COVER FEATURE

Rehabilitation with Brain-Computer Interface Systems

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BCI systems let users convert thoughts into actions that do not involve voluntary muscle movement. The systems offer a new means of communication for those with paralysis or severe neuromuscular disorders.

Not long ago, paralysis and advanced palsy victims had little recourse but to rely on others for the simplest tasks. With the evolution of biotechnology, however, has come the opportunity to give those with neuromuscular disorders a higher degree of self-sufficiency. Through a process that records brain signals combined with the use of special software, an otherwise incapacitated patient can change the television channel, turn lights on and off, and answer e-mail simply by concentrating on moving a cursor to the appropriate box on a screen.

More recent experiments have expanded these possibilities to include neuroprosthetic control. By focusing on moving a specially programmed prosthetic device, a quadriplegic can grasp a glass of water and raise it to his lips or pick up any other graspable object simply by thinking about doing it. Each thought aims toward a specific goal such as spelling the letter B or opening the hand or closing it. The brain translates the goal-directed thought into a specific spatiotemporal activation pattern, suitable for recording and online detection. Of special interest are mental strategies that reveal strong activations of neural networks in primary sensory and motor areas. These activations occur when the user focuses attention on one of these areas.

All these applications involve brain-computer interface (BCI) systems. In neurological rehabilitation, applications target the motor cortex localized in the precentral gyrus and the visual cortex in the occipital region. In both cases, the patient uses a particular mental strategy to focus attention either on a specific body part or on one of several flickering lights, flashing items, or letters. Motor imagery can modulate the sensorimotor rhythms, while a directed gaze can increase the P300—the positive component of the visual evoked potential (VEP)—or enhance a steady-state VEP (SSVEP). With the proper feedback and training, patients can learn to modulate their slow cortical potentials (SCPs).[1]

BCI system applications can be either invasive—requiring the direct implantation of electrodes in the user's brain—or noninvasive—in which the system captures brain signals through an electroencephalogram (EEG) recording, with electrodes attached to the patient's scalp. Unlike invasive systems, which entail the risks associated with any brain surgery, noninvasive systems are basically harmless.

Perhaps for that reason, noninvasive BCI systems show the most promise in practical neurological rehabilitation. The applications we describe are only a sampling of the many efforts to address the use of BCI systems in this important field. The "Additional Reading" sidebar lists more sources for those who want to explore further.

NONINVASIVE SYSTEMS

As Figure 1 shows, a noninvasive BCI system captures brain signals through the EEG, extracts and classifies certain signal features, and feeds them to the application. New uses of noninvasive BCI systems are continu-

