraction technique that uses common spatial pattern filtering combined with band power to form feature vectors. LDA was employed to classify two types of MI task (right and left hand). In addition, we have developed a posture-dependent control architecture (shown in Fig. 4a) that translates the obtained MI into four robot motion commands: going forward, turning left, turning right, and stopping. The EEGs of eight healthy volunteer male subjects were recorded and employed to navigate a simulated robot to a goal in a VE. For a predefined task (shown in Fig. 4b), the developed BCI robot control system achieved its task in 170 s with a collision number of 0.65, distance of 23.92 m, and successful command rate of 80%. Although the performance of the complete system varied between subjects, the robot always reached its final position successfully.

3.2 SSVEP and P300 BCIs (synchronous BCIs)

This section presents a review of brain-controlled mobile robots, the control of which follows the SSVEP and P300 BCI strategies. Recall that both SSVEP and P300 BCIs depend on external stimuli. Square flickers, checkerboards, gratings, and light-emitting diode (LED) are examples of the repetitive visual stimuli that are used to evoke SSVEP [23]. In the case of P300, brain activity is produced when specific mental action occurs or a specific stimulus acts on the sensory system of the brain [24]. Graser et al. applied an SSVEP approach for designing a brain-controlled wheelchair. In their study, the stimulus used was an LED panel with four different diodes oscillating at 13, 14, 15, and 16 Hz. These diodes represented turn to left, turn to right, go forward, and go backward, respectively [93]. In the same context, Zhao et al. presented an SSVEP-based experimental procedure to establish a brain-robot interaction system for humanoid robots by integrating multiple software programs, such as OpenViBE, Choregraph, C++, and MATLAB. Figure 5 shows the structure of their system [68]. The subject in the experiment completed specific closed-loop robot control tasks within different environments, i.e., walking through obstacles and pushing a light switch and delivering a balloon to the subject, via the visual stimuli of four different diodes oscillating at 4.615, 12, 15, and 20 Hz on the user interface. Shao et al. applied an SSVEP approach for designing Wall-Crawling Cleaning Robot. In their study, the stimulus used was four flicker pieces oscillating with different frequencies at 6, 7.5, 8.57, and 10 Hz [76]. Other similar investigations were reported in [25, 27, 62, 149]. Several researchers have also investigated brain-controlled wheelchairs following a P300-based BCI approach. To the best of the authors' knowledge, Rebsamen et al. were the first to propose a P300 BCI system for wheelchair control [126].

Jing et al. presented a practical study in which the control performance of SSVEP and P300-based models was comparatively evaluated using a mind-controlled humanoid robot platform (Fig. 6). The average accuracy rate achieved using the 4-class SSVEP model was 90%, while the 6-class P300 model achieved a rate over 90.0%. The average success rates achieved using the 4-class SSVEP and 6-class P300 models were 90.3% and 91.3%, respectively. The average response times of the 4-class SSVEP and 6-class P300 models were 3.65 s and 6.6 s, respectively. The average information transfer rates (ITR) achieved by both 4-class SSVEP and 6-class P300 models were 24.7 bits/m and 18.8 bits/m, respectively. According to the results of the experiments, the authors concluded that an SSVEP BCI achieves a faster response to the subject's mental activity, whereas a P300 BCI is appropriate for a greater number of targets [69].

SSVEP and P300 BCIs require minimal training but can provide a more stable performance and a higher accuracy rate than ERD/ERS BCIs. However, SSVEP and P300 BCIs rely on external stimulation, whereas ERD/ERS BCIs do not. Therefore, the latter may appear to be more desirable because the user can focus on driving the robot rather than on the stimuli [150]. Table 7 summarizes the motion commands of mobile robot applications in the three BCI categories, ERD/ERS, SSVEP, and P300. The table shows

