Noninvasive Brain–Computer Interfaces for Augmentative and Alternative Communication

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Methodological Review

***Abstract*—Brain–computer interfaces (BCIs) promise to provide a novel access channel for assistive technologies, including augmentative and alternative communication (AAC) systems, to people with severe speech and physical impairments (SSPI). Research on the subject has been accelerating significantly in the last decade and the research community took great strides toward making BCI-AAC a practical reality to individuals with SSPI. Nevertheless, the end goal has still not been reached and there is much work to be done to produce real-world-worthy systems that can be comfortably, conveniently, and reliably used by individuals with SSPI with help from their families and care givers who will need to maintain, setup, and debug the systems at home. This paper reviews reports in the BCI field that aim at AAC as the application domain with a consideration on both technical and clinical aspects.**

***Index Terms*—Augmentative and Alternative Communication (AAC), brain–computer interface (BCI), electroencephalography (EEG).**

I. Introduction

BRAIN–COMPUTER INTERFACE (BCI) is now considered a possible access method for communication by individuals with severe speech and physical impairments (SSPI) who cannot meet their expressive language needs through natural speech, handwriting, or typing. BCIs interpret brain activity directly, bypassing physical movement and relying on neurophysiologic signals as an access method [164]. BCI for communication falls into a class of assistive technology (AT) and is placed with other augmentative and alternative communication (AAC) devices as an access means for language expression [66], [168]. Historically, AAC devices with different interfaces (i.e., mouse, joystick, binary switches, head control, or eye gaze) have offered individuals means to generate and speak messages, when speech and writing are no longer functional [16]. A number of recent developments in AAC access strategies for people with minimal movement have been proposed that involve tracking of head and eye movement, recognition of residual speech, and of gestures. BCI is one recent development that relies on monitoring the electrical activity of the brain [47]. Together, these strategies should provide even greater access to face-to-face and electronic communication options to support engagement for health management and social interactions [131] for people with SSPI.

As with any AT for communication, BCI translational research and development can be discussed in regards to five components [51]:

1) the input modalities for the device [for this paper, we limit our discussion to electroencephalography (EEG)];
2) the processing demands of the device (here we refer to the signal detection and classification options);
3) language representation (for BCI, this refers to the graphical user interface (GUI) for language presentation and the manipulation of language units by the device);
4) the output modalities (for BCI, this is usually text output, though speech output is a possibility);
5) the functional gains of the device (here we refer to the target populations and the clinical demands they bring to the task of BCI use).

The long-term objective of BCI translational research is to find a reliable means to enhance communication and control so that individuals with the most severe disabilities have a means to participate in daily life for health, employment, social interaction, and community involvement.

Critical to any discussion of BCI for communication is the concept of the user-centered design. Based on the needs and preferences of the target population who will use this technology for verbal engagement, we must evaluate functionality, satisfaction, and expected outcomes of the users. We must consider the homes and environments where BCI will be implemented and the involvement required of the care providers and family members who will be operating the systems. The time for set up, the demands for technical assistance, and the ease of problem solving for this new technology must be considered with the users. These factors will ultimately be the true measures of success [85]. Even though BCIs are shown to achieve certain level of success in laboratory environments, we must caution that BCI is not a practical, dependable application for AT at this time. The sophisticated operations of the technology and the challenges of the target population are huge; obstacles to

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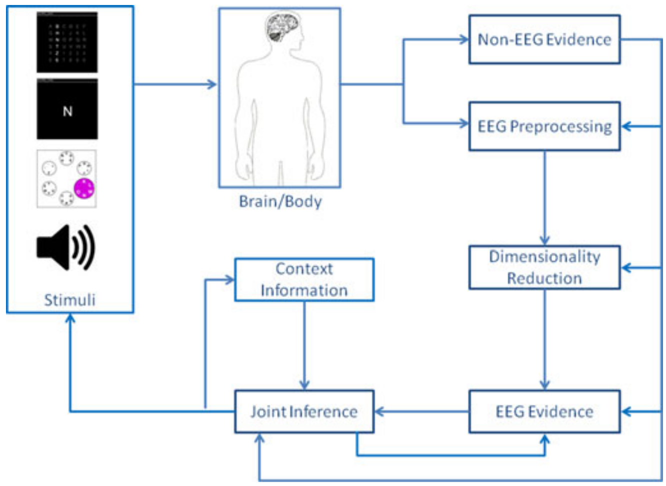

Fig. 1. BCI system flowchart. Note that this figure in general represents a processing flowchart for Human Computer Interface (HCI) systems, and BCI is a special case of HCI.

functional use have not yet been solved for independent implementation in users' homes. Expert end users have told us that our challenge is to design a BCI that is safe, reliable, and that restores function at near normal levels [63]. Despite the benefits that AAC technologies offer people with disabilities, the potential of independent communication has not been fully realized for a group of individuals who present with such severe physical impairments that they cannot reliably or consistently control devices through available access methods. BCI is the hopeful, though not yet practical, solution for them.

In this paper, we report on noninvasive EEG-based BCI systems used as AAC devices, and we will review the different components of BCI for communication from the AT perspective.

II. Overview of BCI Components

The typical components of a noninvasive BCI system and their interactions are shown in Fig. 1: 1) stimulus presentation paradigm (e.g., auditory, visual, tactile, etc.); 2) signal acquisition (EEG data or other modalities such as eye tracker, etc.); 3) preprocessing (signal filtering, artifact removal, etc.), 4) dimensionality reduction; 5) EEG evidence (feature extraction); 6) contextual evidence (e.g., language model or word completion); 7) joint inference (system decision by classification).

A. Input Modalities to the BCI

EEG-based BCIs have become increasingly popular due to their portability, cost-effectiveness, high temporal resolution, and demonstrated reliability in laboratory environments. In the following sections, we will categorize noninvasive BCI systems for expressive communication based on the first component (stimulus presentation paradigms) of the flowchart and analyze the rest of the components for these systems in more detail.

A number of physiological signals have been used in noninvasive BCI to detect user intent. Most popularly, BCI systems have exploited the following potentials.

1) *Auditory and visual event related potentials (A-ERP/V-ERP):* As a response to infrequent novel/target stimuli, the brain generates a P300 response, a positive deflection in centro-parietal scalp voltage with a typical latency just over 300 ms [148] and other accompanying waves. This natural novelty detection or target matching response of the brain allows designers to detect user intent from EEG signals, using either auditory or visual stimuli to elicit this response.
2) *Volitional cortical potentials (VCP):* Volitional synchronization and desynchronization of cortical electrical activity have been utilized in numerous BCI systems that control external devices, including, cursors, avatars, and robotic agents to perform simple activities of daily living, as well as to control typing interfaces for communication.
3) *Steady-state evoked potentials (SSEP):* Fluctuating auditory or flickering visual stimuli (following periodic or other structured patterns) will elicit steady-state auditory/visual evoked potentials (SSAEP/SSVEP) in the auditory and visual cortex areas, respectively. Focusing auditory or visual attention on one of several such stimuli causes temporally matching electrical oscillations in the cortex. Time-frequency features can be analyzed to identify with high accuracy which stimulus the attention is placed on.

1) Event-Related Potentials: In their pioneering work, Farwell and Donchin illustrate the feasibility of P300 as a control signal for BCI-based communication [48]. In this study, the subjects view a 6×6 matrix (matrix speller) consisting of letters in the English alphabet, numbers from 1 to 9 and a space symbol (see Fig. 2). Since the publication of this study, extensive research has focused on various configurations or algorithms designed to improve the speed and the accuracy of communication with the matrix speller, as well as other audio, visual, and tactile stimulus presentation techniques for eliciting P300 responses. In the following sections, we will first review these stimulus presentation techniques and then the signal processing and inference techniques used.

a) Visuospatial presentation techniques: Existing visuospatial presentation techniques can be categorized under the following heading.

b) Matrix presentation: The Matrix Speller generally uses an $R \times C$ matrix of symbols with R rows and C columns (see Fig. 2(a) depicts a 6×6 symbol matrix with the second column highlighted with the intention of inducing an ERP if the target letter is in this column). To generate an oddball paradigm, traditionally each row and column (and in modern versions each one of alternatively designed subsets of symbols) are intensified in a pseudorandom fashion, while the participants count the number of highlighted rows or columns (or, in general, subsets) that include the desired symbol. Usually a sequence is defined as the intensification of all the rows and columns in the matrix. The highlighting of the row and column containing the target symbol are rare events, and will induce a P300 response. The objective of the BCI system is to detect these deviations to identify the target letter to enable typing.

