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Chapter 7

Brain-computer interfaces for communication

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Abstract

Locked-in syndrome (LIS) is characterized by an inability to move or speak in the presence of intact cognition and can be caused by brainstem trauma or neuromuscular disease. Quality of life (QoL) in LIS is strongly impaired by the inability to communicate, which cannot always be remedied by traditional augmentative and alternative communication (AAC) solutions if residual muscle activity is insufficient to control the AAC device. Brain-computer interfaces (BCIs) may offer a solution by employing the person's neural signals instead of relying on muscle activity. Here, we review the latest communication BCI research using noninvasive signal acquisition approaches (electroencephalography, functional magnetic resonance imaging, functional near-infrared spectroscopy) and subdural and intracortical implanted electrodes, and we discuss current efforts to translate research knowledge into usable BCI-enabled communication solutions that aim to improve the QoL of individuals with LIS.

Worldwide, thousands of people have an injury or disorder that leaves them awake and aware, but unable to move or speak. This condition is referred to as locked-in syndrome (LIS). In this chapter, we discuss research and development of brain-computer interface (BCI) systems that aim to restore communication to people with LIS.

LOCKED-IN SYNDROME

Definition

"Classic" LIS is defined by five criteria: (1) sustained eye opening, (2) preserved cognitive abilities, (3) aphonia or severe hypophonia, (4) quadriplegia or quadriparesis, and (5) preserved eye movements or blinking that allows for simple communication (American Congress of Rehabilitation Medicine, 1995). Indeed, eye movements are often the last remaining functional motor output for people with LIS. When some movement is preserved in addition to eye movements, the condition is called "incomplete" LIS. When the person cannot move his or her eyes (i.e., meets criteria 1–4 but not 5), the condition is called "total" or "complete" LIS (CLIS) (Bauer et al., 1979).

Etiology

LIS has a highly variable etiology. The condition can result from a brainstem lesion, typically affecting the ventral pons and thereby interrupting the corticospinal tracts, caused by sudden events such as stroke (most often infarction) or trauma (Bauer et al., 1979; León-Carrión et al., 2002; see also Chapters 3 and 5). In addition, advances in life support (e.g., artificial ventilation) over the last several decades have allowed people with progressive neuromuscular diseases (see also Chapter 4) such as amyotrophic lateral sclerosis (ALS), which is characterized by degeneration of both the upper and lower motor neurons (Rowland and Shneider, 2001), to live beyond the point of respiratory failure (Hayashi and

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Kato, 1989) and thereby risk progressing to a locked-in state. A recent study from the Netherlands found that neuromuscular disease is the most common cause of LIS in that country (Pels et al., 2017).

Prevalence

The total prevalence of LIS in the world can be estimated based on studies of the prevalence in individual countries. For example, the prevalence of LIS in France is estimated at 8 per 1,000,000 inhabitants (see Snoeys et al., 2013). Kohnen et al. (2013) surveyed Dutch care facilities and found 2 people with classic LIS and 6 with incomplete LIS among a total population of about 16 million people. Importantly, however, a significant percentage of people with LIS do not live in care facilities, but at home with their family (Bruno et al., 2011). Surveying the entire Dutch population, a second study estimated the total prevalence of LIS in the Netherlands at 7.3 per 1,000,000 inhabitants (Pels et al., 2017), which corresponds closely with the French estimate. Generalizing to a world population of roughly 7.5 billion, there could be about 55,000–60,000 people worldwide with LIS.

However, it is likely that the prevalence of LIS varies across countries, driven, for example, by a difference in attitude toward end-of-life decisions and respiratory support. For example, the percentage of people with ALS who receive tracheostomy invasive ventilation (TIV) is lower in the United States and many European countries (United States: 6%, Tsou et al., 2012; United Kingdom: 0%, Germany: 3.3%, Neudert et al., 2001; the Netherlands: 1.3%, Pels et al., 2017; Italy: 10.6%, Chio et al., 2010) than in Japan (29.3%, Atsuta et al., 2009). Interestingly, this large difference between Japan and other countries does not seem to be caused by a difference in the number of individuals with ALS who state they would favor TIV, as these numbers are similar between the United States and Japan (16% vs 18%, respectively; Rabkin et al., 2014). Rather, the positive opinion of Japanese caretakers about TIV and encouragement by neurologists in Japan seem to have been quite influential in the decision-making process (Rabkin et al., 2013; Christodoulou et al., 2015).

Quality of life

Quality of life (QoL) plays an important role in decisions about ventilation and other assistive technology (AT) for and by people with LIS (Ando et al., 2015). Perhaps surprisingly, most studies on QoL indicate that people with LIS rate their QoL in the same range as the general population (Lulé et al., 2009). This phenomenon is called the *disability paradox*, and appears to be explained largely by the person's ability to maintain a "harmonious set of relationships within the person's social context and external environment" (Albrecht and Devlieger, 1999). Indeed, preserved social interaction—particularly via preserved communication—is a strong determinant of QoL in LIS (see Lulé et al., 2009). In fact, in a study by Rousseau et al. (2015), the only parameter associated with a decreased QoL in LIS was the restriction of communication to only binary (yes/no) responses to others' questions, which makes self-initiated and more nuanced communication difficult.

TRADITIONAL SOLUTIONS FOR COMMUNICATION

A range of augmentative and alternative communication (AAC) approaches are available to people with severe paralysis who have some residual muscle control (for review, see Fried-Oken et al., 2015). No-tech solutions only rely on the human body without involving any other equipment, and include the use of eye movements or blinks in response to closed yes/no questions, or to select a letter or option among those recited one-by-one by a communication partner. Low-tech solutions use some equipment to facilitate communication but still rely on a communication partner. An example of a low-tech solution is a letter board, in which the person with LIS focuses his or her gaze on a particular letter, number, or icon, and a caregiver or communication partner deduces their focus of gaze, allowing the person to string together words and sentences. High-tech solutions provide the user with more autonomy. They include speech generating devices and offer computer cursor or joystick control using, for example, the eyes, hand or mouth, or switch scanning access, where small residual movements are used to select (groups of) letters or icons that are highlighted sequentially and automatically by a computer. Depending on the individual situation and remaining motor function, one or more solutions may be used in different stages of recovery after traumatic brain injury or along the progression of the neuromuscular disease.

A high-tech solution available to people with residual eye movements is the eye-tracking device, which converts eye movements to motions of a cursor on a computer screen, allowing the person to control various software applications for speech generation, internet access, and environmental control with their eye movements. However, eye-tracking devices do not always meet the needs of the user. In fact, among a group of 30 people with late-stage ALS in Italy who were provided with an eye-tracking device (70% of whom had TIV), 13.3% did not use the system and 23.3% used it infrequently (Spataro et al., 2013), often because of oculomotor dysfunction and/or eye-gaze tiredness.

Abandonment of AT, which includes AAC devices, is a well-described phenomenon (Scherer et al., 2005;

Martin et al., 2011; Geronimo et al., 2015; Larsson Ranada and Lidström, 2017; Sugawara et al., 2018). In fact, it has been reported that up to 30% of AT is not used (see Wessels et al., 2003; Federici and Borsci, 2016). Factors influencing use and abandonment of AT are the person, the device, the environment, and professional support or intervention (Kraskowsky and Finlayson, 2001; Wessels et al., 2003; Federici and Borsci, 2016). Personal factors include for example age and aspects of the disability such as diagnosis, acceptance, severity, and progression. For instance, older people and people with more severe disabilities are more likely to use AT, but people who have more difficulty accepting their disability are less likely to use it, often because the devices constantly remind them of their disability. Factors related to the device include quality, cosmetic appearance, and ease of use. Complicated devices of low quality are less likely to be used, as are devices that draw negative attention to the individual using it. Environmental factors comprise, for example, the social and physical environment of the user: having a supportive social network and a living environment that does not physically hinder AT use reduces the likelihood of AT abandonment. Finally, professional support or intervention affects how often AT is used. Including the wishes and opinions of the user in the selection of the device, an adequate delivery and instruction process and the availability of high-quality follow-up service will increase the likelihood that a device is actually used. When developing communication BCI solutions, all of the factors influencing AT abandonment should be taken into account.