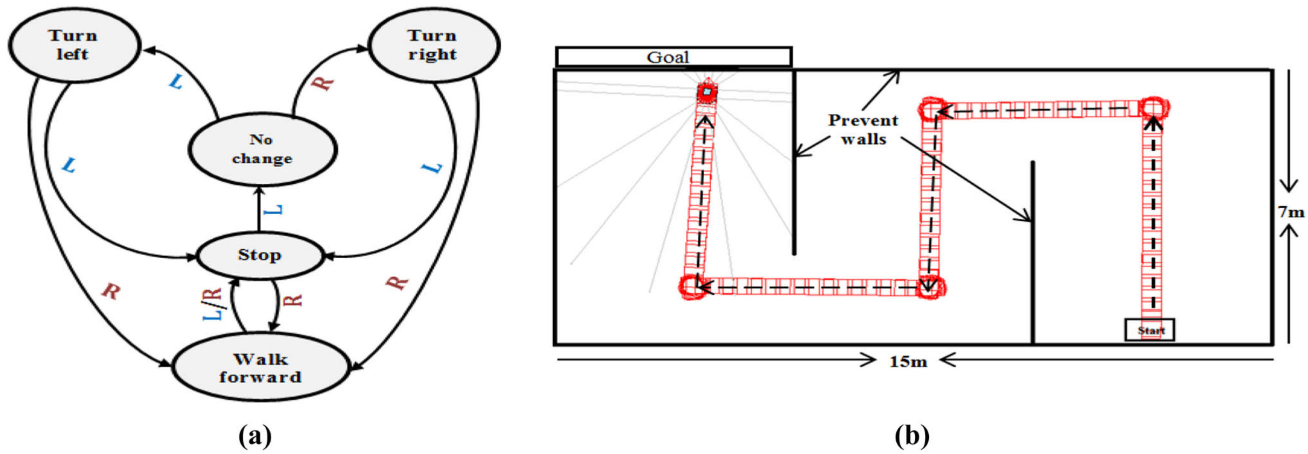


Fig. 4 **a** Developed posture-dependent control architecture, **b** the tracked path in one attempt from [58]

Fig. 5 System structure for brain–robot interaction with a humanoid robot from [68]

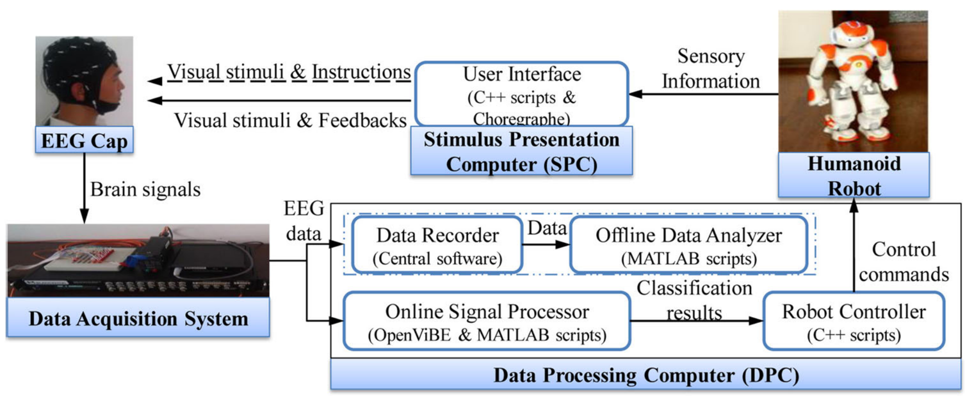
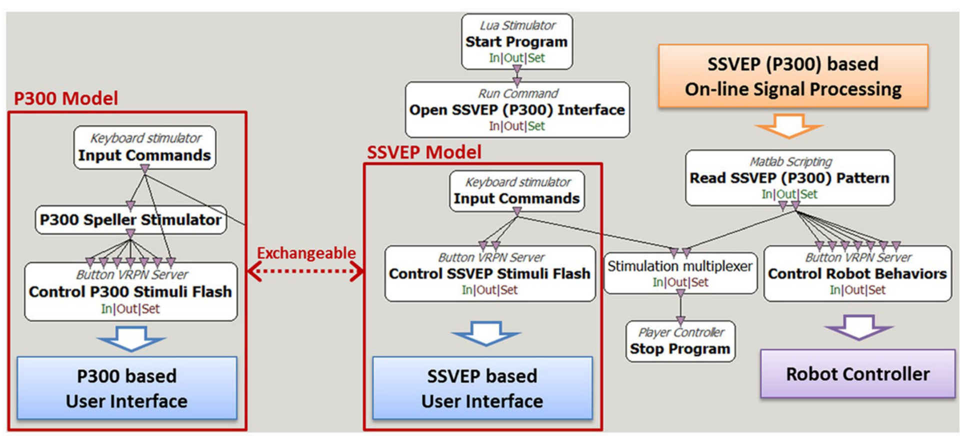


Fig. 6 Comparative study of SSVEP- and P300-based models for control of humanoid robots from [69]



actions including stop, turn to the left, turn to the right, and walk forward, and turn head left and right. As shown in the table, the P300-based BCIs may include a large number of motion commands, while the ERD/ERS-based BCIs include a small number. In Table 1, it can be observed that the classification accuracy in the P300-based BCIs is high, which allows these systems to lead robots in many directions. In contrast, in the ERD/ERS-based BCIs, the signal generated by the user's MI is very small and contains a considerable amount of noise. In this case, the classification accuracy is low, which causes a reduction in the number of categories that can be classified. However, the ERD/ERS-based BCIs are the most widely used, because they do not require an external stimulus, which may disturb users, as do the P300 and SSVEP-based BCIs.