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Additional Reading

- O. Bai et al., "A High-Performance Sensorimotor Beta Rhythm-Based Brain-Computer Interface Associated with Human Natural Motor Behavior," *J. Neural Eng.*, Mar. 2008, pp. 24-35.
- L. Bianchi et al., "Performance Evaluation and Optimization of Brain-Computer Interface Systems in a Copy Spelling Task," *IEEE Trans. Neural Systems and Rehabilitation Eng.*, June 2007, pp. 207-216.
- M.W. Keith et al., "Implantable Functional Neuromuscular Stimulation in the Tetraplegic Hand," *J. Hand Surgery*, May 1989, pp. 524-530.
- G. Krausz et al., "Critical Decision-Speed and Information Transfer in the 'Graz Brain-Computer Interface'" *Applied Psychophysiological Biofeedback*, Sept. 2003, pp. 233-240.
- D.J. Krusienski et al., "A Comparison of Classification Techniques for the P300 Speller," *J. Neural Eng.*, Dec. 2006, pp. 299-305.
- N. Murase et al., "Influence of Interhemispheric Interactions on Motor Function in Chronic Stroke," *Ann. Neurology*, Mar. 2004, pp. 400-409.
- C. Neuper, A. Schlögl, and G. Pfurtscheller, "Enhancement of Left-Right Sensorimotor EEG Differences during Feedback-Regulated Motor Imagery," *J. Clinical Neurophysiology,* July 1999, pp. 373-382.
- B. Obermaier, G.R. Müller, and G. Pfurtscheller, "'Virtual Keyboard' Controlled by Spontaneous EEG Activity," *IEEE Trans. Neural Systems and Rehabilitation Eng.*, Dec. 2003, pp. 422-426.
- G. Pfurtscheller and C. Neuper, "Motor Imagery Activates Primary Sensorimotor Area in Humans," *Neuroscience Letters*, Dec. 1997, pp. 65-68.
- G. Pfurtscheller et al., "Brain Oscillations Control Hand Orthosis in a Tetraplegic," *Neuroscience Letters*, Oct. 2000, pp. 211-214.
- G. Pfurtscheller, C. Neuper, and N. Birbaumer, "Human Brain-Computer Interface," *Motor Cortex in Voluntary Movements*, A. Riehle and E. Vaadia, eds., CRC Press, 2005.
- M. Pregenzer, G. Pfurtscheller, and D. Flotzinger, "Automated Feature Selection with a Distinction Sensitive Learning Vector Quantizer," *Neurocomputing*, vol. 11, 1996, pp. 19-29.
- R. Scherer et al., "Sensorimotor EEG Patterns during Motor Imagery in Hemiparetic Stroke Patients," *Int'l J. Bioelectromagnetism*, Dec. 2007, pp. 155-162.
- E.W. Sellers and E. Donchin, "A P300-Based Brain-Computer Interface: Initial Tests by ALS Patients," *Clinical Neurophysiology*, Mar. 2006, pp. 538-548.
- E. Taub, G. Uswatte, and T. Ebert, "New Treatments in Neurorehabilitation Founded on Basic Research," *Nature Rev. Neuroscience*, Mar. 2002, pp. 228-236.

ing to appear in the literature, particularly recently. The most noteworthy classes of such systems are based on SCP, the P300 component, SSVEP, and event-related desynchronization (ERD).

Slow cortical potentials

SCPs are slow EEG shifts that last fractions of a second to several seconds. Negative deflections reflect a summation of excitatory postsynaptic potentials and indicate longer-lasting depolarization of dendritic networks. As far back as 1979, Niels Birbaumer and colleagues published a series of experiments demonstrating operant control of SCPs.[2] Researchers have since used the operant conditioning technique to enable participants to self-regulate brain potentials such as SCP shifts with the help of suitable feedback.

Although this process does not require continuous feedback, it does require a reward for achieving the desired brain potential change. In the thought-translation device,[3] selection, such as selecting a target letter, takes four seconds. Two alternating tones of different pitch, which follow each other in an interval of 2 seconds, indicate a

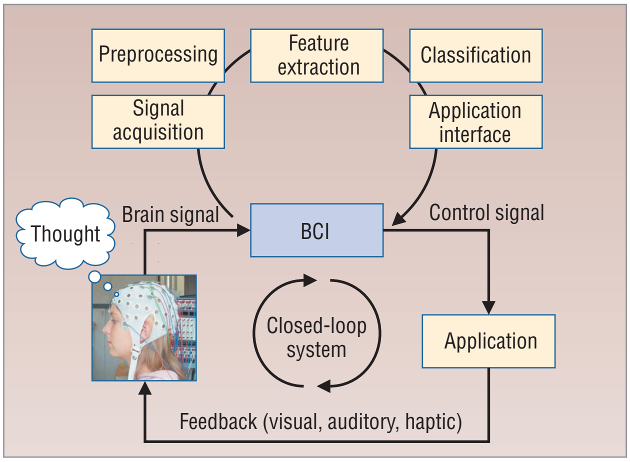

Figure 1. Elements of a noninvasive BCI system. With the user's EEG recording as input, the system digitizes the brain signals, extracts and classifies signal features, and feeds the results to the application interface. The user controls the application and receives visual, auditory, or haptic feedback on the accuracy of the focused thought. In this way, the system becomes a closed loop.

baseline period and selection period of 2 seconds each. Only during the 2-second selection time can the user select a target by decreasing or increasing the SCP's voltage level.