BCI SOLUTIONS FOR COMMUNICATION

BCIs may provide a solution for communication in situations where traditional AAC technology falls short. Direct neural control of assistive technologies could tap into otherwise unused but well-functioning brain areas (e.g., those formerly used to control speech or arm and hand movements) to provide natural, intuitive control over assistive devices. Below, we review the current state of research and development of the most common varieties of BCIs that are used for communication, we discuss the pros and cons of each, comparing not only relative invasiveness, accuracy, and speed but also other factors that may influence user satisfaction, such as system complexity and ease of use.

Noninvasive BCIs for communication

Functional magnetic resonance imaging

Functional magnetic resonance imaging (fMRI) measures the hemodynamic response, with a spatial resolution of $\sim$1–4 mm, that occurs as a result of neural activity changes (see Chapter 21). Besides playing an important role in the presurgical localization of target areas for implantable BCIs (Ramsey et al., 2006; Hermes et al., 2011; Vansteensel et al., 2016), fMRI is also increasingly used in “biofeedback” research (Stoeckel et al., 2014), providing study participants with real-time feedback about the blood–oxygen level-dependent (BOLD) signal in specific brain areas in an attempt to help them learn how to self-regulate this brain activity and thereby induce changes in cognition and behavior. The number of studies that have used fMRI for communication, however, is relatively limited (see also Chapter 21 for a review).

One of the most important issues to families and loved ones of motorically nonresponsive patients is whether or not the person is still conscious. Several reports have described individuals who had been diagnosed as minimally conscious or in a vegetative state showing clear task-related BOLD signal activation at brain locations known to be activated in able-bodied people performing the same mental task (Owen et al., 2006; Monti et al., 2010; Naci and Owen, 2013). Moreover, Monti et al. (2010) showed that a group of 16 able-bodied study participants, as well as a person diagnosed as being in a minimally conscious state, were able to use BOLD signal changes associated with motor imagery and spatial imagery to answer yes/no questions with high accuracy (100% and 83%, respectively). The possibility of fMRI-based communication in situations where it was believed that there was absence of consciousness was confirmed by Naci and Owen (2013) and indicates that fMRI could be used not only to check for residual awareness, but also potentially to allow for basic communication in people with LIS and CLIS.

In an effort to improve communication bandwidth, several studies have attempted to increase the number of distinguishable classes that can be decoded from fMRI signals. For example, using 7-T fMRI, four different hand gestures from the American Sign Language alphabet could be decoded with 63% accuracy from the BOLD signals in a small area of the sensorimotor cortex in able-bodied subjects (Bleichner et al., 2014). In a follow-up study, four different speech articulator movements (lips, tongue, jaw, and larynx) could be decoded with high accuracy (77.5%–100%) from the ventral part of the sensorimotor cortex (Bleichner et al., 2015). In a study by Sorger et al. (2009), able-bodied participants were asked to perform mental tasks (chosen from mental calculation, inner speech, and motor imagery) at specifically timed intervals. The appropriate timing of the activation in the associated brain regions allowed these study participants to give accurate responses (ranging from 75% to 100% correct) to multiple choice questions with four options. Following up on these results, and using a similar approach that combined 3 mental tasks, 3 different onset delays, and 3 different signal durations, 27 different hemodynamic response profiles were generated and assigned to 26 letters and a space. Six able-bodied study participants were able to have online mini-conversations by spelling their answers to simple questions letter by letter using the spatiotemporally defined fMRI responses, with 82% accuracy (chance level = 3.7%) and at a rate of ~1 letter per minute (Sorger et al., 2012). Together, these studies suggest that both spatial and temporal aspects of the fMRI signal can be utilized to classify multiple distinguishable codes for communication.

Advantages and disadvantages of fMRI-BCIs

Despite the promising results described in the earlier paragraph, the usability of fMRI for communication in people with LIS is very limited. Because of the size and expense of the extremely powerful magnet and the precautions that must be taken around them, MRI scanners are not suitable for continuous at home use. Moreover, because the hemodynamic response is inherently sluggish (changes in the BOLD signal typically occur several seconds after a stimulus or mental act), any fMRI-based BCI will be similarly slow. However, it is noninvasive, widely available in hospitals and research centers worldwide, and requires very little training; thus, fMRI-BCI may become a useful tool for basic communication in clinical settings, such as in the acute phase after brainstem stroke, and for diagnostic purposes (such as in probing for the presence of consciousness in people thought to be in a vegetative state).

Functional near-infrared spectroscopy

Another brain recording modality used for BCI research is functional near-infrared spectroscopy (fNIRS). fNIRS uses the levels of oxy-hemoglobin (HbO) and deoxy-hemoglobin (HbR) as a measure of blood flow, which (as with the fMRI BOLD response) changes as a result of neural activity. The value of the technique for BCI-enabled communication, first introduced by Coyle et al. (2004), has been investigated in both able-bodied study participants and people with LIS, mainly employing binary switch applications allowing for yes/no communication. Using movement imagery as a control strategy, for example, able-bodied study participants reached an accuracy of around 80% in a task in which two items were highlighted sequentially (for 15 s each, with 15 s rest in between) and the target item could be selected with the imagery-induced changes in the HbO signal (Coyle et al., 2007). Mental arithmetic-induced changes in prefrontal areas have been used as an alternative control strategy, with similar accuracy scores and similar rates, in a task in which able-bodied participants were asked simple yes/no questions, which they answered by performing mental serial subtraction for "yes" and resting for "no" (Naseer et al., 2014). Using prefrontal cortical activity, Luu and Chau (2009) were able to decode subjective preference between two drinks, presented sequentially for 15 s each, without the person having to perform any explicit mental strategy. Classification accuracy was ~80%, indicating that this approach, which is thought to require minimal effort from the user, may be used to communicate preference-related decisions.

Fewer studies have investigated fNIRS for communication in participants with LIS and CLIS. In one study, binary yes/no communication using signals from the prefrontal area was possible in ~70% (16/23 cases) of study participants with LIS and ~40% (7/17 cases) of study participants with CLIS, with about 80% accuracy (Naito et al., 2007). Here, study participants were asked to perform mental calculation or mental singing to answer "yes" and a less cognitively taxing task (e.g., counting or imagining landscapes) for "no." Each answer took 36 s: 12 s of rest, followed by 12 s of answer time and another 12 s of rest. More recently, a woman with CLIS was asked to simply think "yes" or "no" in response to binary questions with known answers. The mean accuracy decoded from her fNIRS signals in 3 different periods, each containing 200–280 binary choices spread over 12–27 measuring sessions, was 71.67%, 75.71%, and 76.30%, respectively, with each choice being based on a 25 s trial after presentation of the cue (Gallegos-Ayala et al., 2014). In a more extended study employing a similar control strategy, four people with CLIS were able to achieve a performance accuracy of around 70% (Chaudhary et al., 2017).