EEG signals suffer from a low signal-to-noise ratio; therefore, to achieve a desired accuracy level, matrix speller systems require multiple presentation sequences before a decision can be made. For example, using bootstrapping and averaging the

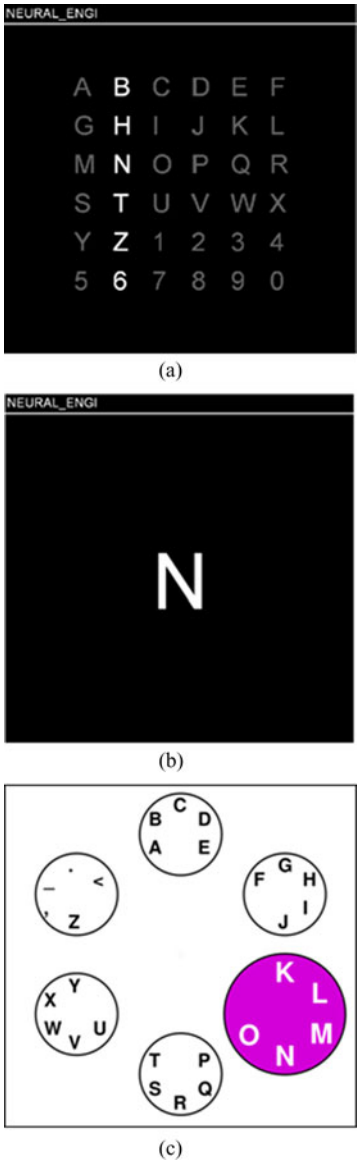

Fig. 2. Different visuospatial stimulus presentation techniques: (a) matrix speller, (b) rapid serial visual presentation, and (c) Hex-o-Spell.

trials in different sequences, it was demonstrated that the matrix speller can achieve 7.8 characters/min with 80% communication accuracy [43]. This speed and accuracy may not satisfactorily meet the needs of the target population. Therefore, various signal processing and machine learning techniques have been proposed to develop ERP-based matrix speller systems with higher speed and accuracy [17], [27], [35], [37]–[39], [70], [77], [78], [81], [82], [91], [102], [118], [123], [124], [127], [129], [138], [139], [142], [144], [150]. Following the BCI system flowchart provided in Fig. 1, we will review these systems in terms of preprocessing, dimensionality reduction, classification, and use of context information.

The matrix speller was shown to be highly accurate in overt attention mode, but in covert attention mode its performance degrades significantly [153]. To overcome such performance drops, BCI researchers have proposed gaze-independent stimulus presentation techniques, such as rapid serial visual presentation and balanced-tree visual presentation.

c) Rapid serial visual presentation (RSVP): RSVP is a technique in which stimuli are presented one at a time at a fixed location on the screen [as depicted in Fig. 2(b)], at a rapid rate and in a pseudorandom order. When the target is presented (a rare event since there is one target symbol in the entire alphabet) and observed by the user, ERP containing the P300 wave is generated in EEG as a consequence of the target matching process that takes place in the brain. Consequently, BCI systems can be designed to detect these responses for typing. By utilizing temporal separation of symbols in the alphabet instead of spatial separation as in the matrix speller, RSVP aims to be less dependent on gaze control [2], [3], [114]–[116].

RSVP-based BCIs that use only EEG evidence may be slower than matrix spellers, as the binary tree that leads to symbol selections in a matrix speller could exploit the opportunity to highlight multiple symbols at a time to reduce expected bits to select a symbol (determined by entropy), while RSVP must follow a right-sided binary tree, which is highly structured and could lead to larger expected bits per symbol. RSVP-based typing has been demonstrated to achieve up to 5 characters/min by Berlin BCI and RSVP Keyboard groups [2], [3], [115], [116]. Color cues and language models have been used in an attempt to improve typing speeds with RSVP [2], [115]. On the positive side, RSVP is potentially feasible even for completely locked-in users, who may have difficulty with gaze control. RSVP BCIs, such as the RSVP Keyboard [115] and Center Speller [154] have similar signal processing and machine learning demands as matrix presentation-based BCIs.

d) Balanced-tree visual presentation paradigms: Balanced-tree visual presentation refers to a technique in which visual stimuli are distributed into multiple presentation groups with equal numbers of elements. A variation would have been distributing elements into groups balanced in probability according to a Huffman tree based on a language model [128], but we have not encountered this approach in the BCI literature. In Berlin BCI's Hex-o-Spell, a set of symbols is distributed among multiple presentation groups; for example, 30 symbols may be distributed among 6 circles each containing 5 symbols, as shown in Fig. 2(c). Every presentation group is highlighted in a random fashion to induce an ERP for the selection of the group that contains the desired symbol. After the initial selection, the symbols in the selected presentation group are distributed individually to different presentation groups, typically with one empty group which represents a command to move back to the first presentation stage. At this point, the individual symbols are highlighted to elicit an ERP for selection of the desired symbol within the selected group [154], [155]. In Geospell, 12 groups of 6 symbols are arranged in a circular fashion similar to Hex-o-Spell presentation [10], [133]; and in another study these 12 groups are presented to a user in an RSVP manner in a random order to be employed in an ERP-based BCI speller [93]. In these systems, the 12 groups represent all the possible rows and columns of the 6×6 matrix speller such that the intersection of the selected row and column gives the desired symbol.

e) Other visual presentation paradigms: The visual presentation paradigms explained above do not exhaustively cover all the possible presentation techniques that could be (and have been) used in an ERP-based BCI system for communication. Various alternatives have been proposed and tested for limited communication. Here, we categorize systems that vary in their vocabulary extent from a few icons all the way down to binary (yes/no) communication as limited communication systems. Examples are as follows.

1) Icon-based limited communication—for example a) systems for appliance or gadget control in which icons are flashing in sequences of random order one at a time [64], [14], and b) a system for expressing basic needs and emotions by answering yes/no questions [23]. RSVP icon-Messenger (unpublished at the time of submission) is a variation of RSVP Keyboardthat uses limited-vocabulary icon representations (based on Rupal Patel's iconCHAT system).
2) Cursor control—for example, a system in which four flashing stimuli map to movements of the cursor to one of the four directions (up, down, left, right) [98]–[100], [120]. Exogenous-icon (four arrows or four icons flashing on the sides of the screen) and endogenous-letter (letters representing directions) paradigms were tested on users with ALS, revealing that the endogenous paradigm provides better performance for a gaze-independent BCI [100]. Qualitatively, results were similar when the signal processing approach was improved [99].
3) Web browser—-for example, a) the Virtual Keyboard (RoBIK) project, which employs a matrix-speller paradigm to provide the user with different tags which are mapped to elements of the web browser [170]; and b) a system that employs a matrix speller paradigm to allow complete keyboard and mouse control to navigate through web browser options [23], [24].

f) Auditory presentation techniques: A-ERP signals have recently drawn attention for BCI design as an alternative or supplement to visual presentation methods due to their applicability in the population of users with impaired vision. Most A-ERP-based BCIs employ a *sequential stimulus arrangement*. In these arrangements, there exists a single stream of stimuli, and users are expected to attend to the targets in the stream. Examples of stimulation methods include various combinations of tones for target and nontarget stimuli [58], [59], [178], utilization of cues with different pitch [61], [71], [171], [179], utilization of different sounds (bell, bass, ring, thud, chord, buzz) [80], and pronunciation of the stimuli [8]. These techniques induce ERPs when the target stimulus is perceived. Some groups also add directionality to the cues to improve discriminability or to utilize it as an additional stimulation method [61], [71], [171], [178], [179]. In most A-ERP-based BCIs, auditory presentation is utilized as a potential supplement for visual presentation and audio-visual presentations are done jointly. Accompanying the visual cue with an auditory one resulted in increased P300 amplitude and detection accuracy compared to only visual correspondence. Systems relying only on auditory stimulation performed significantly worse than visual BCIs [59], [171]. Although they are currently less accurate than visual BCIs, auditory BCIs are an important alternative for people who are unable to use visual BCIs.

g) Tactile presentation techniques: For users who cannot control their eye gaze or who have visual and/or hearing impairments, a tactile presentation technique could be used as an alternative to visuospatial and auditory presentation methods in BCI speller design [29]. One tactile speller interface assigns a set of symbols to each of the six fingers, with six symbols in each set [158]. Symbols are selected in a two-stage process, as in the balanced tree presentation techniques described above. The user first selects a symbol set by focusing on a specific finger. The six letters in the selected set are then assigned to the six fingers, and the user again focuses on a specific finger to select the desired symbol. A BCI system that employs this tactile presentation technique was shown to demonstrate a typing accuracy performance similar to matrix and Hex-o-Spell presentation techniques.

2) Volitional Cortical Potentials: Starting with motor imagery-induced synchronization and desynchronization of cortical potentials, BCI designs quickly started exploiting the ability of the brain to learn new skills, including the volitional control of time–frequency characteristics of cortical potentials [174]–[177]. Consequently, among all designs, BCIs based on these synchronization and desynchronization effects of volitional user brain activity can benefit most from user training. In fact, it has been observed that subjects may achieve some level of proficiency in highly variable durations, from a few hours of practice to tens of hours or more [103]. It has also been noted that individual characteristics may be influential factors in the ability to generate mu rhythms (see below) [125]. By training and reinforcement, users can improve their skills and accordingly system performance. The following VCP have been exploited to design BCI systems for communication.

1) Slow cortical potentials (SCP) are gradual changes in the EEG voltage. These fluctuations can last from hundreds of milliseconds to several seconds. Movement-related potentials (MRP) are instances of SCPs; some include P300 and N400 in this category as well [62], [86], [109], [110].
2) Mu rhythms (also known as comb, wicket, or sensorimotor rhythms), are 8–13 Hz synchronized patterns found primarily over the motor cortex in brain regions that control voluntary movements. The mu pattern is suppressed when a motor action is performed or even thought about. This phenomenon is an example of event-related desynchronization (ERD). Alpha rhythm, a signal with similar frequency range, but observed primarily over the visual areas of the brain while eyes are closed and the brain is at rest, is not to be confused with mu rhythm in the BCI design [107], [111].
3) Beta rhythms, occurring in the frequency range 12–30 Hz, are typically considered in three subbands: low beta (12–16 Hz), beta (16–20 Hz), and high beta (20–30 Hz). These waves are suppressed over the motor cortex when there is a muscle contraction prior to and during movement. Beta energy is increased when movement has to be resisted or voluntarily suppressed [107], [111].