Table 7 Motion commands and their application in mobile robots

Category	Motion commands	Robot examples
ERD/ERS	Turn left and right	[36, 48, 49]
	Turn left and right and go forward	[29, 33, 46, 56, 85]
	Go forward	[30]
	Turn left and right, and stop	[31]
	Turn left and right, and go forward and backward	[57, 111]
	Turn left and right, go forward and stop	[37, 58, 112, 151]
	Go forward, stop, turn left and right, head left and right	[84]
	Go forward, turn left, turn right, go backward, and stop	[61]
SSVEP	Turn left and right, go forward and stop	[73, 152]
	Turn left and right, and go forward and backward	[65, 69, 71, 90, 153]
	Turn left and right, and go forward	[64]
	Human face detection and tracking	[154]
	Move forward, stop, head left, right, camera top or bottom, object grasping and lifting	[72]
P300	Go forward and backward, turn left and right	[155]
	Stop + eight motion directions	[28]
	Go forward and backward, shift left and right, turn left and right	[69, 70]
	Go forward, stand up, sit down, wave hand, turn on/off the system	[81]

Table 8 Hybrid systems and their application in brain-controlled mobile robots

Hybrid system	Robots examples
ERD/ERS + intelligent controller	[35, 38, 42–45, 47, 50, 73, 127, 132, 159, 160]
SSVEP + intelligent controller	[62]
P300 + intelligent controller	[77–79, 101, 126, 173]
ERD/ERS + P300 + intelligent controller	[123–125]
SSVEP + P300 + intelligent controller	[113]
SSVEP + P300	[69, 174]
SSVEP + ERD/ERS	[175]
ERD/ERS + P300	[168, 176]
ERD/ERS + SSVEP + P300	[99]
BCI + fNIRS	[57, 167–172]
P300 + eye blinking + intelligent controller	[105, 165]

3.3 Hybrid control and intelligent controllers

The examples of BCI systems discussed in the previous sections, most of them, use only one EEG recording technique that is ERD/ERS, SSVEP, or P300 alone. They do not combine between these methods and also with other electrophysiological recording such as electrooculography (EOG) (EOG is a technique for measuring potential in the human eye and thus can be used for recording eye movements). Moreover, they also did not use intelligent controller or autonomous navigation system. In pure BCI approach, the users are fully responsible for controlling the mobile robots while in the hybrid approach, the system also has intelligent control to automatically navigate the device by using several sensors attached to the device such as laser sensor, sonar, and camera [77]. The most important advantages of BCI systems that do not include an intelligent controller are their low cost and low computational complexity. However, the performance of such systems is not good, because it depends heavily on the BCI system's performance, which is slow and uncertain. To improve the performance of the BCI system, researchers proposed developing a hybrid BCI system, such as described in [156–158]. A hybrid system may be a combination of one BCI and a second system, which can be a second BCI. In the case of shared control, the BCI system collaborates with the intelligent controller to perform a certain task. The robot in this case is a semiautonomous robot, which requires the user to issue only very limited high-level commands. In a common scenario of shared control, the user needs to send only one command to select a task type using the BCI, and then, the rest of work is completed automatically by the robot based on an intelligent controller. Leeb et al. [159] showed the manner in which users can mentally control a telepresence robot with a BCI to perform a navigation task in daily environments. Carlson et al. [160] and Millán et al. [42] demonstrated the control of an intelligent wheelchair with a BCI that can navigate in a room by jointly utilizing the mental command of the user and the environment information. Table 8 shows some developed hybrid systems and their application in brain-controlled robots.

Some researchers have combined one or more BCI systems with an autonomous system for controlling mobile robots; for instance, see [35, 62, 77, 123]. In this approach, the user and the intelligent controller exchange the driving of the robot, according to a switching scenario. SSVEP and P300 BCI systems offer a large number of choices, and the user chooses the destination from a predefined list of these choices. The intelligent controller is then responsible for taking the robot to the destination. Since the time required to generate a command in ERD/ERS and the SSVEP systems is short, they can be used for issuing fast and urgent commands, such as “stop.” A typical example of this scenario is described in [123]. Indeed, Rebsamen et al. developed a BCI system with an intelligent controller in which one of nine destinations was selected using a P300 BCI system and the intelligent controller was responsible for the automatic navigation, in a well-known environment, to the destination. In this example system, the user can stop the robot using an ERD/ERS BCI. A similar study was presented in [161], in which the user selected a destination using an MI- or P300-based BCI. According to the determined destination, the navigation system planned a short and safe path and navigated the wheelchair to the destination. During the movement of the wheelchair, the user could issue a stop command using the BCI.