Advantages and disadvantages of fNIRS-BCIs

The advantages of fNIRS as a signal acquisition technique for communication BCI applications include the fact that it is affordable, portable, and noninvasive. However, as with fMRI, the speed of the system is limited by the inherently slow hemodynamic response it relies upon, which precludes decoding faster and more temporally complex events such as speech. Furthermore, the need for accurately placed sensors on the head will impede 24/7 availability, and may negatively affect user friendliness and the sense of esthetics perceived by the user. Also, binary classification accuracy with fNIRS has rarely exceeded 80%, and would have to improve for fNIRS-enabled communication BCIs to gain wider appeal as a potential clinical tool.

Electroencephalography

Physicians and researchers have been recording and interpreting the electrical signals produced by the brain since Hans Berger first described human electroencephalography (EEG) in 1929 (Berger, 1929). EEG (see Chapter 18) is generally recorded from electrodes placed on the surface of the scalp and represents the summed activity of neural cell populations of 100 million to 1 billion neurons (Lopes da Silva, 1991; Nunez, 2012). EEG has been used to control BCIs via two major sets of methodologies: (1) methods using power in the frequency bands that are present in the spontaneous EEG and that can be modulated with different mental tasks (for example "Sensorimotor rhythms"; see following text) and (2) methods that use specific features of the EEG time series that are automatically evoked by various kinds of sensory stimuli ("evoked potentials" or "event-related potentials" (ERPs), such as the so-called "P300" response; see later text). To elicit such responses, a sensory stimulus (e.g., visual or auditory) is required, with specific salient properties. This feature requires that the relevant sensory modality be intact and that it be partly or wholly dedicated to BCI operation. Spontaneous EEG methodologies focus on oscillatory features or slow voltage changes (slow cortical potentials—SCPs) of the EEG and do not require an evoking stimulus or the commitment of a sensory modality (Wolpaw et al., 2002).

Sensorimotor rhythms

The term sensorimotor rhythm (SMR) refers to oscillations in the electric or magnetic fields recorded over the sensorimotor cortex that are described by their frequency, bandwidth, and amplitude. For example, the μ rhythm (8–12 Hz) is attenuated by movement (Gastaut et al., 1952; Fisch, 1999). It is most prominent in awake, relaxed individuals with eyes open, and is usually reduced, or desynchronized, by contralateral movement (Pfurtscheller and Aranibar, 1979) or the imagination of that movement (McFarland et al., 2000). Changes in the μ rhythm are often accompanied by changes in related β (18–30 Hz) and γ (30–200+ Hz) rhythms. These changes in SMRs can be detected on the scalp by EEG (McFarland et al., 2000) and magnetoencephalography (MEG) (Mellinger et al., 2007) or on the surface of the brain by electrocorticography (ECoG) (Crone et al., 1998).

Studies over the past 25 years have demonstrated that people can learn to change the amplitude of their SMRs to control physical or virtual devices in one or more dimensions (reviewed in Yuan and He, 2014). These studies have used linear regression and classification algorithms. Using regression analysis, where the output variable is continuous, able-bodied subjects have learned to control a cursor on a computer screen in up to three dimensions (McFarland et al., 2010). Individuals with ALS have learned, in sessions spanning several weeks or months, to move a cursor in one dimension (average accuracy 78%; Kübler et al., 2005). Ninety-four individuals achieved classification accuracies of 60% or better on a two-choice task after two sessions of training (Guger et al., 2003). SMRs have also been the basis for a number of communication systems: a yes/no system for answering questions (Miner et al., 1998) and spelling using a variety of virtual keyboards (Perelmouter and Birbaumer, 2000; Wolpaw et al., 2003; Scherer et al., 2004; Müller et al., 2008).

Movement or movement imagery is also known to generate relatively slow voltage changes (from about 300 ms to several seconds) in the sensorimotor cortex, called SCPs. In one seminal study, two individuals with advanced ALS used SCPs to type messages, one letter at a time, using a series of binary selections that sequentially spliced the alphabet until the desired letter was obtained (Birbaumer et al., 1999). In later studies, others with advanced ALS (Kübler et al., 2001; mean accuracy 70% and 91%) and an individual with severe cerebral palsy (Neuper et al., 2003; mean accuracy 70%, rate 1 letter/min) learned to slowly, but effectively, communicate using this method.

The P300-BCI

As mentioned earlier, an ERP is the measured brain response to a specific event, such as a visual or auditory stimulus. The P300 ERP, discovered more than 60 years ago (Sutton et al., 1965), is defined by a large vertex-positive (P) component that occurs ~300 ms after an evoking stimulus (hence the "300"). It appears in the EEG whenever a person detects a rare or meaningful event, especially among a series of other, more frequent events. For example, if a subject is watching a flashing visual stimulus, the appearance of a deviating visual stimulus will induce a P300 response. The P300 be can elicited reliably with relatively simple paradigms, including flashing letters on a virtual keyboard, and its evocation by attention to a particular salient icon or letter presented on a computer screen when it is flashed can be harnessed as a command signal for a BCI by persons with paralysis.

The P300 response was established as a means of selecting letters from a virtual keyboard as early as 1988 (Farwell and Donchin, 1988). In this method, the user faces a 6 × 6 matrix containing letters and symbols, focusing attention on the desired item while every 125 ms a row or column of the matrix is illuminated for 100 ms. Illumination of the row or column containing the desired symbol elicits a P300 evoked response (for review, see Sellers et al., 2012). There have been over 2000 studies published on the P300 through 2015 (Powers et al., 2015). These studies generally seek to improve efficacy by increasing signal-to-noise ratio or by manipulation of the stimulus features for optimal brain responses (Kaufmann et al., 2011; reviewed in Cecotti, 2011; Sellers et al., 2012). Some of these efforts have shown promising results.

P300 devices may be useful to people with ALS as their disease progresses, but results are mixed for people with severe paralysis. Several comparison studies show that participants with motor impairment attain lower accuracy and communication rates than able-bodied participants (Piccione et al., 2006; Ikegami et al., 2014; Oken et al., 2014), which may be related to the (in)ability to move the eyes, training time, signal artifacts, and signal variability (Sellers et al., 2006; Ortner et al., 2011; Kaufmann et al., 2013). Other studies, however, have demonstrated high mean accuracy (95%) and typing rates of 6–12 characters per minute in people with ALS (Speier et al., 2017), or reported only minimal or no differences in performance between motor impaired people and healthy participants (Pires et al., 2011; McCane et al., 2015). In a large study by McCane et al. (2014), individuals with late-stage ALS used a standard 6×6 matrix for a copy-spelling task. Of the 25 participants, 17 could communicate with an accuracy of $92 \pm 3\%$ (range 71%–100%). The other eight individuals had accuracies below 40%, which was ascribed to their visual impairments. Indeed, in a follow-up study, no significant difference in performance was observed between a group of 14 participants with late-stage ALS without visual impairments and a group of 14 age-matched able-bodied controls (mean maximum accuracy $95.7 \pm 2\%$ and $98.8 \pm 1\%$, respectively, mean communication rate 2.1 ± 0.3 and 2.6 ± 0.2 characters/min, respectively; McCane et al., 2015).

Despite the large body of research on P300-BCIs over the past decades, very few reports exist on the usability of P300-BCIs in the daily home life of people with paralysis. One study reports on an individual with late-stage ALS who used this system in his daily life at home for more than 2.5 years for communication without technical oversight, and who performed with 83% accuracy on regular copy-spelling tasks (Sellers et al., 2010). Another individual with ALS has used a P300 device for artistic expression for more than 14 months, and reported high user satisfaction (Holz et al., 2015). A recent study by Wolpaw and coworkers investigated home use in a large number of individuals with ALS. Of the 42 people studied, 33% were able to use the system at home. Nonuse was related to disease progression and to properties of the BCI itself (Wolpaw et al., 2018). More research is needed on the broader usability of P300-BCIs by people with motor disabilities.