The thrust of this BCI system is on clinical applications, especially providing late-stage amyotrophic lateral sclerosis (ALS) patients with basic communication functions.[4]

P300 component

Randomly presented rare target stimuli in the so-called oddball paradigm evoke the P300, the positive component of the evoked potential, at a latency of approximately 300 ms. Emanuel Donchin and colleagues used the P300 to develop a communication system.[5] With this BCI, the user sees a 6 × 6 letter matrix in which one row or column is flashing in 125-ms intervals. The user's focus on a certain letter produces a larger P300 amplitude than that of other possible letter choices. Some researchers have achieved a communication rate of approximately seven items per minute with this system.[5]

The user must learn to enhance the EEG patterns associated with a particular motor imagery type.

Advantages of the P300 BCI system include a relatively short training time and a much faster selection of letters than any other BCI system.

Steady-state visual evoked potential

Steady-state evoked potentials (SSEPs) occur when the system repetitively delivers sensory stimuli at a high enough rate to keep relevant neuronal structures from returning to their resting states. Ideally, the amplitude and phase of discrete frequency components remain constant within an infinitely long period. The components have the same fundamental frequency as the stimulus, but often include higher or subharmonic frequencies.

In an SSVEP BCI system, the user gazes at one of several lights, which flicker at different rates. The gaze-directed flickering light evokes SSVEPs over the visual cortex, which means that the system can detect them and use them for control. Multiple flickering lights enable higher dimensional discrimination. Ming Cheng and colleagues[6] reported a BCI with 13 flickering lights and a mean high information transfer rate of 27 bits per minute.

Event-related desynchronization

Sensorimotor rhythms can display either an ERD, which is an amplitude decrease, or an event-related synchronization (ERS), which is an amplitude increase.[7] A localized ERD is an electrophysiological correlate of an activated cortical network, and a localized ERS in the alpha band is typically viewed as a correlate of a deactivated or even inhibited cortical network, corresponding to a disengaged or deactivated state (at least in some instances).

ERD BCI systems encompass the range of BCIs that analyze and classify the dynamics (ERD and ERS) of either one single-frequency component, such as a BCI based on mu or beta rhythms or multiple components of sensorimotor rhythms.[8-10] Also, the sensorimotor rhythm BCI[11] uses the mentally induced increase (ERS) or decrease (ERD) of sensorimotor rhythms to control a hand orthosis.

One of the first reports on classifying ERD/ERS patterns induced by motor imagery appeared in the early 1990s.[12] Several years later, other systems began to use ERD/ERS patterns as features for single-trial EEG classification, including the Wadsworth,[1] Berlin,[9] and Graz[13] BCIs, as well as variants of the Tübingen BCI.[11] Bit rates were between 3 and 35 bits/min.[9]

ERD BCIs operate in either a cue-based (synchronous) or a self-paced (asynchronous) mode. The cue-based mode restricts data processing and classification to a predefined time window of a few seconds. In self-paced mode, data processing is continuous.

Training sessions. To ensure that the ERD BCI system operates as intended, users first undergo training sessions in which they learn to control their brain signals so that the system can more accurately classify brain states. These states are essentially the user's brain patterns relative to motor imagery types. Before starting online feedback sessions, users imagine movements of specific body parts, such as a hand, foot, or tongue. They do so repeatedly in intervals of several seconds while the system records their EEG. By applying feature-selection algorithms to the screening data, such as the distinction-sensitive learning vector quantization algorithm, the system attempts to identify the frequency components and electrode positions that best discriminate between two brain states.

After the system sets up a classifier, the user must learn to enhance the EEG patterns associated with a particular motor imagery type. Thus, in follow-on training sessions, the user receives online feedback about EEG changes related to motor imagery.