In another scenario of a hybrid system, the user is primarily responsible for driving the robot most of the time, but the intelligent controller is responsible for obstacle avoidance [162, 163]. This scenario is particularly useful in unknown environments. The systems developed in [149] and [164] are good examples of this scenario. In the study reported in [149], the user controlled the robot by means of MI in an unknown environment. However, the collision and obstacle avoidance were implemented using an automatic intelligent controller. These two scenarios allow the robot to be controlled within a switching protocol between the user and the controller. A third scenario requires the user to manually switch the control, a particular example of which is the robot system developed by Geng et al. [50, 129]. In this example, turning right or left was controlled only by the user imagining moving the hand right and left, while going forward was controlled by the autonomous system at different times via the user imagining moving the feet.

Each scenario has various advantages and disadvantages. In the second scenario, a user can freely control the wheelchair’s direction. However, controlling a wheelchair (or a robot) for a long distance would fatigue the user. In the first scenario, the user needs to select only the destination command and then he or she allows the navigation system to steer the wheelchair automatically. This type of automatic navigation system is very convenient. However, the user lacks freedom and is limited to moving to the predefined destinations. Dilok et al. [165] combined the two scenarios in one system. The users who participated in this study were able to make a selection from nine possible destination commands in the automatic mode and from four directional commands (forward, backward, turn left, and right) in the shared control mode. The users selected the commands using the designed P300 processing system. The wheelchair was steered to the desired location by the implemented navigation system. The safety of the user during wheelchair navigation was ensured by the included obstacle detection and avoidance features. A combination of P300 and electrooculography (EOG) technology was used as a hybrid BCW system. The user could fully operate the system such as enabling P300 detection system, mode shifting, and stop/cancelation command by performing a different consecutive blinks to generate eye blinking patterns [165].

More recently, functional near-infrared spectroscopy (fNIRS) has emerged as a suitable candidate for next-generation BCIs. fNIRS measures the hemodynamic response in a manner similar to functional magnetic resonance imaging (fMRI), but by using miniaturized sensors that can be used in field settings and even outdoors [166]. It also provides a balanced trade-off between temporal and spatial resolution as compared to fMRI and EEG, Thus, fNIRS presents unique opportunities for investigating new approaches, mental tasks, information content, and signal processing for the development of new BCIs [23]. Batula et al. presented the results of a four-class MI-based online fNIRS-BCI for robot control. Thirteen participants performed upper- and lower-limb MI tasks (left hand, right hand, left foot, and right foot) that were mapped to four high-level commands (turn left, turn right, move forward, and move backward) to control the navigation of a simulated or real robot (a DARwIn-OP humanoid robot). Batula et al. concluded that the use of an fNIRS-BCI could be feasible with sufficient subject training [167]. Other similar systems have also been investigated for use in robot control [168–172]. In the study in [105], the authors combined EEG and EOG signals to drive a TurtleBot robot. In this study, each subject controlled the robot such that it walked along the track by using EEG and EOG signals and then allowed the robot to autonomously return to its starting position along the original track.

In the area of vehicles, Tianwei et al. [73] developed a BCI system based on brain signals to control an unmanned aerial vehicle. The developed system includes two subsystems. The first subsystem, the decision subsystem, relies on MI-based EEG signals and is responsible for decision making. The second subsystem, a semiautonomous navigation subsystem, is responsible for avoiding obstacles automatically and provides the first subsystem with possible directions. In this experiment, the research team demonstrated the possibility and effectiveness of controlling a vehicle using a BCI system in conjunction with an intelligent controller. The system proposed by Xin-an et al. [113] is based on using P300 and SSVEP signals to control intelligent vehicles. The authors suggested a system whereby the user can select the destination of the vehicles using a P300 BCI and confirmation using an SSVEP BCI. Researchers remain interested in developing and improving hybrid systems, in which a combination of either BCI systems or other systems is integrated. Despite the significant improvement in the performance of hybrid BCI systems, they are still not used in the real world. This would require the development of additional systems to ensure the overall performance of brain-controlled mobile robots under the limitations of the BCI system.