VCP-based BCIs typically require long user training sessions [62], [86], [109]–[111]. The thought translation device (TTD) [86] is an example of this type of system. The TTD utilizes SCP, which are known to be producible in every subject, unlike EEG rhythmic components. Although improvements in classification algorithms [62] and determination of mental strategies for more effective control of VCP [110], [111] have enhanced performance, long training sessions are still necessary. Some researchers, including the Berlin BCI group, have shifted the burden of adaptation more toward the machine-learning algorithm to compensate for extensive user training requirements [24], [25], [106], [107].

a) Balanced-tree visual presentation: Hex-o-Spell, discussed above as a visual presentation technique for ERP-based BCI spellers, is also used in VCP-based systems. As in the ERP version of Hex-o-Spell, a total of 30 symbols are distributed equally in 6 groups arranged in a circular fashion around the center of the screen, as shown in Fig. 2(c). The VCP version includes an arrow in the center of the circle. The user controls the movement of the arrow using motor imagery (such as imagined movements of the right or left hand), with the aim of directing the arrow toward the circle which contains the desired symbol. Once a circle is selected (e.g., using foot motor imagery), its contents are distributed to six circles and a second-level selection is made in a similar fashion for selection of the desired symbol [24], [25], [106], [107]. Like Hex-o-Spell, TTD employs a balanced-tree visual approach for stimuli presentation and selection. In TTD, the symbol set is first split into two halves. The user, by generating a shift in SCP, selects the half which includes the desired stimulus. Upon this selection, the chosen half is further split into two halves, and this procedure continues until the two halves include only single symbols and the final selection can be made [19]–[21]. TTD's presentation approach is very similar to the binary tree-presentation technique employed in [86], [110]. In another balanced-tree presentation setup, 27 symbols (26 English letters and a space symbol) are separated into three blocks, each associated with a mental task [41], [105]. The user selects the desired symbol by imagining these mental tasks in a multistage selection scheme similar to the other balanced-tree presentation techniques.

b) Other presentation techniques: Serial visual presentation is another presentation paradigm used in VCP-based BCI, in which each symbol is presented on a predefined location of the screen for a limited duration; for example, on the bottom or top of the screen. In this setup, the user typically attempts to select the intended symbol by moving a cursor toward the presented symbols using motor imagery [62], [109].

In some VCP-based BCIs, the cursor control presentation paradigm is employed to train the users. For example, in TTD, cursor (or ball) movement toward an indicated target is used as the goal and cursor location or another type of visual (such as a smiley face) or auditory sign is presented as feedback [62], [86], [109]–[111]. In this setup, the user has the option of either moving the cursor toward a target or keeping it in the center of the screen.

3) Steady-StateEvoked Potentials: SSEP-based interfaces include those that use auditory and visual stimulation intended to evoke responses by flickering lights or fluctuating auditory stimuli (such as click trains, tone pulses, or amplitude-modulated sounds). Several SSVEP-based typing interfaces have been developed, beginning with Sutter [146], [147], who uses phase shifted m-sequences to flicker each symbol on a matrix keyboard layout. Spuler *et al* [144] investigate a similar design using phase shifted 63-length m-sequences as stimuli to enable typing on a 32-symbol matrix keyboard. Hwang *et al.* [67] have a 30-symbol matrix keyboard layout, where each symbol has a dedicated flickering LED with a unique frequency (between 5–10 Hz, separated by frequency gaps on the order of 0.1 Hz). Cheng *et al.* [36] utilize a phone key layout for digits and introduce a few additional buttons, all flickering at different frequencies. Yin *et al.* [167] use simultaneously flashing (to elicit ERPs) and different flickering frequencies for a matrix layout keyboard with 36 symbols. Cecotti [34] uses a hierarchical balanced-tree approach and breaks the alphabet of 29 symbols into a three-level tree with three branches at each (nonleaf) node. With this, they have three boxes that contain symbols and two additional stimuli that represent delete and repeat commands, leading to five flickering frequencies. On the other hand, Bremen BCI uses a 1-g letter probability-based keyboard layout. The user navigates a cursor on it by attending visually to one of four flickering arrows and selects the intended letter when ready using a fifth flickering stimulus in the corner [6], [54], [145], [160]–[162].

In systems using SSAEP, which have been investigated only in recent years, dichotic fluctuating auditory stimuli are presented using speakers or earphones. Specifically, in the s*treaming stimulus arrangement*, the stimuli are presented at the same time as multiple streams and distinguished by detecting the stream the user is attending to [76]. To improve the effectiveness of dichotic presentation, an amplitude modulation on the stream can be induced [61]. Hohne *et al.* [171] combine streaming and sequential stimulus arrangements by considering sequential pitch-based cues applied to left, right, or both ears and utilizing a combination of SSAEP and A-ERP evidence to determine user intent.

B. *Signal Processing and Inference in BCI for Communication*

The signal processing and inference techniques used for BCI-based communication systems can be used with little or no modification for other applications of BCI. However, this particular application also presents some customization opportunities to be exploited by designers of BCI-based communication systems.

1) Preprocessing and Dimension Reduction for EEG Evidence Extraction: EEG signals acquired as a response to presented stimuli are not only noisy, with very low signal-to-noise ratio, but also have nonstationarities due to various factors such as physiological or environmental artifacts, sensor failure, and subject fatigue. To design an effective inference method for BCI, it is essential that the most salient EEG signal features are extracted as evidence. Preprocessing and dimension reduction are steps aimed at such feature extraction. In ERP-based BCIs the P300, in VCP mu rhythms, and in SSVEP occipital rhythms are of primary interest and statistical preprocessing spatiotemporal filters with priors that favor these components can be designed. In all designs, the removal of dc drift (the baseline fluctuations due to frequencies $\ll 1$ Hz) and possibly artifact-related high-frequency components in EEG are partially achieved with a properly designed bandpass filter. This initial bandpass filtering is a common step in all BCI systems. It is recommended that linear-phase FIR (finite impulse response) filters be used to prevent phase-response-induced distortions to waves and rhythms, as well as to make accounting for group delay easy for downstream operations in the signal processing and inference pipeline. In particular, for visually evoked potentials the group delay of the bandpass filter must be considered when aligning (unfiltered) event markers to filtered EEG. This also means that for real-time operation the bandpass filter group delay should be kept as small as possible (considering the tradeoff between having a high quality magnitude response for desired and undesired frequencies and the delay introduced to the inference process and the close-loop control dynamics; the latter consideration is relevant in robotic agent control applications).

After the initial bandpass filtering, time-windowed data from different EEG channels is usually concatenated to obtain the EEG feature vector. Based on the sampling frequency and the number of channels used, this vector could have a high dimensionality. Several methods are employed, before or after concatenation as suitable, for feature dimension reduction and further noise and artifact reduction: grand average over all trials [23], [38], [43], [74], downsampling [17], [43], [64], [69], [123], [124], [154], [155], [158], discrete/continuous wavelet transform [27], [39], [43], feature selection by stepwise linear discriminant analysis (see Section II-A2) [82], decimation by moving average filtering [37], [38], [81], [82], [102], [129], [150], channel selection [35], [81], [82], [123], [124], artifact removal through independent component analysis (ICA) [8], [98]–[100], [120], [138], [166], enhancing P300 response by adaptive spatial filtering including common spatial pattern (CSP) and xDAWN algorithm [35], [39], [126], [127], [139], and dimensionality reduction through principal component analysis (PCA) [115], [150]. For SSVEP-based designs two main inference techniques emerge: if flickering stimuli are discriminated by frequency, then the sum of powers at the first two or three harmonics of candidate frequencies are obtained from a power spectrum estimate [34], [36], [67], [167]; if the flickering stimuli are discriminated by pseudorandom code phase shifts (or with different codes), canonical correlation analysis (acting like a matched filter) is employed [143], [144]. In the following, we describe the most common preprocessing methods in more detail.

a) Downsampling: From each EEG channel, after bandpass filtering, discrete signals $x[n]$, $n = 1, ..., N$ are obtained through the discretization of the continuous signal $x_c(nT_s)$ with $T_s = 1/f_s$ as the sampling period and $\mathrm{f_s}$ as the sampling frequency. To detect a possible change in EEG, usually a time-windowed portion of the EEG signal time-locked to the presentation of each stimulus is extracted. Then, based on the sampling frequency, a high dimensional data vector is obtained from each channel. A very common way to decrease the dimensionality is downsampling, i.e., $x_d[n] = x[nM]$ where M is the reduction factor. M is chosen to prevent aliasing, based on the cut-off frequency f_c of the bandpass filter such that $f_c M/f_s \leq 1/2$.

b) Moving average filtering: An alternative or additional dimensionality reduction technique to downsampling is moving average filtering. For every channel, the signal, $x[n], n = 1, ..., N$, is partitioned into equal non-overlapping segments of, for example, length K (usually N/K is an integer), such that the i^{th} segment is $x[(i-1)K + n]$ for $n = 1, ..., K$. Then, decimation is obtained by taking the average of each segment, ending up with N/K data points to represent the data.