Feedback sessions. Users receive feedback either through a continuous feedback signal, such as cursor movement, or from the trial's success or failure. With trained subjects, system operation does not have to depend on the sensory input the feedback signal provides. In one trial, for example, well-trained subjects still displayed EEG control even after the researcher removed feedback (cursor movement) temporarily. In general, when a naïve user starts to practice hand motor imagery, a contralaterally dominant desynchronization pattern is likely. After several training sessions, in which the user receives feedback about the performed mental task, the user is apt to exhibit changes in the relevant EEG patterns.

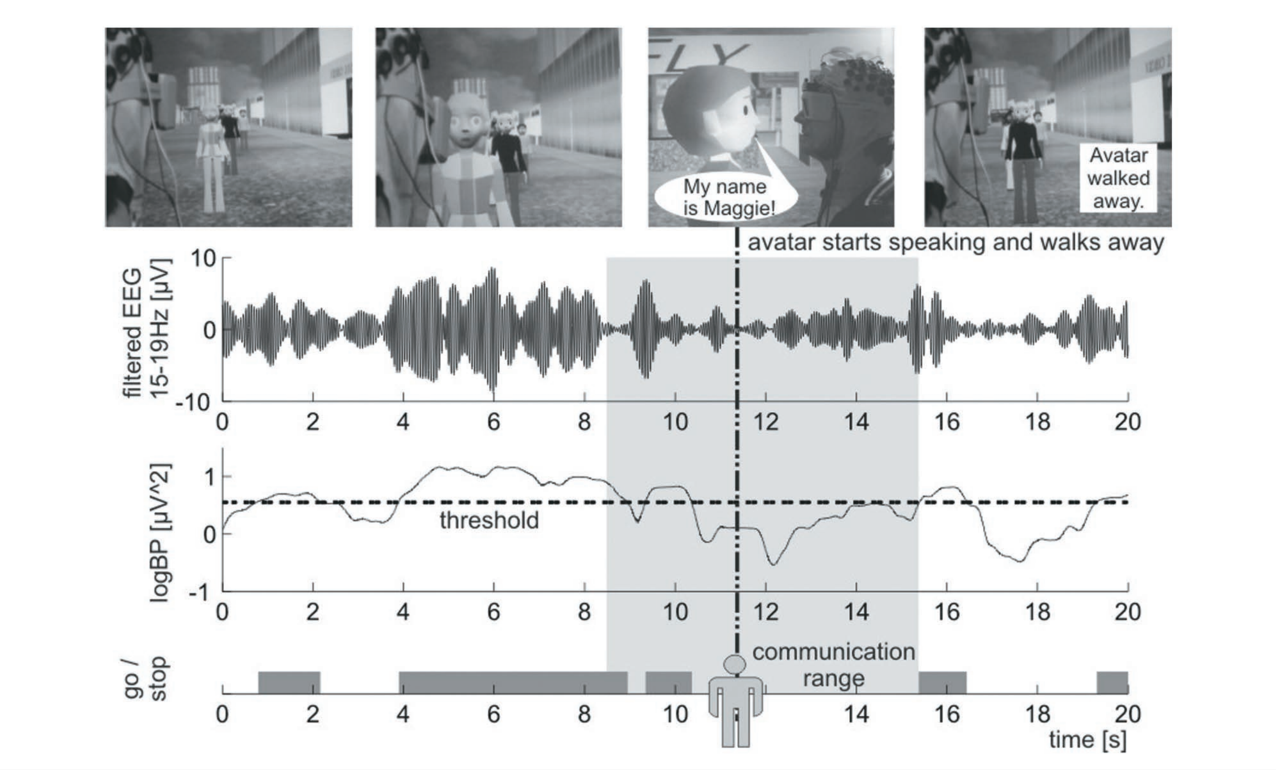

Figure 2. BCI-based control of a complex virtual environment. The user was told to "walk" from avatar to avatar by visualizing foot movements. From the top down, avatars in relation to time axes, the filtered EEG signal (15-19 Hz), time course of band power (spectral power density in a predefined frequency range) with threshold, and the go/stop signal through which the user controls walking.