4 Robotic arms control

A robotic arm is a mechanical device having a certain number of degrees of freedom (DOF), the functions of which are similar to that of a human arm. A robotic arm may terminate in a robotic hand for performing any desired task, such as grasping and moving objects. An important objective of BCIs is to allow the anthropomorphic movement of a highly dexterous prosthetic limb or an exoskeleton as an assistive device through translating the signals generated by the patient's mental tasks [131]. In [177], a review of the recent achievements in motor control BCIs, in particular in terms of kinematics decoding and motor control of localized areas of the limb, was presented. By using BCIs, it will be possible to restore hand functions to patients suffering from hand problems by enabling them to perform tasks such as moving left/right or handling objects using a robot system [135]. Several studies have been conducted in which BCIs utilizing ERD/ERS and SSVEP brain signals were used for these purposes. Li et al. proposed a BCI system for performing the motion of a serial manipulator in the entire workspace. A small-world neural network (SWNN) was used to classify five brain states based on MI and the system featured shared control. The control strategy used six 2-tuple commands to achieve motion control of the manipulator in 3D Cartesian space [121]. Pohlmeyer et al. employed a monkey to control a robot arm to reach objects using a BCI. The monkey was instructed to transfer the arm to one of two LED targets to obtain food as reward [178]. The objective of the BCI system developed by Elstob et al. is to open and close an industrial hand by discovering the left or right MI [179].

As for the methods implemented in EEG-based robot control systems, different feature extraction and classification techniques are required for methods to control a robotic arm. The difference lies in the motion that an arm with different DOFs is required to perform, according to the application. The system described in [180] controlled a 1-DOF prosthetic arm, while controlling a 7-DOF prosthetic arm was presented in [75, 118]. A multi-DOF robotic arm provides more motion types, such as moving in a 3D space and picking up or placing objects. Table 9 shows a summary of examples of different systems that have been published in the literature. A typical example of ERD/ERS-based BCIs is that proposed by Jianjun et al. [131], who developed a brain-controlled 7-DOF robotic arm. Another example is that developed by Wang et al. They developed a BCI based on three-class MI: left/right hand and foot motor imageries. The three classes were translated to eight commands ("left," "right," "up," "down," "ahead," "aback," "hold," and "put") for controlling a 5-DOF robotic arm [181]. Úbeda et al. [182, 183] also employed ERD/ERS to develop a brain-controlled planar arm in 2D using two control strategies, a hierarchical and a directional control of the motion, and validated these strategies in the real world. In a related study, a 9-DOF wheelchair-mounted robotic arm was controlled using a P300 BCI by Palankar et al. In their study, 15 stimuli were included in the BCI to correspond to 15 commands: 14 for the robot arm movements and 1 for the stop command. The stop command was used to interpret the subject's intent to drive the wheelchair along a route to a required point [184]. Some examples that include systems based only on ERD/ERS BCIs were reported in the literature [185]. Müller-Putz et al. [93] used an SSVEP BCI-based system to implement the grasping functionality and wrist rotation (right or left). During training, four healthy participants reached an online classification accuracy between 44% and 88%. Controlling the prosthetic hand asynchronously, the participants reached a performance of 75.5 to 217.5 s to copy a series of movements, whereas the fastest possible duration determined by the setup was 64 s. Chen et al. [75] developed an SSVEP BCI-based system to control a 7-DOF robotic arm. It was asked form 12 healthy subjects to complete a move-grasp-lift task without user training. The subjects completed the task with an average accuracy of 92.78%, resulting in a 15 commands/min transfer rate.

With the purpose of improving the performance of these systems, several researchers developed hybrid BCI systems. A hybrid system may be a combination of one BCI and a second system, which can be a second BCI. For example, the system developed by Pfurtscheller et al. [96] combined ERD/ERS- and SSVEP-based BCIs. In this system, an ERS-based BCI was used to actuate on the SSVEP-based orthosis when necessary and to deactivate the LEDs in the resting periods. Four out of the six subjects succeeded in operating the self-paced hybrid BCI with a good performance (positive prediction value PPVb > 0.70). Úbeda et al. [129] combined a BCI with the use of the radio frequency identification (RFID) technology in order to control a robotic arm performing pick and place operations. In this system, the RFID system saves the object information to assist the BCI system, which is responsible for differentiating three mental tasks. Four volunteers have successfully controlled the robot arm, and time and accuracy have been measured. Another hybrid system was developed by Chu et al. [100]. The functional electrical stimulation (FES) system is triggered based on the SSVEP classification results. The FES is controlled using an iterative learning control approach in order to stimulate the relevant muscles of the upper limbs, tracking the intended speed and position. The authors of [100] concluded that the feasibility of BCI integrated with upper extremity FES toward improved function restoration for an individual with upper limb disabilities, especially for patients with tetraplegia. The system