c) Independent component analysis: Assuming that the measured EEG data are a linear combination (mixture) of signals of interest, artifacts, noise, and other brain activity irrelevant to the task, blind source separation techniques such as ICA are used to separate sources of interest from other contributing signals [99], [120], [126], [138], [166]. Assuming statistical independence between mixed sources, ICA tackles the problem of source separation on the basis of optimizing an objective function that is appropriate even with limited assumptions on source statistics, including non-Gaussianity, nonwhiteness, or nonstationarity [119]. Statistical properties of separated source estimates commonly used in objectives include kurtosis (the fourth-order cumulant), negentropy (the difference between the differential entropy of a multivariate Gaussian random variable that has the same covariance as the source estimate vector and the differential entropy of the source estimate vector), mutual information, maximum likelihood fit under the parametric density-mixing model (with Infomax providing one possible realization) [40].

d) Channel selection: Another common way to decrease the dimensionality of the EEG data is to choose which EEG channels to use in the BCI setup. Using a limited number of sensors has other practical benefits, such as reduced preparation time, which is an important consideration for in-home use of BCI systems. One common way to choose the set of channels to retain is to use channels previously shown in the literature to exhibit event detection. For example, in addition to the Fz, Cz, and Pz locations of the International 10–20 system, posterior sites and occipital regions are shown to improve BCI performance for ERP/P300 detection [17], [82]. Rather than using preselected sets of channels in BCI systems to consider possible performance changes across different users, adaptive channel selection methods have also been developed. Recursive [123], [124] and backward–forward [35] channel selection methods that optimize typing accuracy, and a channel-selection method based on maximizing the mutual information between class labels and channel features [88], [46], [139], are shown to improve BCI performance.

e) Common spatial patterns (CSP): CSP is a commonly used spatial filtering method that attempts to exploit the high spatial correlations in extracting common underlying responses for a trial in the BCI presentation paradigm. Obtained by determining the linear projection that maximizes signal-to-noise power ratio, CSP leads to an explicit generalized eigenvalue type solution that can be easily obtained. For a two-class classification problem, by maximizing the variance of one class while minimizing the variance of the other, CSP calculates the direction for maximum discriminability. More mathematically, in a binary classification problem, let the recorded EEG signal for the k^{th} trial be $\mathbf{X}_k$ (an $N_c \times N_t$ matrix where N_c is the number of channels and N_t is the number of temporal samples following stimulus/cue onset), and define index sets I_1 and I_0, where $k \in I_1$ or I_0 if k^{th} trial belongs to class C_1 or C_0. Then, for $c \in \{0, 1\}$ the class-conditional sample covariance estimates are

$$\mathbf{S}_c = \sum_{k \in I_c} \frac{\mathbf{X}_k \mathbf{X}_k^T}{\text{trace}\left(\mathbf{X}_k \mathbf{X}_k^T\right)} \tag{1}$$

and the CSP filter coefficients $\mathbf{W}$ are calculated by solving

$$\max_{\mathbf{W}} \text{trace}\left(\mathbf{W}^T \mathbf{S}_1 \mathbf{W}\right) \text{ subject to } \mathbf{W}^T \left(\mathbf{S}_1 + \mathbf{S}_0\right) \mathbf{W} = \mathbf{I}. \tag{2}$$

By equating the gradient of the Lagrangian for this equality constrained optimization problem to zero and solving for the parameters, it is found that generalized eigenvectors of the matrix pair (pencil) $(\mathbf{S}_1, \mathbf{S}_1 + \mathbf{S}_0)$ are candidates in this first-order analysis. Relating the generalized eigenvalues to the objective being optimized reveals that projection vectors can be selected by sorting according the eigenvalues and selecting the vectors accordingly.

f) xDAWN algorithm: This algorithm specifically aims to provide an unsupervised spatiotemporal filter design method to project raw EEG on the estimated ERP (P300) subspace by maximizing the signal-to-signal-plus-noise ratio (SSNR) such that the evoked potentials are enhanced by the applied projection [see (3)] [35], [126], [127]. Let the number of sensors be denoted with N_s, the total number of temporal samples with N_t, and the number of temporal samples corresponding to an ERP with N_e (which is typically chosen to extend over 600 ms to 1 s long post-stimulus intervals—a longer than necessary interval, in our opinion, for pure P300 response, possibly with the purpose of capturing potentially useful motor activity in the brain in case the user engages in motor responses for each target stimulus). Assume that the target stimuli elicit P300 evoked potentials and the measurement model are written as $\mathbf{X} = \mathbf{DA} + \mathbf{N}$, where $\mathbf{X}$ is an $N_t \times N_s$ matrix, $\mathbf{A}$ is an $N_e \times N_s$ matrix of ERP signals, $\mathbf{D}$ is an $N_t \times N_e$ Toeplitz matrix (first column elements all null, but $\mathbf{D}_{\tau_k,1} = 1$ with τ_k as the stimulus onset time of the kth stimulus $(1 \le k \le K)$, with K denoting the total number of target stimuli), and $\mathbf{N}$ is an $N_t \times N_s$ noise matrix (other brain and artifact activity). $\mathbf{A} = \mathbf{A}_1 + \mathbf{A}_2$ is assumed to contain a response common to all ERPs, $\mathbf{A}_1$ and a random spatiotemporal pattern $\mathbf{A}_2$. Then, the aim of the algorithm is to estimate spatial filter $\mathbf{U}$, an $N_s \times N_f$ matrix, with N_f denoting the number of spatial filters, by solving the optimization problem

$$\begin{aligned}\mathbf{U} &= \text{argmax}_{\mathbf{V}} \, \text{SSNR}\left(\mathbf{V}\right) \\ &= \text{argmax}_{\mathbf{V}} \frac{\text{trace}\left(\mathbf{V}^{\mathrm{T}} \mathbf{A}_1^{\mathrm{T}} D^{\mathrm{T}} \mathbf{D} \mathbf{A}_1 \mathbf{V}\right)}{\text{trace}\left(\mathbf{V}^{\mathrm{T}} \mathbf{X}^{\mathrm{T}} \mathbf{X} \mathbf{V}\right)}\end{aligned} \tag{3}$$

after which the filtered signals are obtained by $\hat{\mathbf{X}} = \mathbf{XU}$.

g) Principal component analysis: The dimension of EEG evidence (feature) vectors obtained upon concatenation of data from each channel can be reduced using PCA, which projects the feature vectors to the subspace spanned by the largest eigenvectors of the feature covariance matrix in order to preserve high power (since EEG is made zero-mean by bandpass filtering) bands. Note that PCA applied to time-delay vectors acts as energy-selective FIR bandpass filters. Eigenvectors corresponding to eigenvalues smaller than a predefined threshold are discarded in this process. It should be noted that PCA may be used for regularization purposes with care as described, but it should not be used with the intent of finding the discriminant projections in general.

2) Classification: The purpose of the classifier in ERP-based systems is to detect the existence of ERP (especially P300) in the EEG response following each stimulus (e.g., intensification of rows/columns/subsets in the matrix speller, presentation of letters/symbols in the RSVP paradigm, or finger tapping events in a tactile stimulation paradigm). In SSVEP/SSAEP-based systems, the classifier uses temporal or frequency domain features to detect which stimulus the user is attending to (e.g., flickering arrows or textures on the screen for SSVEP/codeVEP or tones/clips in SSAEP paradigms). In VCP, the classifier attempts to identify which imagery-induced brain rhythm is prominent in EEG, especially over motor cortical areas for motor imagery paradigms, using spatiotemporal filtering and feature extraction. We will survey the most commonly used classification approaches, which include 1) linear discriminant analysis (LDA)-based classifiers [e.g., Fisher LDA (FLDA), Stepwise LDA (SWLDA), and Bayesian LDA] (BLDA [17], [23], [27], [35], [43], [55], [59], [64], [69], [71], [80]–[82], [84], [93], [102], [111], [127], [129], [133], [142], [144], [154], [155], [167], and 2) support-vector machine (SVM) [8], [37]–[39], [70], [81], [91], [98]–[100], [124], [123], [150]. Other classifiers for the BCI system include genetic algorithms [99], logistic linear regression [61], [158], neural networks [41], [105], [120], matched filters [138], Pearson's correlation method [81], and regularized discriminant analysis (RDA) and its special cases [2], [3], [26], [115], [116], [171].

In addition, unsupervised and semisupervised methods including those that assume hierarchical Gaussian distribution models for EEG [78], [77], that are based on cotraining of FLDA and BLDA [95], and that are based on offline learning of the ERP classifier from EEG using data from a pool of subjects followed by online adaptation for different individuals [118] have also been employed. Semisupervised classifier adaptation promises to reduce calibration data collection duration and possibly adaptability against nonstationarities in EEG during the test phase.