Other evoked potentials

The steady-state visual evoked potential (SSVEP) is an evoked brain response that can be detected in the EEG over occipital areas in response to a visual stimulus that oscillates (or flickers) at a fixed frequency. In a BCI application, different blinking stimuli may be presented, each with their own frequency and/or phase (see for review, Vialatte et al., 2010). The user can then select the target stimulus by simply focusing his or her attention on it. SSVEP-BCIs have been studied for their application for communication in able-bodied participants, initially using a limited number of virtual buttons (Middendorf et al., 2000), and later using more complex decision-tree-based spellers (Cecotti, 2010). More recently, SSVEP-BCIS have used a full QWERTY keyboard (Hwang et al., 2012) or a 5×8 matrix with 40 individual stimuli including characters and digits (Nakanishi et al., 2017), in which each stimulus can be selected in a single step. In general, able-bodied participants are able to achieve high accuracies ($\sim$90%) and speeds up to 75 selections/min in cue-guided online experiments, with an average free-spelling speed of 36 characters/min (Nakanishi et al., 2017).

However, as with P300-BCIs, very few studies have investigated the performance and usability of SSVEP-BCIs for communication in people with paralysis, and these studies have shown mixed results. Combaz et al. (2013) reported on seven individuals with severe paralysis who were able to use an SSVEP speller with four quadrants with an accuracy of 70% or more, and Hwang et al. (2017) showed that five people with late-stage ALS reached a mean classification accuracy of 76.99% within a four-class SSVEP paradigm. In a study by Lim et al. (2017), participants used the SSVEP to create a brain switch that activated an emergency call system for alerting a caretaker. The brain switch could be generated by gazing for several seconds at a continuously flickering visual stimulus in the corner of a screen. Three individuals with late-stage ALS were able to make these emergency calls within about 7 s. However, in a study by Lesenfants et al. (2014), only two out of six people with LIS reached above-chance accuracies in a two-class SSVEP paradigm, and one out of four achieved online yes/no communication (vs 8 out of 12 able-bodied participants). The potential advantages of SSVEP-BCIs include relatively high information transfer rate and relatively short training time for the user (Cecotti, 2010). However, despite the promising results obtained with able-bodied participants, more work is needed to obtain

SSVEP-BCI performance levels that meet the standards required for day-to-day use by people with paralysis.

Yet another type of evoked potential is the broad-band visually evoked potential, also called the code-modulated visual evoked potential, which is generated by a specific pseudorandom flash sequence (Bin et al., 2009). So far, there has been only limited work using this type of signal for BCI communication, but the approach has been tested in free-spelling paradigms with able-bodied participants using, for example, 6×6 or 8×8 matrices of keys (Sutter, 1992; Spüler et al., 2012; Thielen et al., 2015). Across 12 participants, Thielen et al. (2015) reported a mean accuracy of 86% and a spelling rate of about 9 characters/min in a copy-spelling task, and a rate of 8 characters/min in free-spelling mode. Using online adaptation, 9 participants of the study by Spüler et al. (2012) were able to reach, on average, 96% accuracy. In a free-spelling session by 6 participants, mean accuracy was somewhat lower (85.4%), but speed was high, more than 21 error-free characters per minute. Although very promising, these findings need to be further validated, and the usability of this approach in daily life by people with paralysis needs to be investigated.

Advantages and disadvantages of EEG-BCIs

EEG is highly attractive as a signal recording technique for BCI because it is safe, cost-effective, and noninvasive. Over the past decades, EEG-based BCIs have shown great promise, especially in fundamental research and in studies with able-bodied participants. The relatively small number of studies in people with LIS show that they also can achieve accurate communication, but more work needs to be done to validate these findings. Also, other drawbacks of EEG that decrease the usability of EEG-BCIs for communication by people with LIS need to be addressed. For example, electrodes on the scalp are sensitive to signal artifacts (e.g., line noise, muscle activity), and their relatively large distance to the brain restricts the usable frequency range as well as the spatial resolution of EEG. In addition, the need for an able-bodied caregiver to place electrodes on the scalp, sometimes requiring conductive gel to be applied for each electrode that needs to be shampooed out afterwards, limits the 24/7 availability, comfort, and practicality of EEG-BCIs. Efforts are ongoing to address these issues.

Implanted BCIs for communication

Electrocorticography

Electrocorticography (ECoG) involves the placement of disk electrodes, typically as a part of strips or grids containing multiple contacts, on the cortical surface, either epidurally or (most often) subdurally. Electrode diameter is typically 2.3 mm exposed surface, with 1 cm interelectrode distance, but layouts with higher density and smaller electrodes are increasingly used (Flinker et al., 2011; Bouchard et al., 2013; Bleichner et al., 2016; Hotson et al., 2016). The use of ECoG signals for BCI has been demonstrated mostly in able-bodied epilepsy patients who already have the ECoG arrays implanted as part of seizure focus localization prior to resective surgery. As with EEG, there is evidence that cognitive control areas in the brain can be used for controlling ECoG BCIs (Vansteensel et al., 2010), but the majority of ECoG-BCI studies use neural signals recorded from the motor areas, which are modulated by imagined or executed movement, to control, for example, a cursor on a computer screen (for review, see Schalk and Leuthardt, 2011).

Direct decoding of speech and language using ECoG BCIs

Recent studies have focused increasingly on the use of ECoG signals for communication. Many of these are based on the principle that the somatosensory (S1) and motor (M1) cortex are inherently topographically organized, such that neighboring body parts have neighboring representations on the cortical surface. The cortical surface is composed of so-called "cortical columns," which are roughly 300–600 µm in diameter each (for review, see Mountcastle, 1997) and encompass several 100,000 neurons exhibiting similar functions. This allows the cortex to be probed for constellations of neuronal ensembles that respond to, or trigger, specific movements and that are distinct enough from each other to be separately recorded, much like discriminating different patterns on a display.

Taking advantage of this detailed topographic organization, one group was able to distinguish four communicative hand gestures from the American Sign Language finger spelling alphabet using high-density ECoG electrodes over the primary motor and primary somatosensory hand areas in able-bodied participants (Bleichner et al., 2016; Branco et al., 2017). Classification accuracy among the four gestures was >75% for all participants and reached 100% in one of them (mean accuracy, $n = 5$ subjects, for S1: 76%, for M1: 75%, for S1 + M1: 85%, Branco et al., 2017), suggesting that this approach may be used to classify a larger number of gestures and to control output devices with multiple degrees of freedom.

The ultimate communication BCI would use neural signals associated with attempted or covert speech and translate them into overt speech, all at the speed of verbal communication. This approach would, in principle, supersede letter-by-letter spelling and provide people with LIS with a highly intuitive, easy, and fast method of communication. Several studies have decoded *perceived* speech from the auditory cortex (Pasley et al., 2012; Akbari et al., 2019). These studies are not discussed further in this chapter because of space limitations. In decoding of *produced* speech, the language production and comprehension areas (Broca's and Wernicke's areas) and the regions associated with the motor control of speech articulation have been important targets. Indeed, the different speech articulators (larynx, tongue, and lips; Fig. 7.1) show a somatotopic organization within this area (Bouchard et al., 2013; Conant et al., 2014), which should help facilitate decoding when recording from larger neuronal ensembles.