Table 9 Summary of existing brain-controlled robotics arm systems

Author(s)	System(s)	Assistive device to be controlled	Classification	Motion Type	Performance/conclusion
Müller-Putz et al. [95]	SSVEP	Two-axes electrical hand prosthesis	Based on PSD to produce HSD	Grasp function (fingers opening/closing), and wrist rotation (left/right)	Online classification accuracy between 44% and 88%.
Pfurtscheller et al. [96]	ERD/ERS + SSVEP	Hand orthosis	SSVEP: Based on PSD to produce HSD ERD/ERS : LDA	Switch on/off SSVEP BCI for grasping objects using ERS	Performance (positive prediction value PPVb >0.70)
Ortner et al. [97]	SSVEP	Hand orthosis	Based on PSD to produce HSD	Grasping objects	Performance (positive prediction value: $78 \pm 10\%$)
Úbeda et al. [182, 183]	ERD/ERS	Planar arm in horizontal Plane	EEG mapping classifier based on a normalized cross-correlation	2D	The hierarchical control is slower but more reliable, while the directional control is much faster, but less precise
Bougrain et al. [128]	ERD/ERS	JACO robotic arm	LDA	2D	–
Wenjia et al. [118]	ERD/ERS	7-DOF robotic arm	(MLP) Neural Network	Drop, lift, rotate right, and rotate left	As the number of EEG based commands increases, the training time required increases significantly.
Úbeda et al. [129]	ERD/ERS + RFID	6-DOF robot arm	LDA	Move left, move right, pick or place	Four volunteers have successfully controlled the robot arm, and time and accuracy have been measured.
Chu et al. [100]	SSVEP + FES	Upper limbs rehabilitation system	LDA	—-	Average accuracy of 73.9%. BCI integrated with FES toward improved function restoration with upper limb disabilities.
Li et al. [119]	ERD/ERS + shared control	Multi-DOF manipulator	Small-world neural network (SWNN)	3D	The feasibility of the proposed BMI method for 3D motion control of a manipulator using EEG during motor imagery.
Hortal et al. [133]	ERD/ERS	Planar arm in horizontal Plane	SVM	Reaching four targets in 2D	Such as in [174, 175]
Saugatet al. [134]	ERD/ERS + P300 + ErPP	Jaco robot arm	SVM	Reaching a target in 3D	The average rate of reaching the target is 95%.
Saugat et al. [120]	ERD/ERS	6-DOF robotic arm	Interval type-2 fuzzy logic and ANFIS	Forward, backward, turn left, and turn right	Average success rate of reaching a target to 65% and 70%.

Table 9 continued

Author(s)	System(s)	Assistive device to be controlled	Classification	Motion Type	Performance/conclusion
Hortal et al. [135]	ERD/ERS	6-DOF robot arm	SVM	Forward, backward, left and right in 2D	Volunteers are able to control the robot in a real-time activity.
Jianjun et al. [131]	ERD/ERS	7-DOF robotic arm with 3 fingers	Linear classifier	Reaching and automatic grasping in 3D	By validation with several tasks, subjects were able to control reaching of the robotic arm.
Rinku et al. [136]	ERD/ERS	Simulated hand	SVM	Reaching a goal in 2D using genetic algorithm	Classification accuracy of 76%
Jingsheng et al. [141]	P300	5-DOF robot arm (Maro)	Threshold	Move in 2D, grasp and release	–
Zhijun et al. [104]	P300 + intelligent controller	A robot manipulator	Bayesian LDA + Threshold	Grasp, deliver and drink	The average accuracy of 97.5%,
Gao et al. [94]	ERD/ERS + SSVEP + EMG	A robotic arm (Dobot)	Thresholds	Moving in 3D for writing task	The mean decoding accuracy of writing the word “HI” was 93%.
Jessica et al. [130]	ERD/ERS	Hand orthosis	LDA	–	Stroke patients’ average performance was 74.1 ± 11%.
Chen et al. [75]	SSVEP	7-DOF robotic arm with 2 fingers	Filter bank canonical correlation analysis (FBCCA)	Move-grasp-lift	Average accuracy of 92.78%, and 15 commands/min transfer rate.
Xu et al. [189]	ERD/ERS + intelligent controller	6-DOF UR5 robotic arm	LDA	Reach and grasp	The average success rate is above 70%
Mishchenkoet al. [193]	ERD/ERS	Virtual 3-DOF prosthetic arm manipulator	SVM / LDA	Move the manipulator forward, backward, left, and right	Out of 12 subjects, only 2 are able to complete 100% of the tasks, on average the accuracy rate of 80% and requiring 5–10 s to execute a manipulator move.