A BCI system's performance depends not only on the choice of classifier, but also on preprocessing methods, selected features, the users who participate in the study, and a multitude of other factors [94]. Therefore, a comparison among different studies to choose the "best" classifier for a BCI speller system is not feasible. However, within individual studies, comparisons among classifiers have been attempted. For example, using offline EEG data, it was demonstrated that SWLDA and FLDA provided better overall classification performance compared to Pearson's correlation method, linear SVM, and Gaussian Kernel SVM [81], a matched filter-based classifier outperformed a maximum likelihood-based classifier

[138], and BLDA outperformed LDA, SWLDA and neural networks [97].

a) LDA-based classifiers: LDA is a supervised method for classification. For two classes C_0 and C_1 consider samples (EEG features) given in the form $\mathbf{X} = \{\mathbf{x}^t, r^t\}$ such that $r^t = 1$ if $\mathbf{x}^t \varepsilon C_1$ and $r^t = 0$ if $\mathbf{x}^t \varepsilon C_0$. LDA finds the vector $\mathbf{w}$ that maximizes some measure of class separation for projected data. A typical approach is to maximize Fisher's discriminant [7]

$$J(\mathbf{w}) = \frac{(m_1 - m_0)^2}{s_1^2 + s_0^2}. \tag{4}$$

Here, $m_1 = \mathbf{w}^T \left(\sum_t \mathbf{x}^t r^t\right) / \left(\sum_t r^t\right) = \mathbf{w}^T \boldsymbol{\mu}_1$ and $m_0 = \mathbf{w}^T \left(\sum_t \mathbf{x}^t (1 - r^t)\right) / \left(\sum_t (1 - r^t)\right) = \mathbf{w}^T \boldsymbol{\mu}_0$ with $\boldsymbol{\mu}_1$ and $\boldsymbol{\mu}_0$ denoting the class-conditional mean vectors of features from C_1 and C_0, respectively. Also, $s_1^2 = \sum_t (\mathbf{w}^{\mathrm{T}}\mathbf{x}^t - m_1)^2 r^t$ and $s_0^2 = \sum_t (\mathbf{w}^{\mathrm{T}}\mathbf{x}^t - m_0)^2 (1 - r^t)$ indicate the class-conditional variances of projected samples from C_1 and C_0. Noticing that and $(m_1 - m_0)^2 = \mathbf{w}^{\mathrm{T}}\mathbf{S}_{\mathrm{B}}\mathbf{w}$ and $s_1^2 + s_0^2 = \mathbf{w}^{\mathrm{T}}\mathbf{S}_{\mathrm{W}}\mathbf{w}$, with $\mathbf{S}_{\mathrm{W}} = \mathbf{S}_1 + \mathbf{S}_0$ where $\mathbf{S}_1$ and $\mathbf{S}_0$ denote the class-conditional covariances of the feature vectors and $\mathbf{S}_{\mathrm{B}} = (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)^{\mathrm{T}}$, the optimal FLDA projection vector is found as the generalized eigenvector of the matrix pencil $(\mathbf{S}_{\mathrm{W}}, \mathbf{S}_{\mathrm{B}})$ corresponding to the largest generalized eigenvalue. After some simplifications, the resulting vector is $\mathbf{w}_{\mathrm{FLDA}} = \mathbf{S}_{\mathrm{W}}^{-1}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)$ [7]. The discriminant score is then simply

$$\mathbf{w}^{\mathrm{T}}\mathbf{x} + w_0 \tag{5}$$

where w_0 is a threshold, and it specifies a hyperplane classification boundary along with $\mathbf{w}$. Note that the FLDA solution is minimum-risk optimal under the assumption of equal covariance Gaussian class distributions, which is typically reasonable for EEG if one assumes EEG is a superposition of background brain activity and stimulus/event-related brain activity with a wide-sense stationary Gaussian background process model; and it is also a special case of linear regression [22].

In (5), $\mathbf{x}$ is the feature vector and $\mathbf{w}$ is the vector of feature weights. In P300 matrix speller applications, to combine multiple trials in a sequence (see Section II-A for the definition of a sequence for matrix spellers), it is assumed that the user is focusing on a single symbol during a sequence, and this symbol is inferred by the intersection of the predicted row and the predicted column. Denoting with $T_{i_{\mathrm{row}}}$ and $T_{i_{\mathrm{col}}}$ the index sets of the trials (row and column highlights) where the ith symbol is highlighted, the following equations are used to obtain predicted row and column indices:

$$\text{Predicted Row} = \underset{i_{\mathrm{row}}}{\operatorname{argmax}} \sum_{t \in T_{i_{\mathrm{row}}}} \mathbf{w}^{\mathrm{T}}\mathbf{x}^t$$
$$\text{Predicted Column} = \underset{i_{\mathrm{col}}}{\operatorname{argmax}} \sum_{t \in T_{i_{\mathrm{col}}}} \mathbf{w}^{\mathrm{T}}\mathbf{x}^t. \tag{6}$$

SWLDA [44] is an extension of LDA to choose the feature values to be used in (5). The significant features are chosen using a combination of forward and backward stepwise regression. SWLDA has an inherent automatic feature selection property and is commonly used in P300-based BCI systems and other BCI designs. SWLDA consists of two loops: one for forward selection and one for backward elimination (see Algorithm 1).

In BLDA [64], to design a separating hyperplane as shown in (5), a prior distribution is assumed for the weight vector $\mathbf{w}$. Then, a predictive feature distribution is obtained using the posterior distribution of the weight vector, and this predictive distribution is used to make an inference on the stimuli/options. The targets t_{r^t} for $r^t \in \{0, 1\}$ and feature vectors $\mathbf{x}^{\mathrm{t}}$ are assumed to be linearly related in the presence of additive white Gaussian noise n, such that

$$t_c = \mathbf{w}^{\mathrm{T}}\mathbf{x} + n. \tag{7}$$

Here, $t_1 = N_1/N$ for C_1 and $t_0 = -N_0/N$ for C_0 with N_0 and N_1 denoting the number of calibration samples corresponding to C_0 and C_1, respectively, and $N = N_0 + N_1$.

Using (7) and considering all feature vectors for both classes, the conditional distribution of the targets, $p(t_c|\mathbf{w}, \mathbf{X}, \theta)$, with θ denoting the noise distribution parameters vector, can be calculated, where $\mathbf{X} = \{\mathbf{x}^t, r^t\}$ is defined as above. In addition, assuming a prior distribution for the weight vector $\mathbf{w}$, $\mathrm{p}(\mathbf{w}|\alpha)$, with α denoting the weight prior parameters, the posterior distribution for the weight vector $\mathbf{w}$ is computed using Bayes' rule as

$$p(\mathbf{w}|t_c, \mathbf{X}, \theta, \alpha) \propto= p(t_c|\mathbf{w}, \mathbf{X}, \theta)p(\mathbf{w}|\alpha). \tag{8}$$

Usually, the prior distribution for $\mathbf{w}$ is chosen as the conjugate prior to the assumed noise model such that $p(\mathbf{w}|t_c, \mathbf{X}, \theta, \alpha)$ has a closed-form solution. Then, a predictive distribution for the target variable for a new input $\hat{\mathbf{x}}$ can be calculated as in (9) for inference on the class label r corresponding to this new input [64]:

$$p(\hat{t}|\hat{\mathbf{x}}, \mathbf{X}, \theta, \alpha) = \int_{\mathbf{w}} p(\hat{t}|\mathbf{w}, \hat{\mathbf{x}}, \theta)p(\mathbf{w}|t_c, \mathbf{X}, \theta, \alpha)d\mathbf{w}. \tag{9}$$

b) Support-vector machine: SVM classifiers provide the optimum separating hyperplane in feature space (linear SVM) or in the transformed feature space (kernel SVM) by not only putting a constraint that the separated features are on different sides of the hyperplane (similar to LDA), but also maximizing the distance between the features closest to the hyperplane and the separating hyperplane (this distance is called the margin). In the event of nonseparable classes, the misclassified samples are penalized by their distance to the boundary (see (11)).

For two classes C_1 and C_{-1} (changing label values), given labeled samples (EEG features) $\mathbf{X} = \{\mathbf{x}^t, r^t\}$ such that $r^t = 1$ if $\mathbf{x}^t \varepsilon C_1$ and $r^t = -1$ if $\mathbf{x}^t \varepsilon C_{-1}$, the solution to the following problem provides the optimal separating hyperplane in SVM:

$$\min_{\mathbf{w}} \frac{1}{2}\mathbf{w}_2^2 \text{ subject to } r^t\left(\mathbf{w}^{\mathrm{T}}\mathbf{x}^t + \mathrm{w}_0\right) \geq 1 - \xi^t \tag{10}$$

where $\xi^t \geq 0$ are slack variables storing variation from the margin. The Lagrangian for this optimization problem can be written as

$$L = \frac{1}{2}\mathbf{w}_2^2 + C\sum_t \xi^t - \sum_t \alpha^t\left[r^t\left(\mathbf{w}^{\mathrm{T}}\mathbf{x}^t + w_0\right) - 1 + \xi^t\right] - \sum_t \mu^t\xi^t \tag{11}$$

where α^t and μ^t are the Lagrange multipliers, and C is the complexity parameter penalizing the boundary violations by nonseparable points. This is a quadratic convex optimization problem that should be minimized with respect to $\mathbf{w}$ and w_0 and maximized with respect to α^t and μ^t. The solution is obtained by maximizing the dual problem in terms of α^t, and then setting $\mathbf{w} = \sum_t \alpha^t r^t \mathbf{x}^t$. By calculating $g(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + w_0$, one decides on C_1 if $g(\mathbf{x}) > 0$ and C_{-1} otherwise. This classifier is commonly referred to as linear SVM.