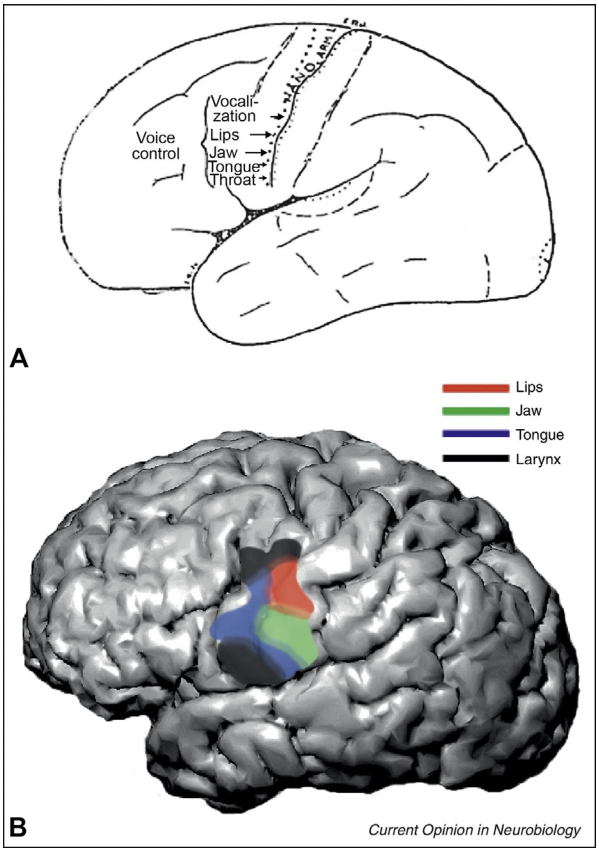


Fig. 7.1. Spatial organization of motor speech actuators in the lower sensorimotor areas. (A) Location of speech actuators, as originally determined by electrocortical stimulation in the 1950s. (B) Location of speech actuators determined by electrocorticographic recordings largely matches the pattern obtained with electrocortical stimulation studies in panel (A). Note that there are two areas associated with the larynx, and that the representations of the different actuators often overlap. Reproduced, with permission, from Conant, D., Bouchard, K.E. and Chang, E.F., 2014. Speech map in the human ventral sensory-motor cortex. *Curr Opin Neurobiol* 24, 63–67.

In a study that used neural signals acquired with micro-ECoG electrodes (interelectrode distance 1 mm) from both the motor face area and Wernicke's area, Kellis et al. (2010) were able to distinguish pairs of articulated words with high accuracy (85.0% and 76.2%, respectively). The spectral power changes associated with word articulation, as well as classifier performance, were particularly promising using signals recorded from the motor face area. Pei and coworkers also showed that articulated vowels and consonants (as parts of words) produce differential patterns of ECoG activity in the motor areas of speech (Pei et al., 2011), and Ramsey and colleagues reported high-accuracy decoding of four phonemes from high-density grids on the sensorimotor face area, taking advantage of the inherent topographical organization of M1 and S1 (72% accuracy; Ramsey et al., 2018). Mugler et al. (2014) demonstrated decoding, with up to 36% accuracy, among the entire set of American English phonemes using electrodes over speech motor areas.

As described in the earlier text, approaches to optimize decoding of continuous speech from neural signals may benefit from high spatial density electrode grids (Kellis et al., 2010; Herff et al., 2015). In addition, there is evidence that a joint neuroscientific/linguistic approach, in which ECoG signal processing techniques are combined with language models and/or a dictionary, can be helpful. The latter has been used in a group of seven epilepsy patients who were asked to read sentences aloud while their ECoG signals were recorded. These signals were subsequently used to decode phonemes and reconstruct continuous speech. Interestingly, for one subject, who had a high-density grid implanted, 75% of the decoded words were placed in the correct position of the sentence when using a dictionary size of 10 words, suggesting that this approach is usable to reconstruct speech from brain signals (Herff et al., 2015). Recently, signals from high-density electrodes over the frontal and temporal regions, including the ventral motor areas, were demonstrated to allow for direct speech synthesis (Anumanchipalli et al., 2019). Using a two-stage recurrent neural network-based decoder that translated neural activity to the estimated movements of the vocal tract and then converted this kinematic representation into acoustic features of sentences, participants were able to generate synthesized speech using neural activity. The synthesized speech of one participant was tested for intelligibility. People who listened to 101 synthesized sentences could understand 70% of the words on average, and whole sentences could be transcribed correctly by naïve listeners in 43% of the cases when word choices were selected from a 25-word pool, and in 21% of the cases using a 50-word pool.

Despite the promising findings described here, current ECoG-based speech decoders have not yet reached the level of accuracy needed for implementation in applications for home use by people with LIS, and more work is needed to reach that goal. It is also important to note that most ECoG speech decoding studies have been performed with able-bodied people producing overt speech. However, early attempts to decode *covert* or *imagined* speech suggest that this should be possible as well. One study showed that classification accuracy for decoding overt and covert vowels was $40.7 \pm 2.7\%$ and $37.5 \pm 5.9\%$, respectively, and for decoding overt and covert consonants was 40.6 ± 8.3 and $36.3 \pm 9.7\%$, respectively (chance level 25%), and that there is some overlap between the informative brain areas for overt and covert speech decoding (Pei et al., 2011). Future studies should investigate how well the currently available data on *overt* speech translates to attempted or imagined speech in people with LIS, and which approach is most usable for daily, real-time communication.

P300 from ECoG

Inspired by the success of EEG P300 studies, several researchers have assessed the use of ECoG signals for control of the P300 matrix speller in epilepsy patients with subchronic electrode implants. Although the number of studies is still very limited, the ECoG signal has been shown on several occasions to produce reliable P300 matrix speller control (Brunner et al., 2011; Krusienski and Shih, 2011). Important for future applications with people with LIS is that only a very limited number of electrodes appears to be needed (thus requiring a small surgical procedure), especially over occipital areas, for high accuracy and high information transfer rates (i.e., almost 100% classification accuracy and about 69 bits/min or 17 characters/min; Brunner et al., 2011; see also Speier et al., 2013). Combining the event-related response with spectral features and incorporating a model of the structure of language may contribute to even better ECoG P300-speller performance (Speier et al., 2013). Future research should determine whether the accuracy and speed reached in the studies above generalize to a larger number of people, including people with LIS, and test the usability of ECoG P300 BCIs for communication in daily life.

ECoG brain clicks for communication in LIS

Despite the significant progress and promising BCI findings with ECoG signals measured in able-bodied epilepsy patients, the application of ECoG-based BCIs for communication by people with LIS has received very little attention. This may be related to the burden and the risk that is associated with electrode implantation. The first attempt to use epidural ECoG-BCI for communication in a person with ALS was not successful, which may have been at least partially attributable to the transition from LIS to CLIS (Murguialday et al., 2011). More recently, ECoG-BCI was successfully applied for communication in LIS (Vansteensel et al., 2016; Fig. 7.2). The participant of that study was a woman with late-stage ALS who had voluntary control over her eye movements, which she used to communicate informed consent to participate and to provide feedback to the research team during the study. Subdural strips of electrodes were placed over the sensorimotor hand area and were connected, via subdural leads, to an amplifier/transmitter device that was implanted subcutaneously under the clavicle. The device wirelessly transmitted signals through the skin to an antenna attached to her clothing. Using attempted hand movement, the participant was able to produce neurally decoded clicks (brain clicks), which she could use to control commercial communication software in so-called "switch scanning" mode. This control was reliable, with close to 90% accuracy, but not very fast (~2 characters/min). Despite the limited speed, the participant still uses the system on a regular basis at home for communication (as of the writing of this chapter), in situations where her eye-tracking device does not work accurately, and to call her caregiver when she needs assistance. She has indicated high user satisfaction with the system. This promising study indicates that ECoG signals from motor areas can produce reliable brain clicks for BCI control for an extended period of time (she has been using it for more than 3 years), even in people with ALS. Future studies should test whether these findings can be extended to other people with LIS due to late-stage ALS and from other etiologies, and also should work toward improving speed and dimensionality of control.