Feedback is most often visual in BCI research,[9] although some BCI experiments involved complex virtual reality environments.[8] Figure 2 shows the BCI-based control of a virtual street, for example.[14]

Recently, Aniruddha Chatterjee and colleagues[15] presented an ERD BCI system that uses a motor imagery paradigm and haptic feedback provided through vibrotactile stimuli to the upper limb. Although the experiments did not determine how the neural correlates of vibrotactile feedback affect the modulation of the mu rhythm, the effort underlines the importance of haptic information. Indeed, such information might become a critical component of BCIs that control an advanced neuroprosthetic device.

Desirable features. ERD BCI systems for home application and everyday use must be robust, light, wireless, and simple to use, considering only one or two EEG channels. It would be interesting to compare the classification results of multichannel (full-head) EEG studies when the BCI system considers all EEG channels and when it considers only one or two.

The standard method for processing multichannel data and discrimination between two brain states is the common spatial pattern (CSP) algorithm.[16] In one experiment that used the CSP algorithm applied to a 30-channel EEG of 10 naïve subjects, classification accuracy was 88.8 ± 5.5 percent for discrimination between hand and foot motor imagery.[10] With only one subject-specific Laplacian EEG derivation, the corresponding accuracy was 81.4 ± 8.7 percent.

It is surprising that such high classification accuracy is possible with only one channel. To achieve this accuracy, system developers must carefully select features, such as electrode locations and frequency bands, and optimize each feature for a particular user.

In another experiment with a 55-electrode EEG montage, classification accuracy was approximately 80 percent for the discrimination between hand and foot motor imagery.[9] With two individually selected bipolar EEG channels, the classification accuracy was about 10 percent lower.

On the basis of these results, we recommend starting the first BCI training session with a full-head EEG montage (> 30 channels), selecting the best performing electrodes and frequency bands, and continuing the training procedure with feedback using the fewest possible EEG derivations.

NEUROPROSTHESES CONTROL

Figure 3 shows how a BCI controls a neuroprosthesis. Spinal cord injury, with its associated disruption of nerve fiber tracts in the spinal cord, results in a loss of sensory

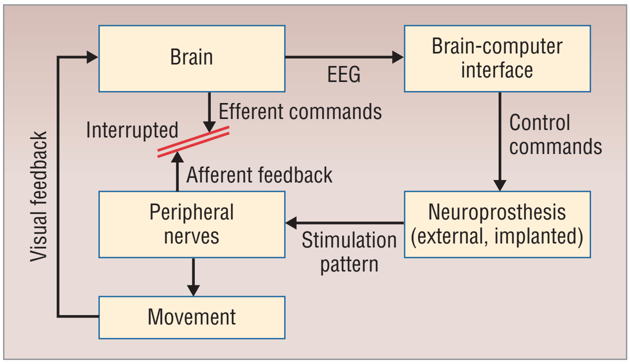

Figure 3. Using a BCI system to control a neuroprosthesis. By coupling a BCI system with a neuroprosthesis, scientists can artificially bridge a spinal cord lesion that has interrupted efferent and afferent fiber tracts. In this application, the provided feedback is exclusively visual.

and motor functions. Neuroprostheses guided through functional electrical stimulation (FES) can compensate for the loss of voluntary functions by artificially eliciting muscle contractions. Such techniques provide the possibility of restoring movement, such as grasping, in quadriplegic patients.

High-level SCI patients are much less able to activate external controllers on their own volition, and that ability decreases the higher the lesion in the cervical vertebrae. For these patients, brain activity recorded with the EEG in concert with a neuroprosthesis and BCI might be a viable alternative means of control. Combining a neuroprosthesis and a BCI could enable thought-driven, complete restoration of hand and arm function in patients with a spinal cord injury. Figure 4 shows two possible applications.