Kernel SVM is a generalization such that the feature vectors are first transformed $\mathbf{z} = \phi(\mathbf{x})$ from a finite dimensional space to possibly an infinite dimensional space through basis functions, then using $\mathbf{w} = \sum_t \alpha^t r^t \mathbf{z}^t = \sum_t \alpha^t r^t \phi(\mathbf{x}^t)$, the discriminant is

$$g(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}) = \sum_t \alpha^t r^t \phi^{\mathrm{T}}\left(\mathbf{x}^t\right)\phi(\mathbf{x}) = \sum_t \alpha^t r^t K\left(\mathbf{x}^t, \mathbf{x}\right) \tag{12}$$

where the kernel function $K(\mathbf{x}^{\mathrm{t}}, \mathbf{x}) = \phi^{\mathrm{T}}(\mathbf{x}^t)\phi(\mathbf{x})$ is the inner product of the basis function vectors. Different kernel functions are used to design SVM classifiers, most popularly Gaussian kernel or higher order polynomials.

The presence of artifacts, sensor failure, or other effects such as BCI user fatigue cause nonstationarity in EEG signals. These nonstationarities change the underlying distribution of the EEG data; therefore, a classifier designed based on a training dataset may not always work with the predicted accuracy or speed. To overcome such issues two SVM-based classifiers are proposed.

An ensemble of SVMs is proposed to classify EEG data [123], [124]. In this method, the training data are separated into multiple parts, and for each part a separate linear SVM is trained. The score for each row/column is then calculated as the summation of the scores of the ensemble of SVMs. The authors show that with fewer sequence repetitions they achieve similar results compared to an LDA-based classifier tested on the same dataset [27].

A self-training SVM is proposed to deal with nonstationarities of the EEG data [91]. A linear SVM is first designed using the training dataset. Then during the testing phase of the BCI system, each decision made by the classifier is assumed as correctly labeled EEG data. Then, using these new labeled data, the SVM classifier is retrained. It was shown that for a desired communication accuracy, this method significantly reduces the training session length.

c) Regularized discriminant analysis: RDA is a supervised quadratic classification algorithm [52] that assumes multivariate normal distributions as the class-conditional distributions. To alleviate the rank deficiency of the maximum likelihood estimates of class-conditional covariance matrices due to the curse of dimensionality caused by low number of samples in calibrations, shrinkage, and regularization operations are applied, respectively, as

$$\begin{aligned}\boldsymbol{\Sigma}_r(\lambda) &= \frac{(1-\lambda)\mathbf{S}_r + \lambda\mathbf{S}}{(1-\lambda)\mathbf{N}_r + \lambda\mathbf{N}},\\ \boldsymbol{\Sigma}_r(\lambda,\gamma) &= (1-\gamma)\boldsymbol{\Sigma}_r(\lambda) + \frac{\gamma}{p}\mathrm{trace}\left[\boldsymbol{\Sigma}_r(\lambda)\right]\mathbf{I}\end{aligned} \tag{13}$$

where λ and γ are hyperparameters that need to be optimized, for instance, using cross validation. Shrinkage operation makes the class covariances closer to an overall covariance matrix (suitable for EEG assuming equal covariances for classes for reasons explained in the LDA section) and regularization makes them more circular and primarily, nonsingular.

C. Factors that Affect Speller Performance

1) Odd-Ball Effect: The standard presentation setup in matrix spellers consists of a 6×6 matrix with rows or columns intensified one at a time. As mentioned above, a sequence includes $(6 + 6 =)$ 12 flashes when all the rows and columns are intensified. The 6×6 matrix structure presents 36 symbols, including the 26 English letters and 10 more choices, which can contain digits or other choices like delete or space. With the assumption of one target item in each sequence, there are only 2 flashes containing the desired symbol; and hence the probability of oddball paradigm is $2/12 \approx 0.17$. This probability is sufficiently low for generating a P300 response [48]. Many criteria have been considered to increase the ERP detectability.

2) Intersymbol Interval (ISI): ISI [including a related measure, target to target interval (TTI)] is one of the most effective factors to be studied. Short intervals between target flashes would result in repetition blindness (attention blink) and habituation, which decrease ERP amplitude and hence its detectability. Many papers have studied this factor along with other parameters like matrix size [4], [135] or different presentation paradigms [49], [60], [68], [69], [151], [152]. In the matrix speller, the optimal ISI varies depending on the matrix size and presentation paradigm; for example, [135] reported the best performance with an ISI of 175 ms for a 3×3 matrix and row/column paradigm (RCP), and [101] showed that lower flash rates in the range of 8 to 32 Hz result in the best performance for an 8×9 matrix with flashes of 6 items at a time. They also demonstrated that variation in stimulus-on and stimulus-off time does not affect the performance.

Matrix spellers are typically set up to avoid the possibility of consecutive target flashes. Similarly, in the RSVP paradigm, one would avoid consecutive presentations of the same symbol for the same reason. Lu and colleagues studied BCI performance as a function of stimulus-off time, ISI, flash duration, and flash rate as 4 timing parameters [172]. They suggested that BCI accuracy is a function of the number of trial repetitions, and BCI performance is enhanced when stimulus-off time and ISI are increased. These studies suggest that optimal ISI depends on the number of nontarget flashes between targets. Jin *et al.* [69] studied the effect of TTI on BCI performance. They employed a 7×12 matrix of characters with 16, 18, and 21 flashes in each sequence, with a flash pattern optimized to minimize TTI while avoiding repetition blindness. To avoid repetition blindness a minimum of one (for 16 flashes), two (for 18 flashes), and three (for 21 flashes) non-similar symbol presentations between two flashes of the same item has been proposed. Here, the 18-flash pattern showed the best performance in terms of classification accuracy and information transfer rate.

3) Different Matrix and Stimuli/Flash Organizations: The unpredictability of the target letter and the physical arrangement of items on the presentation screen are other factors which can affect ERP amplitude. Changing the size of a matrix will alter the location of items on the screen, as well as the number of items displayed, resulting in changes to the probability of the target item [135]. Increasing matrix size decreases the probability of the target letter and hence enhances the ERP's SNR. However, the required time for highlighting all the columns and rows will increase, so this does not necessarily lead to improved typing speed [4]. Smaller matrix sizes flashing with shorter ISI seem to yield better typing speeds in a typical RCP [135]. Remodeling the flash paradigm from an RCP to a group-based paradigm is another phenomenon that has been analyzed. In the matrix speller, a non-row/column subset-based flash paradigm is studied on a 12×7 matrix [68]. Subsets are selected such that each sequence contains 9, 12, 14, or 16 flashes. The 16-flash paradigm shows better performance than the other subset-based options and RCP. Townsend and colleagues proposed the checkerboard paradigm (CBP) to avoid adjacency distraction error [151]. This paradigm is a special case of the previous flash paradigm in which subsets of symbols in an 8×9 matrix are flashed by alternatingly selecting a row or column from one of two 6×6 matrices of symbols, forming a checkerboard pattern for each flashing subset. CBP demonstrates a significant improvement in accuracy compared to RCP. Another flash paradigm known as $\mathrm{C}(m, n)$ is introduced in which m is the number of flashes per sequence and n is the number of flashes per item [152]. Specifically, the C(36,5) known as the five-flash paradigm (FFP) has been compared against CBP. Both have high accuracy, but the FFP offered a higher information transfer rate.

To consider an error correction code approach, Hill and colleagues assume a noisy communication channel and assign a code word to each item with a length equal to the number of flashes in each sequence [60]. Code words are all zeros except for a single one at times corresponding flashes. Extra flashes are employed to generate redundancy and the codebook is optimized to have a maximal–minimum Hamming distance between pairs of codes. The TTI is constrained to be larger than a threshold. Results indicate that RCP demonstrates better performance than one would expect according to its Hamming distance and TTI. Moreover, the optimal stimulus type is a subject-specific parameter. Imposing transparent familiar or well-known faces (like those of family members) on matrix elements is another method which can lead to increased SNR [72], [73].

Reshaping the fixed matrix arrangement of items into various forms has been another strategy for matrix spellers. One proposed method is the hierarchical region-based flash paradigm [49]. In this setup, 49 items equally distributed in seven groups are positioned in different regions of the screen. At the first level, each region would intensify one by one. Then, the letters in the (inferred) intended region would be distributed at seven locations on the screen and the user can proceed by making further selections to reach the intended item. In a similar paradigm, one can use a language model to decide on the hierarchy of characters to be used in the presentation layout [96]. The lateral single-character paradigm (LSCP) is another proposed technique in which items are arranged in a circular layout on the screen [121]. Only one item would flash at a time and two consecutive flashes cannot be from the same side (left or right) to reduce cross-talk from nontarget flashes.

4) Gaze Dependence: The P300 matrix speller is a gaze-control dependent design [31]. Hence, users with limited gaze control will experience significant difficulty. To address this, a new presentation paradigm called the gaze independent block speller (GIBS) has been proposed to reduce the dependence on gaze control [122]. Here, 36 items are distributed into four groups, one block at the center of the screen and three blocks at three corners. Central block items flash one by one, and other blocks flash as a group. If the intended character is in another block, the user should aim for that block and if selected, that block will move to the center. Results indicate that without eye movements (fixating at the center) this system offers a bit ratio similar to the standard RCP. In contrast, for SSVEP stimuli, selective attention to a flicker pattern even with overlapping stimuli groups may provide sufficiently discriminative signals for BCI [173]. In a similar observation for auditory BCIs, Hohne and colleagues observed that discriminating different pitches was easier than discriminating direction of arrival [171].