Intracortical spike-based BCIs for communication

Intracortical microelectrode arrays, in combination with high sampling frequency (> ~15 kilosamples/s), allow for the measurement of single action potential (spiking) activity from large ensembles of individual neurons, thus potentially allowing as much information to be extracted about the person's movement intention from the recorded neurons as the rest of the brain would receive. At the scale of typical interelectrode distances in microelectrode arrays (< ~400 µm), neurons in the motor cortex have "salt-and-pepper" tuning: neurons recorded by neighboring electrodes are generally not tuned to similar movement intentions. Thus, large electrodes, such as external scalp electrodes, record a blurred version of

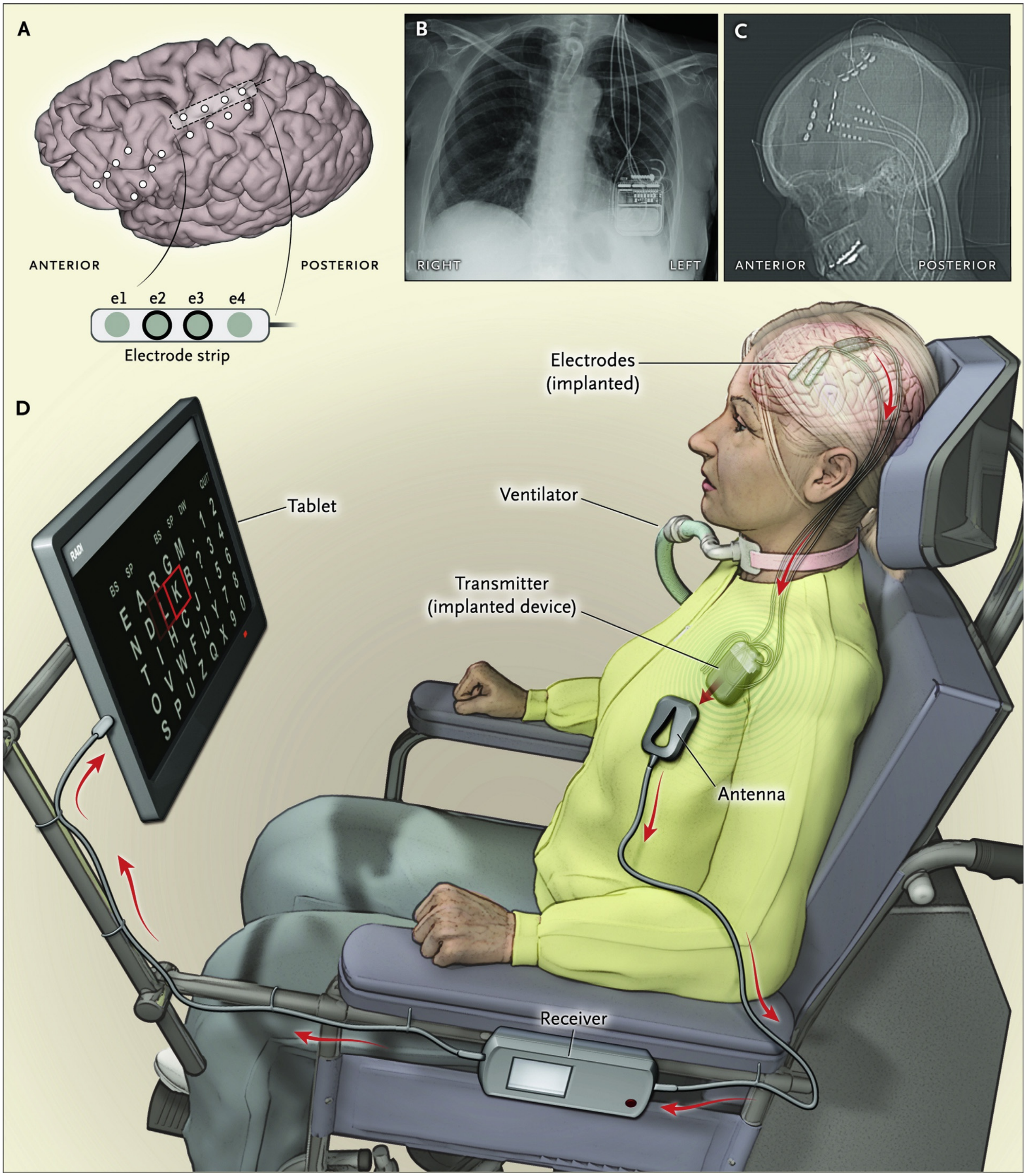


Fig. 7.2. Schematic representation of a fully implantable ECoG-based system. (A) Four strips of subdural electrodes were implanted through burr holes, two over the dorsolateral prefrontal cortex, and two over the sensorimotor hand area. (B) Chest radiograph showing the location of the fully implantable amplifier/transmitter device, which was placed subcutaneously under the clavicle. (C) CT scan showing the location of the four subdural electrode strips and their leads running toward the amplifier/transmitter device. (D) All components of the fully implantable ECoG-based BCI system: subdural electrodes, implantable amplifier/transmitter device, antenna, receiver, and tablet computer running signal processing software and the communication application. Using a combination of high and low frequency power of the bipolar electrode pair "E2–E3," the participant, a woman with late-stage ALS, was able to reliably control the communication application on the tablet computer. The application ran in "switch scanning mode," and the participant generated brain clicks to select letters or groups of letters, which were highlighted automatically and sequentially by the computer, by appropriately timed movement attempts of her right hand. Reproduced, with permission, from Vansteensel, M.J., Pels, E.G., Bleichner, M.G., et al., 2016. Fully implanted brain-computer interface in a locked-in patient with ALS. *N Engl J Med* 375, 2060–2066. Copyright © 2016 Massachusetts Medical Society.

the signals that remain distinct when recording from single neurons. Using electrode arrays that record the spiking activity of dozens of individual neurons, then, may allow the user to deploy intuitive, biomimetic motor imagery to control the BCI, rather than having to learn new mappings between imagined movement (or other cognitive processes) and its consequences on the computer screen. In other words, using a BCI controlled with signals from intracortical microelectrode arrays, the user might simply imagine moving his or her hand to the right to move a computer cursor to the right (as described in more detail in the next section). Furthermore, the rich information content that can be extracted about movement intention using intracortical BCIs enables high-quality neural control to be obtained within minutes of beginning decoder calibration (Brandman et al., 2018), with little or no training required on the part of the user and minimal cognitive load.