developed in the study in [186] uses a combination of EEG and EOG signals, while the system reported in [187] uses EEG and fMRI. Qiang et al. recently developed a robotic arm system that combines MI, EMG, and SSVEP for performing a writing task. The MI-based BCI was used as a single-pole double throw brain switch (SPDTBS). By combining the SPDTBS with 4-class SSEVP-based BCI, the movement of the robotic arm was controlled in 3D space. In addition, the muscle artifact (EMG) of the "teeth clenching" condition recorded from EEG signals was detected and employed as an interrupter, which can initialize the SPDTBS statement. The subjects who participated in the study succeeded in manipulating the robotic arm to write the word "HI" [94].

As in brain-controlled mobile robots, intelligent controllers have been significantly used in robotic arms. In this type of hybrid system, the intelligent controller shares the control of the prosthesis with the user to perform a specific task. A particular example of this type is the robotic arm system developed by Zhijun et al. [104]. In this example, the subject is required to transmit only one intention command using the P300 system for one drinking task and the autonomous robot completes the rest of the specific control task, delivering the desired container to the mouth of the subject and then replacing it in the original position. Another example of a shared control system was described in [188]. The authors presented a hybrid EEG-based BCI system for controlling a robot's grasp. First, the objects in the scene are recognized by computer vision using a Kinect system, while SSVEP is responsible for selecting the target object. Second, the shared control paradigm is responsible for the grasp task. Xu et al. also developed a hybrid system to accomplish reach and grasp tasks. In this system, shared control is applied to control a robotic arm by a MI-based BCI and computer vision guidance. A subject, joining the experiment, was just asked to perform different mental tasks (left and right movement) to move the end point of the robotic arm to the area around the target. Then, the robotic arm will independently grasp the target [189].

Other types of EEG signals may be used to control a robotic arm. In the study reported in [190], a system was developed that can control a robotic arm using EEG signals generated by facial expressions. The arm is designed such that it makes four movements: flex and extend the elbow, make, and release a fist. Each movement is controlled by one facial expression, left smirk, right smirk, raise brow, and look left/ right. The authors in [191] employed blinks and teeth clenching for manipulation of a robotic arm in 3D to perform a pick and place task. In another study reported in [192], the authors developed a hybrid gaze-BCI system, which combines an EEG signals-based BCI and an eye tracking system to achieve intuitive and effective control of the robotic arm.

5 Evaluation and challenges

5.1 Evaluation

The main goal of the EEG-based robot control systems is to allow disabled people to control a mobile robot or robotic arms. By using mobile robot, disabled people are able to move independently. They may also control robotic arms to perform efficiently certain tasks, such as grasping and carrying objects, by just using their brain signals. We can divide the performance of EEG-based robot control into two levels, BCI performance and complete system performance. The performance of the BCI system is represented mainly in terms of classification accuracy by measuring the effectiveness of the BCI system in terms of differentiating between the implemented mental tasks. On the other side, the complete system performance is evaluated by the effectiveness of EEG-based robot control systems in terms of performing a specific task. In general, there is no standard metric for performance evaluation of the complete system. However, most authors used the success rate, such as those of [33, 36, 91], and the completion time, such as those of [33, 90, 93], as metrics to evaluate brain-controlled robot systems. The success rate is a widely used task metric that quantifies the level of achievement for the task. The completion time is the time consumed to accomplish the task. Other metrics can be also used to evaluate EEG-based brain-controlled mobile robots, such as the number of collisions [33], especially in the case of mobile robots. The training time and workload are also widely used ergonomic metrics. In this case, the workload is the measure of the mental effort required of the user to perform a certain task using brain-controlled robot systems. Moreover, cost should also be taken into account in this evaluation, as it is an indicator of the system's practicality. In general, in the evaluation of different brain-controlled robotic arms systems, their high accuracy and the time they require to perform various tasks, such as reaching a destination and grasping, should be considered.

5.2 Challenges

In recent years, considerable research has been done on the development of brain-controlled systems. However, the development of such systems is still in the process of scientific research so that the designers of these systems face many challenges. We describe some of them.

- *Classification accuracy* The basic and most widely used measure of the accuracy of the BCI system is called the classification accuracy. The accuracy is calculated by dividing the number of trials (one mental task) that were correctly classified over the total number of trials. The classification accuracy of any BCI system is influenced by many factors, such as the following.