5) Feature Attention: This corresponds to the attention of a BCI user to different properties of the presented stimuli, and has been shown to affect BCI performance. The original ERP-based Hex-o-Spell has been compared to its variants, Cake Speller and Center Speller, which feature different colors and forms for the visual stimuli. Cake Speller is similar to Hex-o-Spell in terms of design except that the symbol groups are located in triangles rather than circles, and these triangular groups form a hexagon. In Center Speller, symbol groups are presented within various shapes of various colors in the center of the screen, in RSVP fashion [154]. The results showed that the Center Speller has higher P300 response and higher classification accuracy. In the matrix speller, a green/blue color change during highlighting was shown to be superior to white/gray color change [149]. A visual stimuli scheme based on color change and movement of the stimuli has been employed in a matrix speller design. This scheme induces P300 and motion onset visual evoked potential, and was shown to outperform a scheme based only on color or motion [69]. In RSVP-based BCIs, assigning colors or different capitalization to the cues led to an increase in the spelling rate [2].

6) Error-Related Potentials (ErrPs): ErrPs are EEG potentials induced by the user's recognition of an error. These potentials are detectable in the anterior cingulate cortex over the fronto-central regions of the scalp when the decided action shown on the interface is not the user's intended symbol [37], [38]. Detection of ErrPs in EEG, and their integration into P300-based intent classifiers by error correction after P300 detection, can improve the accuracy and speed of BCI systems [14], [143], [144].

7) Context Information: Context information refers to evidence from non-EEG-sources that complement EEG data in inference. Word completion and use of language models are well-known examples. BCI communication systems specifically designed for typing benefit greatly from probabilistic language models. Various predictive word completion methods integrated into the intent detection process [75], [90], [129] and Bayesian fusion methods that combine probabilistic n-gram language models with different classifiers, as in RSVP Keyboard

[114]–[116] and other systems [130], [142], [157], have been demonstrated to enhance the accuracy and speed of communication.

D. Output Components

BCI communication systems have three options for output: text, text-to-speech, and speech. The output option most often referred to in the noninvasive BCI literature is text, but off-the-shelf text-to-speech modules can be appended with relative ease. The widely researched P300 Speller [134] that is also used by the BCI2000 system has been validated for text output tasks like spelling, email, or internet browsing [79], [84], [137]. Text-to-speech requires a speech synthesizer for conversion of normal language text into artificial verbal production; such synthesizers are available on virtually all modern personal computers. To employ this output method, the user must simply enable this feature on his or her computer and have a way to interface with it. Various groups report people with advanced amyotrophic lateral sclerosis (ALS) effectively using BCI-controlled text-to-speech applications in their daily lives [137]. The option of direct speech output has been investigated by a group working with an invasive BCI; initial results indicate the potential to use speech motor imagery to produce vowel sounds, and the researchers' eventual goal is to develop a BCI capable of producing synthetic speech in real time [30], [57].

Although excellent advances have been made since P300 and SSVEP BCIs for communication were introduced in late 80 s [48], [146], [147], researchers agree that slow information transfer rates continue to plague the technology [104]. Even so, the field remains hopeful about emerging communication applications [50].

III. Current Clinical Applications of BCI for Communication

When considering the clinical application of BCI for communication, individuals with SSPI are an obvious target population. BCI technology has the potential to profoundly change their lives by providing an alternative access method in the absence of reliable motor movement or when other forms of AAC have failed [112], [137], [164]. Indeed, individuals with SSPI are typically unable to use common modes of communication such as speech, writing, or gestures to express themselves.

A. Etiology

Among people with SSPI, communication is a particular challenge for individuals with locked-in syndrome (LIS). LIS is a condition combining tetraplegia and anarthria with preserved consciousness [13]. There are numerous etiologies of LIS, ranging from acute events such as brainstem stroke and severe traumatic brain injury to postinfectious autoimmune disorders such as Guillain–Barre syndrome to chronic degenerative disease such as ALS [17], [19], [63], [84], [87], [104]. LIS has been described in terms of three levels of severity [13], [141]. People with *classical LIS* are completely paralyzed except for blinking or eye movements, which they can use to communicate via yes/no responses or partner-assisted communication methods, or to control a speech-generating device [89], [156]. Those with *incomplete LIS* have additional motor function, and may have other options for gestural communication or alternative access to a speech-generating device [89], [156]. However, even these methods may not be reliable due to fatigue or variability in motor function [141]. *Total LIS* refers to a condition in which all voluntary motor function is lost; BCI offers the only hope of reliable communication for this population. Some BCI researchers have begun to include participants with LIS who may have more motor function than is typically associated with incomplete LIS, but who cannot *consistently* rely on speech, writing, or existing AAC methods to meet their communication needs. In addition to the etiologies listed previously, these forms of incomplete LIS may result from acquired neurological conditions or neurodevelopmental disorders including cerebral palsy (CP), muscular dystrophy (MD), multiple sclerosis (MS), Parkinson's disease, Parkinson's plus syndromes, and brain tumors. This expanded definition of incomplete LIS offers a more inclusive perspective of the multiple diagnoses in which SSPIs necessitate BCI access for communication [47], [113].

B. Value of BCI for People With SSPI

The age of onset of LIS varies between 17 and 52 years old [15], [32], [33], [42]. The youngest patients have a better prognosis for survival, and more than 85% of individuals are still living ten years after onset [33], [42]. Additionally, with advances in medical technology, life expectancy with severe physical impairment has potential to be significantly longer. This is seen with the application of both noninvasive and invasive ventilation in ALS [28]. The availability of BCI as a potential form of AT to enable communication throughout disease progression holds great promise for improving quality of life in this population [12], [47], [63].

How are BCIs valuable for communication for people with SSPI? First, the larger perspective of purposes of communication for all humans must be considered. In 1988, an extensive review of the existing literature on AAC interactions resulted in a standard definition of the four purposes of communication: 1) expression of needs/wants; 2) information transfer; 3) social closeness; and 4) social etiquette [92]. One study questioned a large group of people with ALS regarding areas of potential AT use. They placed the highest priority on communication [56]. Indeed, communication has been one of the first applications of BCIs [48], [86], [164].

For those users with total LIS, the very real and immediate goal of a BCI speller is to provide basic communication capabilities in order to express wants and needs to caregivers or to operate simple word processing programs [9]. Beyond expression of basic wants and needs, use of BCI to communicate messages of the user's choice, to share information regarding opinions and interests, can be accomplished through free spelling in text output. Finally, to achieve the purposes of social closeness and to allow optimal life and activity participation, BCI should provide access to the internet, email, social networking, and other ways of interacting with the world for people with LIS.

C. Communication Competence With BCI

In terms of the future, most researchers agree that the potential for BCI will only be capitalized upon when BCIs are not used in isolation, but rather are part of a suite of AT devices to be used by people with varying degrees of physical ability [66].

Greg Bieker, a man who has lived with LIS for 18 years, predicts that BCI has the potential to give people with SSPI a sense of control and the ability to communicate independently with an unobtrusive and easy device [18]. With this new AAC technology, we must ask ourselves, who would be considered a competent BCI communicator? The concept of communication competence has been divided into four different constructs [92].

1) Operational competence refers to the ability to perform the tasks required of the technology.
2) Linguistic competence refers to the user's ability to manipulate language and generate messages that conform to the linguistic rules of the community.
3) Social relational competence addresses the user's understanding of why and how to engage verbally with others.
4) Strategic competence refers to the user's ability to know what means of communication to use in different settings, with different partners and a range of messages.

If a BCI user is to be considered competent with this new AT, he or she must perform adequately in all four areas. The interaction between the user's skills and the technology's functionality for independent message transmission is the ultimate goal of communication competence with BCI.

D. User Skills Necessary for BCI Operation

As with any communication technology, the skills needed for operation and functional use must be determined, and a comprehensive process is needed to match the device to the user [132]. Fried-Oken and colleagues conducted a careful and repeated clinical task analysis of the RSVP Keyboard BCI by a multidisciplinary team [169]. Additionally, they observed people both with and without disabilities as they used the system and determined the following skills as requisite for successful use of a visual ERP-based BCI: adequate hearing and auditory comprehension for responding appropriately to stimuli, understanding and following instructions; adequate vision, visual perception and sustained visual attention for seeing letters on the screen and attending to the task; and adequate literacy and spelling skills for recognizing letters and words and composing written messages. Vigilance and working memory are necessary for the user to sustain attention to the task as well as to track symbol selections. Potential interference from pain and medications must be identified, and motor function should be assessed for unintentional muscle movements or suboptimal positioning which may affect EEG signal acquisition.

BCI research has primarily taken place in laboratory environments, with setup performed by BCI experts. These tightly controlled conditions bear little similarity to the conditions under which BCI systems will ultimately be used. People with disabilities must use BCIs for communication and control in the home environment, where there are frequent distractions, signals are influenced by interference from other equipment, and family members and paid caregivers with varying levels of technical skills are responsible for system setup and maintenance [136], [159]. In recent years, researchers have begun to bring EEG-based BCI communication systems to the homes of people with disabilities for testing under these challenging conditions [112], [113], [168]. Some BCIs have been placed in users' homes for evaluation of long-term independent use, most notably the Wadsworth BCI Home System (BCI24/7). People with disabilities have been using this P300-based system for communication, computer access, and environmental control in their homes over periods of months or years [137], [163]. These studies indicate that independent home use of BCI is possible and beneficial to the user, but presents considerable challenges related to interference and other characteristics of the home environment, training for users and caregivers, and technical support [137], [159].