Intracortical BCIs for decoding movement intention

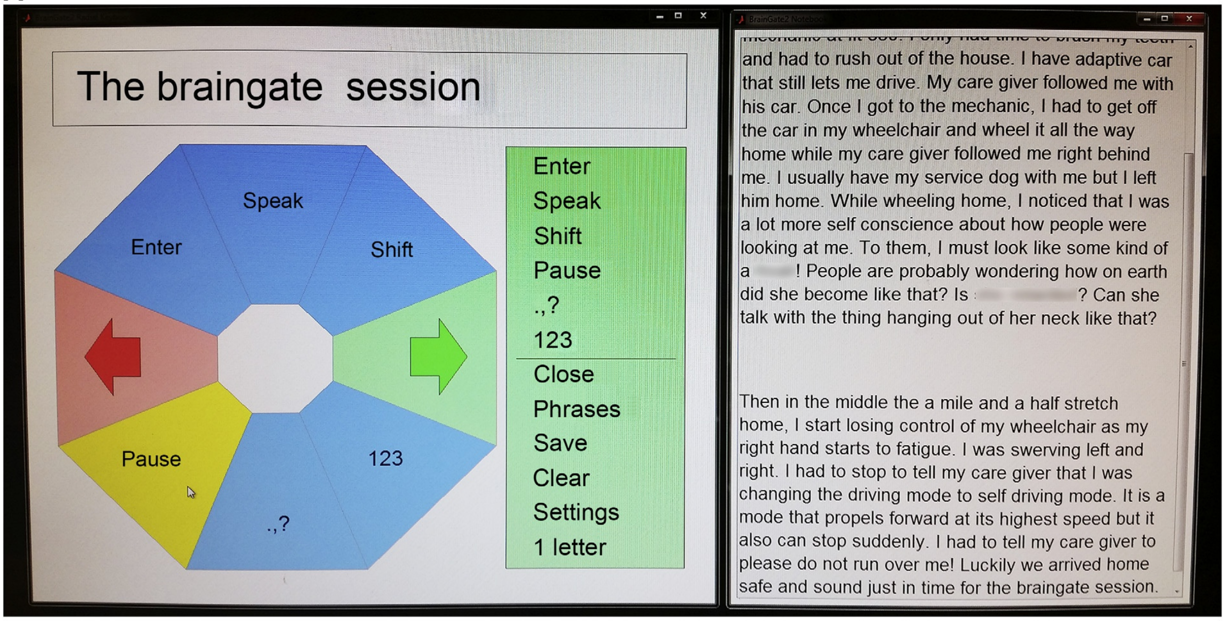
One approach to brain-controlled communication for people with LIS has been to record from large numbers of individual neurons with implanted microelectrode arrays in motor cortical areas with the goal of enabling fast, reliable point-and-click decoding. In pilot clinical trials using silicon microelectrode arrays (typically 4×4 mm arrays of 100 electrodes, each 1–1.5 mm long) one or more arrays are often placed in the arm/hand area of the motor cortex (Yousry et al., 1997), where individual neurons modulate their spiking rates in various ways with different intended movements. Intuitively, if spiking activity is recorded from a population of neurons tuned to (intended) arm movements in space, and the person is asked to imagine moving their arm in known directions, it is possible to map the relationship between neural activity patterns and those intended movement directions (i.e., to "calibrate a decoder"). This decoder can then be used in real time to decode desired cursor movement and a binary click state; these can then be turned into the real-time point-and-click control of a cursor on a computer screen (Kim et al., 2007, 2008, 2011; Simeral et al., 2011). This strategy has allowed pilot clinical trial participants who are paralyzed due to stroke, ALS, or spinal cord injury to, for example, select letters and words on a virtual keyboard for communication (Bacher et al., 2015; Jarosiewicz et al., 2015, 2016; Pandarinath et al., 2017), for real-time electronic "chat" and email communication and more general use of a tablet computer (Nuyujukian et al., 2018). Their use has also been demonstrated in controlling multi-dimensional reach-and-grasp movements of robotic arms (Hochberg et al., 2012; Collinger et al., 2013; Aflalo et al., 2015; Wodlinger et al., 2015) and even of the person's own paralyzed arm (Ajiboye et al., 2017).

One challenge for intracortical BCIs is that recorded spiking signals are not completely stationary, for various physiologic and nonphysiologic reasons. In other words, the relationship between movement intention and the recorded neural signals can change over time and across different contexts (Kim et al., 2006; Jarosiewicz et al., 2013, 2015; Perge et al., 2013). Thus, to prevent neural control from degrading, it is important to recalibrate the decoder periodically. Because it would be tedious for the user to pause BCI control to perform calibration tasks whenever the recorded signals change, one important line of research has been to devise methods by which the decoder can be updated automatically using data acquired during practical use of the BCI, for example by mapping neural activity to retrospectively inferred movement intentions (Jarosiewicz et al., 2015, 2016). These methods have been shown to sustain high-quality neural control, enabling communication rates up to ~30 characters/min across hours, days, and weeks without the need for the user to perform any calibration tasks after day 1 (Fig. 7.3). Similar decoding and hardware approaches have allowed communication rates by people with tetraplegia using intracortical BCIs to reach speeds as high as 40 characters/min without word prediction (Gilja et al., 2015; Pandarinath et al., 2017). Further advances in decoding continue to be made in this increasingly active field, which has the potential to provide easy-to-use, independent, robust, high-performance communication to people with LIS.

Intracortical direct speech BCIs

The brain area chosen for intracortical BCI electrode placement depends on the desired type of control signal and application. As explained earlier for ECoG, one approach is to try to decode intended speech sounds themselves in real time, motivated by a desire to increase communication speed relative to letter-selection-based assistive communication technologies. One group that used this approach with intracortical BCIs placed their electrodes in the left ventral premotor cortex (Günther et al., 2009), which is thought to encode the formant frequencies of desired speech acoustics (Günther et al., 2006). Whole sentences can be transcribed into low-dimensional trajectories through formant frequency space and, despite the absence of harmonics, consonants, and other acoustic cues, can still be parsed as the original sentences by human listeners (Remez et al., 1981). Therefore, trajectories through this formant frequency space could, in theory, be decoded in real time from neural activity to produce understandable speech

A



B

Length (min)	CCPM	CSPM	Typed text
23.3	15.1	25.8	Today, I can not seem to come up with anything really interesting to write about. I went to bed at one thirty in the morning and got up at eight. I planed on getting up at seven but somehow my alarm did not go off. This morning, I had an appointment with a car mechanic at fit 830. I only had time to brush my teeth and had to rush out of the house.
13.3	17.6	24.1	I have adaptive car that still lets me drive. My care giver followed me with his car. Once I got to the mechanic, I had to get off the car in my wheelchair and wheel it all the way home while my care giver followed me right behind me.
19.9	18.2	25.3	I usually have my service dog with me but I left him home. While wheeling home, I noticed that I was a lot more self conscience about how people were looking at me. To them, I must look like some kind of a ____! People are probably wondering how on earth did she become like that? Is ___ _____? Can she talk with the thing hanging out of her neck like that?
21.6	22.4	27.8	| | Then in the middle the a mile and a half stretch home, I start losing control of my wheelchair as my right hand starts to fatigue. I was swerving left and right. I had to stop to tell my care giver that I was changing the driving mode to self driving mode. It is a mode that propels forward at its highest speed but it also can stop suddenly. I had to tell my care giver to please do not run over me! Luckily we arrived home safe and sound just in time for the braingate session.

Fig. 7.3. Example of text written by a participant in the BrainGate clinical trial using a self-calibrating intracortical BCI to control a cursor on a virtual keyboard. The participant selected wedges one by one that contained the letter she wanted to type in a radial virtual keyboard (Bacher et al., 2015) by imagining moving her hand to control the movement of the cursor. She was able to pause typing when she wanted by selecting the right arrow and then the wedge containing "PAUSE." Each pause initiated a decoder calibration that used the data acquired during the preceding free-typing period to update the mapping between (retrospectively inferred) movement intention and neural activity, and then neural control was restored to allow the participant to resume typing when she desired by selecting the right arrow and "UNPAUSE." (A) Photograph of the radial keyboard interface (left) with the PAUSE button about to be selected, and the notebook showing the text she typed in this session, a story about her morning (right). (The blurred words, replaced by underscores in panel (B), were redacted at the participant's request.) (B) Length of each block of free-typing, the number of correct characters per minute (CCPM) and correct selections per minute (CSPM) in that block, and the text entered. From Jarosiewicz, B., Sarma, A.A., Bacher, D., et al., 2015. Virtual typing by people with tetraplegia using a self-calibrating intracortical brain-computer interface. *Sci Transl Med* 11, 313RA179, with permission from the American Association for the Advancement of Science.