- *Non-stationarity* This means continuous changes occur in the frequency and amplitude of the EEG signal over time, either within the recording period or between recording sessions [194, 195]. The emotional state of the participant may also make the EEG signal more volatile.
- *Noise* Unwanted signals from several sources significantly affect the classification accuracy of a BCI system and may cause non-stationarity. The sources of the noise include the power line and the sensing and digitalization processes or may be alterations in the electrode placement and the environment [196]. In addition, artifacts originating in EMG and EOG [197] render the classification process of EEG signals more difficult.
- *Real time* Because EEG-based robot control is a real-time application, it is necessary to optimally decrease the time required to instruct the robot without significantly affecting the output accuracy.
- *Signal processing* The appropriate analysis and processing (filtering, feature extraction, and classification) of EEG signals can ensure an accurate BCI.
- *Subjects* The performance of brain-controlled robots based on EEG is affected by the user's condition, such as his/her level of disability. Some studies have demonstrated that a satisfactory performance rate of a BCI system for normal participants may not be duplicated for disabled participants [21, 198].

- *Safety* Among the commands used to navigate an EEG-based mobile robot is the stop command. This stop command has very important role in providing safety to the user in the event of, for example, a robot's collision with an object. However, considerable research has shown that the implementation of the stop command in EEG-based mobile robot systems is inadequate, and thus, these systems are unsafe and impractical for actual navigation [199]. This is due to the inaccurate classification of the idle and stop states. Therefore, designing a safe and accurate EEG-based mobile robot system is one of the most commonly faced challenges [200, 201].
- *Environment* Simulated, such as those described in [30, 48, 49], or realistic, such as those described in [29, 33, 84], environments should be considered in the development of brain-controlled robots. In addition, known or unknown environments should be also considered.
- *Time consumption* An additional challenge is time consumption, especially during user training and the calibration of classifiers [201]. During the first phase, the user training period, the user is taught to handle the system and to control brain feedback signals. In the second phase, the classifiers are trained using the trained user's signals. Moreover, an additional time-consuming factor is the updating of the navigational system of a robot, especially when the robot is controlled in an unknown environment.
- *Portability and ease of use* The recording of EEG signals is executed by means of sensors (i.e., electrodes) installed on a conventional cap that needs to be connected to a computer via cables. Unlike in the case of dry sensors, such as those developed by Emotiv Systems Inc., Quasar USA and NeuroSky, a gel needs to be applied when moist sensors are used in order to improve the conductivity. This causes the user discomfort.
- *Cost effectiveness* A BCI robot system comprises several components, including an EEG recording device, signal amplifier device, computer, electric wheelchair with navigation system, etc. The total system cost should not be high so that it is accessible to those who need it.

6 Conclusions and future direction

Significant progress in brain-controlled robot systems has been achieved in recent years, making them useful for disabled people or in other applications. In this paper, we presented a comprehensive review of the EEG-based brain-controlled mobile robots and robotic arms systems that have been developed. We first presented a comparison of SSVEP, P300, and ERD/ERS BCI systems, together with examples of their use in robots. Then, we presented and discussed the techniques currently used in these systems, including signal acquisition, preprocessing approaches, feature extraction techniques, and machine learning algorithms for EEG classification, with examples of their use in robots. We also presented and discussed recent developments in EEG-based brain-controlled mobile robots and robotic arms, based on ERD/ERS, SSVEP, P300, and hybrid systems. Output motions of either EEG-based mobile robots or robotic arm systems and evaluation issues were also discussed. Finally, we presented and discussed some challenges that face the developers of EEG-based brain-controlled mobile robots and robotic arms systems.

Further research should be directed toward the development of more robust and accurate brain-controlled mobile robots and robotic arms systems. In fact, the identification of new means of improving the BCI system performance and thus enhancing the overall performance of robotic systems is critical for making them usable in real-world applications. In our recent study [58], we employed a new feature extraction technique that uses CSP filtering combined with band power to form feature vectors for two types of MI tasks (right hand and left hand). An important step in EEG analysis is the preprocessing step, including filtering and artifact removal. Further investigations are needed in the area of EEG preprocessing. Another process for increasing the accuracy of brain-controlled mobile robots (or robotic arms) systems comprises combining EEG with an additional sensor modality such as MEG and electrocardiography (ECG). Brain-controlled mobile robots (or robotic arms) systems should also have an adaptive learning capability to improve their performance over time. The systems should also have robust posture-dependent control architecture that has the ability to correct some classification errors.

A standardized performance evaluation method should be established to evaluate and compare fairly the performance of different systems. Finally, any newly proposed method must be verified and tested intensively using the EEG signals from the targeted population (with adequate samples) before it can be used widely in the real life application.

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