Recent work has focused on using a noninvasive BCI to control neuroprosthetic systems in human subjects. A first attempt in 2000 used EEG-based control systems to restore the hand function in a quadriplegic patient through an electrically driven hand orthosis. In later efforts with the same patient, we used FES controlled through foot motor imagery to realize a hand grasp. We implemented a sequence of grasp phases in the stimulator, and whenever the BCI detected foot motor imagery, the stimulator initiated the next phase and activated muscle groups accordingly, as in Figure 4a.[17]

There are drawbacks to any neuroprosthetic system based on surface electrode stimulation, however, including low selectivity, cable problems, and the need to vary electrode positions almost daily. These disadvantages motivated the development of implantable neuroprostheses, such as the Freehand system. In this system, surgeons implant electrodes in the hand and arm and insert the stimulation unit into the patient's chest as they would a pacemaker. Patterns move from an external device and controller into the implanted system through inductive-coupling energy and stimulation.

In an early feasibility study,[17] we coupled this system and a BCI. A quadriplegic male patient took a daily BCI training session using the Freehand system, and after three days, was able to induce characteristic brain patterns by left-hand motor imagery and perform the grasp sequence. Figure 4b shows the patient with implanted FES electrodes.

In another feasibility study,[18] the BCI was based on a four-class SSVEP, which controlled an electromechanical hand prosthesis that contained flickering lights. One light on the index finger flickering at 6 Hz and one on the pinky finger flickering at 7 Hz translated to commands for turning the hand in supination and pronation. Two lights on the wrist (flickering at 8 Hz and 13 Hz) represented the commands for opening and closing the hand. Four able-bodied subjects followed a given grasping sequence at will. Three of the four could perform the sequence, although sometimes they had to correct their movements within a given time. The fourth subject was not able to obtain SSVEP control.

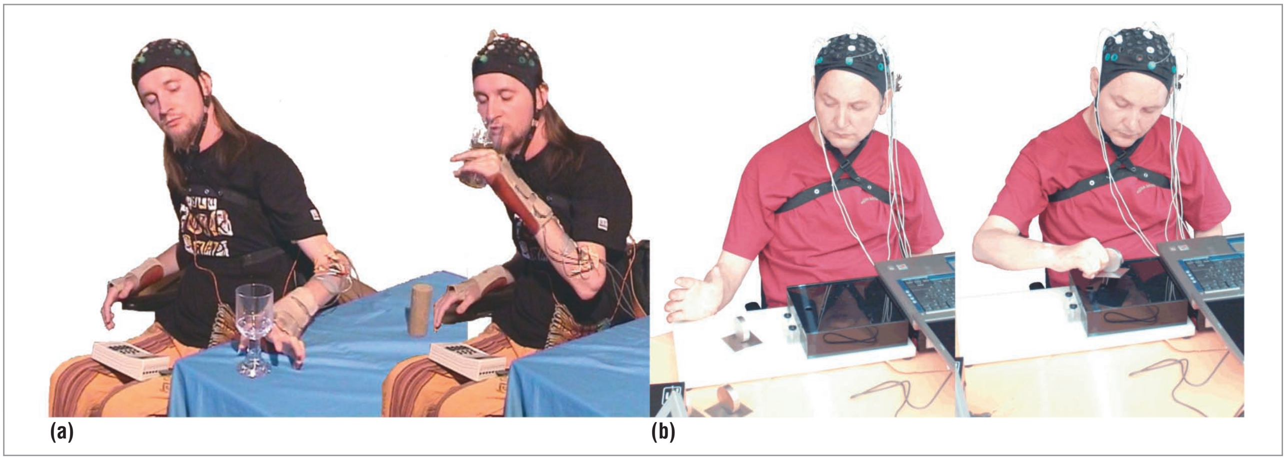

Figure 4. Thought-based control of a neuroprosthesis. (a) A patient uses functional electrical stimulation and surface electrodes to control hand grasp. (b) A patient controls hand grasp with implanted stimulation electrodes.

All these studies report encouraging results in attempts to use an EEG-based BCI to restore grasp functions. However, the system bit rate is still quite low and not suitable for controlling larger objects, such as a full arm neuroprosthesis. To make an EEG-based BCI system practical on a daily basis, the next step might be to develop intelligent controllers that could recognize system errors.