(much like intended hand movement trajectories through extrinsic space can be decoded in real time to move a computer cursor, as described in the previous section).

Using this strategy, one participant, locked-in following a brainstem stroke, improved with practice and was able to achieve above-chance performance at mimicking two-vowel sequences in a 2D neural trajectory through formant frequency space (Günther et al., 2009). In a later offline classification study from the same group, using the neural activity recorded from a single two-channel neurotrophic cone electrode (Kennedy, 1989) implanted in a motor speech production area, it was possible to decode with 16%–21% accuracy which one of 38 phonemes a study participant with LIS had been attempting to generate (Brumberg et al., 2011).

Advantages and disadvantages of implanted BCIs

As discussed here, by extracting neural activity with higher spatial resolution, implanted BCIs have the potential to provide richer information about the person's movement intent, thereby enabling faster and higher-accuracy communication than noninvasive methods could provide (at least with recording technologies currently under development). Intracortical BCIs have already enabled people with paralysis to type for hours with communication rates of up to 30–40 characters per minute (Jarosiewicz et al., 2015; Pandarinath et al., 2017), whereas the fastest communication rates achieved with noninvasive BCIs in people with paralysis, to our knowledge, has been ~12 characters per minute (Speier et al., 2017).

Another advantage of a chronically implanted BCI is the relatively quick and easy daily setup compared to noninvasive methods. Fully implantable systems, including the electrodes and an amplifier/transmitter that wirelessly transmits those signals to the outside world (ECoG: Vansteensel et al., 2016; intracortical: under development, Kim et al., 2009; Borton et al., 2013; Nurmikko et al., 2016), will reduce infection risk by eliminating transcutaneous connections; will satisfy the wish of end users that assistive devices are cosmetically invisible (Nijboer, 2015); and will minimize or even eliminate the need for assistance from an able-bodied caregiver (Brea et al., 2018).

An important advantage to intracortical point-and-click BCIs is their potential for more general-purpose utility beyond communication: having a BCI that replaces a point-and-click bluetooth mouse (Nuyujukian et al., 2018), for example, would allow people with LIS to use any computer or tablet application that an able-bodied person can use, including applications for environmental control (controlling light switches, thermostats, door locks, etc.), entertainment (web browsing, social media, videos, and movies), creative expression (writing, painting, playing, composing music, and photo editing), and even applications enabling gainful employment. Thus, point-and-click BCIs could help to restore not only communication, but also greater independence to people with LIS, conferring additional psychologic and even economic benefits beyond those obtained through BCI-enabled communication alone.

Of course, the chronic implantation of electrodes and associated components carries risks associated with any surgery, and the safety profile of implanted BCIs will only become clear when more data have been collected across larger clinical trials. However, the demonstrated safety of other implanted neurotechnologies such as cochlear implants and deep brain stimulators, both of which are now commonplace, has set a promising precedent.

ISSUES TO BE SOLVED

Despite significant scientific progress and efforts to translate acquired knowledge to daily life applications, communication BCIs are still largely research devices, and still need advances in technology (signal acquisition hardware, signal processing, and algorithms) and in usability (ease of use for both caregivers and patients, effort, and esthetics). Each type of research device comes with its own limitations that need to be overcome, as detailed in their respective sections in the earlier text; in addition, the following issues need to be solved for all types of communication BCIs.

Usability

As with AT in general, the acceptance of BCI technology by potential users will be limited if they are unreliable or difficult to use (Blain-Moraes et al., 2012; Nijboer, 2015). For example, they need to be reliable and robust enough that they work every time, for as long as the person wants to use them. They need to be robust to auditory and visual distraction, and immune to electrical noise from other powered devices. Any external parts of the BCI will need to be easy to put on and take off so as to not overly burden the user or caregiver, and must physically be small enough to fit within the constraints of the living environment. Also, the BCI system must be cosmetically acceptable; ideally, invisible. Any required calibration must be fast and simple, or better still, ongoing and automatic. In the ideal scenario, the patient won't require assistance from an able-bodied caregiver at all to use their BCI. All this may become possible in the future with a fully-implanted system that is always on. Early evidence for the feasibility of an easy-to-use, fully-implanted ECoG-based BCI was recently demonstrated (Vansteensel et al., 2016), and research efforts are underway to develop a fully implanted, easy-to-use, and autonomously updating point-and-click intracortical spike-based BCI that will be available to the user 24/7 (Kim et al., 2009; Borton et al., 2013; Jarosiewicz et al., 2015, 2016; Nurmikko et al., 2016; Brea et al., 2018).

Generalization to people with LIS and CLIS

As mentioned previously, many BCI studies to date have had able-bodied participants, or those who still have intact eye movements or some residual motor function. However, the physical condition of the target user will affect usability and performance in a manner that cannot be predicted from participants without LIS. For example, many current BCI approaches are based on visual stimuli, and thus BCIs depend on the ability to modulate gaze direction (Brunner et al., 2010). Because oculomotor function is often impaired in people with late-stage ALS (Hayashi and Oppenheimer, 2003; Donaghy et al., 2011; Murguialday et al., 2011; Sharma et al., 2011), there is a growing interest in gaze-independent visual, auditory, and tactile BCIs (for a review, see Riccio et al., 2012). Studies investigating these approaches in people with ALS or LIS are scarce, but so far indicate limited usability (Kaufmann et al., 2013; Severens et al., 2014). Current and ongoing efforts to directly decode (covert or imagined) speech from neural signals using subdural or intracortical electrodes may eventually provide a viable alternative, since this approach, if successful, would completely remove any visual gaze limits.

It is not yet known whether BCI communication will be possible for people with CLIS. As described earlier, several studies have attempted to restore communication for people with CLIS, but these efforts are complicated by uncertainty about the person's remaining cognitive capabilities and vigilance state, as well as the importance of using nonvisual paradigms. Whereas EEG studies and one single ECoG case have not been very successful (see for review, Kübler and Birbaumer, 2008; Murguialday et al., 2011; and see Guger et al., 2017), there is some evidence that yes/no communication in CLIS is feasible using fNIRS (Naito et al., 2007; Gallegos-Ayala et al., 2014; Chaudhary et al., 2017). Also, the demonstration of fMRI-based communication in individuals who had been diagnosed to be in the vegetative or minimally conscious state (Monti et al., 2010) suggests that brain-based communication is possible even in people who do not show any overt movement. Importantly, these studies cover only very few CLIS cases, and it is not clear which BCI technique would be the most effective once all residual motor function is lost. Therefore, studies are needed to obtain more insight on this issue and to further investigate the use of neural signals for communication in CLIS.

CONCLUSION

Although communication BCIs for people with LIS still reside mostly within the research domain, efforts are actively underway to improve their speed, robustness, and usability, placing potential clinical utility right on the horizon. Each type of BCI will have its own specific set of advantages and disadvantages, but for input modalities that are currently under development, technologies that are less invasive tend to be more limited in their potential speed, accuracy, usability, and generalizability. Once both noninvasive and implanted BCIs become commercially available, each person will have to decide for themselves which option better suits their needs and preferences.

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