As BCI continues to improve and move toward independent home use as an assistive technology, it is vital that researchers and developers follow the principles of user-centered design [1], [66], involving BCI users or potential users in all steps of development. A number of research groups have begun collecting feedback and suggestions from BCI users, using questionnaires and rating scales [168], interviews [168], anecdotal reports [137], [151], telephone surveys [65], or focus groups [23]. Current user feedback data suggest that people with disabilities expect BCIs to be relatively quick and easy to set up (30 min or less), have high selection accuracy (90% or better), and type much more quickly than current systems (20 or more letters per minute) [65]. Users also want multipurpose BCIs that, in addition to communication, allow for computer access, environmental controls, wheelchair operation, and other functions [23], [65], [168]. Research participants expressed concern about being able to use BCIs for functional communication in the home environment due to personal factors such as fatigue and discomfort, the appearance and complexity of the cap and other hardware, or the burden for caregivers who must set up and maintain the system [23], [168].

E. Future Technical Horizons

From a clinical perspective, BCIs for communication face many of the same challenges as other AAC technologies, reflecting the user feedback described above. AAC in general is much slower than natural speech, can be difficult to learn and use, and requires adequate training for the user, communication partners, and caregivers [11], [53], [108]. Typing rates for current EEG BCI-based communication systems hover near 5 characters per minute [66] or one 5-letter word per minute (wpm). People without disabilities typically speak at a rate of 150–250 wpm (Goldman-Eisler 1986, as cited in [16]). BCI may be even more difficult to learn than movement-based AAC methods, as one must learn not only a new computer interface, but also how to control brain activity. In some studies, people with disabilities have been found to achieve lower levels of accuracy with BCI than people without disabilities [113], [117]. BCI faces additional challenges with reliability and dependability; even in laboratory-based studies under controlled conditions, BCIs have not demonstrated adequate reliability for functional use [165]. The multiple hardware components involved in a typical EEG-based BCI system can be difficult to transport or to mount to the user's wheelchair, reducing system portability and usability in various environments. Finally, system setup is more complex and time-consuming for noninvasive BCIs than for most other AAC technologies, primarily due to the need for electrode application and troubleshooting.

BCI can play a unique and important role in the field of assistive technology, by serving as an access method for people whose severe disabilities prevent them from consistently using other methods such as eye control or switch scanning. Even people with total LIS, who have no volitional muscle movement whatsoever, may someday be able to communicate using only their brain activity. At present, few studies have examined BCI performance among individuals with total LIS, despite the great need for a viable communication method in this population. Kübler and Birbaumer [83] found that people with total LIS were less likely to be successful with BCI than participants with lower levels of disability. Even among users with mild or no disabilities, many people are unable to successfully control existing BCI systems due to individual variations in brain structure or function, such as the absence of a P300 response [5]. The pediatric population has also been largely overlooked in BCI research. Some children with disabilities would certainly benefit from using BCIs for communication and control, and researchers should begin to investigate this possibility. Future BCIs should be functional for users of varying ages and abilities, including those with profound physical disabilities who currently have no functional means of communication. Following a user-centered design model, as described above, will help to ensure that BCI systems meet the needs and desires of the individuals who will use them in everyday life.

IV. Conclusion

BCI research is in the process of revolutionizing the future of human–computer interaction with exponentially increasing number of reported outcomes on many innovative and novel application areas. In this review, we have restricted the discussion to methodologies and outcomes of BCI research that have two features:

1) Noninvasive EEG signals are used as the physiological input modality.
2) AAC is the target application domain.

We omitted an extensive discussion on performance measures used, as information transfer rate (in bits/minute) is the most widely used measure and is supplemented typically by characters/minute. In the review, we avoided a discussion that compares reported accuracy and speeds among various systems, as we think uncontrolled factors among experiments conducted across the globe still pose a great source of variance and making hardline conclusions is difficult. Nevertheless, readers can find reported speed and accuracy details in the cited sources and make such a comparison if interested.

As evidenced by the citation distribution and relative lengths of our sections, ERP-based AAC systems are most widely researched; especially in increasing numbers more recently. VCP-based systems run into user-training difficulties and SSVEP-based systems encounter significant issues related to lack of gaze control in target user populations of AAC systems. Even the widely researched ERP-based matrix speller has been shown to be strongly gaze dependent and much effort went into developing variations that are less prone to performance degradation due to this factor.

Algorithm 1. Stepwise Linear Discriminant Analysis (SWLDA)

Step Index	SWLDA algorithm for feature selection and classification.
0	Initialize $S = \emptyset$ (empty set) (which will iteratively change to keep the indices of selected features). Let $S^c = \{1, \ldots, K\} \backslash S$ be the initial complement (set of non-selected features). Initialize $r_S = r$. Let $\gamma_f(k,l) = F_{(k,l),1-\alpha_f}$ be the confidence threshold for forward selection of a feature. Let $\gamma_b(k,l) = F_{(k,l),1-\alpha_b}$ be the confidence threshold for backward elimination of a feature. These are obtained at each iteration considering the desired confidence levels $(1-\alpha_f)$ and $(1-\alpha_b)$ in the interval $(0,1)$.
1	Let $S_f = S$. Repeat step 2 until all features in S^c are evaluated as described.
2	For each forward selection candidate $s \in S^c$, using linear least squares, fit a line from $\mathbf{x}_{S\cup\{s\}}$ to r_s. Let $\mathbf{w}_{S\cup\{s\}}$ be the regression coefficient vector, $\hat{r}_{S\cup\{s\}}$ be the predicted label and N represent the number of samples in the training set. Then the sum of squared errors over samples is $\mathrm{SS}_{\mathrm{err},S\cup\{s\}} = \sum_{i=1}^{N}(r_{S,i} - \hat{r}_{S\cup\{s\},i})^2$. Let $\bar{r}$ be the average of label r over the sample set and $\mathrm{SS}_{\mathrm{reg},S\cup\{s\}} = \sum_{i=1}^{N}(\bar{r} - \hat{r}_{S\cup\{s\},i})^2$. Given these, the F statistic [45] is computed as $$F^{S\cup\{s\}}_{(\lvert S\cup\{s\}\rvert, N-\lvert S\cup\{s\}\rvert-1)} = \left(\frac{(\lvert S\cup\{s\}\rvert, N-\lvert S\cup\{s\}\rvert-1)\cdot \mathrm{SS}_{\mathrm{reg},S\cup\{s\}}}{\lvert S\cup\{s\}\rvert \cdot \mathrm{SS}_{\mathrm{err},S\cup\{s\}}}\right)$$ If $F^{S\cup\{s\}}_{(\lvert S\cup\{s\}\rvert, N-\lvert S\cup\{s\}\rvert-1)} > \gamma_f(\lvert S\cup\{s\}\rvert, N-\lvert S\cup\{s\}\rvert-1)$, then $S_f \leftarrow S\cup\{s\}$.
3	Let $S_b = S_f$. Repeat step 4 until all features in S_b are evaluated as described.
4	For each backward elimination candidate S_b, evaluate $$F^{S_b-\{s\}}_{(1,N-\lvert S_b\rvert-1)} = \left((N-\lvert S_b\rvert-1) \cdot \frac{\mathrm{SS}_{\mathrm{reg},S_b-\{s\}} - \mathrm{SS}_{\mathrm{reg},S_b}}{\mathrm{SS}_{\mathrm{reg},S_b}}\right)$$ If $F^{S_b-\{s\}}_{(1,N-\lvert S_b\rvert-1)} > \gamma_b(1, N-\lvert S_b\rvert-1)$, then $S_b \leftarrow S_b - \{s\}$.
5	If $S_b = S$, the algorithm converged; stop. Otherwise, let $S \leftarrow S_b$, for the new S, $r_{S,i} \leftarrow r_{S,i} - \hat{r}_{S,i}$ for $i \in \{1,2,\ldots,N\}$ and $S^c = \{1,\ldots,K\} - \mathrm{S}$. Go to step 1.

The signal processing tends to be relatively simple, linear classifiers are widely used, context information could have been exploited in significantly greater amounts, and most importantly, real-time artifact handling issues in EEG preprocessing for various populations of potential BCI-AAC system users need to be addressed further. Also, signal models are almost completely lacking in the literature which makes simulation-based engineering design followed by experimental validation with human-in-the-loop testing infeasible for the most part. This is a significant problem, because time donated for experiments by individuals with SSPI is extremely valuable and extensive experimentation for trial-and-error-based development and design is not feasible.

At this time, the most important issues that we think should be addressed include:

1) training users to produce good EEG signals during BCI-AAC system use;
2) improved signal processing to handle subject-specific conditions that degrade signal quality and discriminability;
3) improved incorporation of context and language information in designs;
4) developing accurate EEG signal models that can allow simulation-based designs, which can then be validated with experiments involving individuals with SSPI;

The research community has taken great strides towards making BCI-AAC systems a practical reality for individuals with SSPI in the past decades; however, there is still much work to be done.

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