A myoelectrical prosthesis shows promise in restoring lost motor function in patients with amputated hands or arms. The patient controls prosthetic movement with myographical signals from the remaining arm muscles. In one patient, whose arm was amputated to the shoulder, a procedure surgically connected the nerves governing the arm muscles with the nerves that contract the pectoral muscle, which was subdivided in distinct parts.[19] Whenever the patient thinks about a movement, the pectoral muscle parts activate in a certain pattern. By using an electromyographic recording and classifying the resulting patterns, such a system can control an artificial arm.

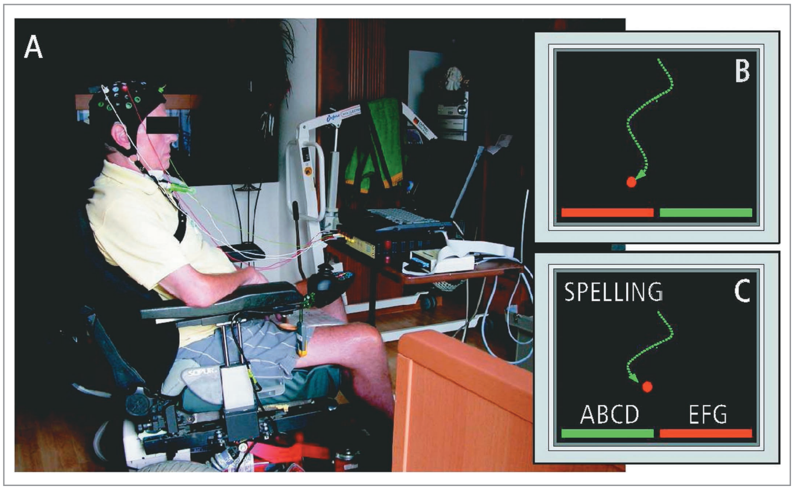

Figure 5. Training to use a spelling system. (a) An ALS patient during BCI training at home. (b) What the patient sees using the basket paradigm, in which the patient is asked to move the falling ball into a target, in this case, a red or green rectangle. (c) What the patient sees using copy spelling, in which the task is to isolate a particular letter.

SPELLING SYSTEMS

Figure 5 shows a patient training to use a spelling system by selecting letters to form words and sentences. In early training, the patient uses basket feedback training, and then later letters replace the baskets. In copy spelling, one strategy is to split the alphabet iteratively according to a predefined procedure, until the user isolates the desired letter.

The simplest method uses a binary control signal, which requires two distinct mental activities. Patients suffering from ALS learned to control their SCPs in operating the thought-translation device.[3,20] In two other studies that used the same dichotomous selection strategy, patients used motor imagery to modulate the ERD and ERS changes in oscillatory EEG activity. Both the ALS patient in Figure 5a[8] and a patient suffering from severe cerebral palsy[21] learned to operate the Virtual Keyboard spelling application in this manner. In these studies, the performance measure was spelling rate, or the number of correctly selected letters per minute. Unfortunately, study parameters tend to differ, making direct comparison difficult. Alphabet size varies, as do paradigm timing and user training periods. For these studies, spelling rates varied from 0.15 to approximately 1.0 letter per minute.

Splitting the alphabet into more than two parts might increase the spelling rate, or more generally the information transfer rate, but again, there must be some way to reliably discriminate or map brain patterns. A study using a three-class BCI[22] reported an average spelling rate of ~3.0 letters per minute, but the study also used an asynchronous (self-paced) communication protocol.

An asynchronous protocol was also the basis for a novel spelling concept, in which users employed a three-class BCI to select letters by scrolling through the alphabet.[23] The volunteers used foot motor imagery to rotate two wheels, one on each side of the screen, on which the letters appeared alphabetically. With left- and right-hand motor imagery, a subject could select the item on the left or right wheel. Healthy users were able to achieve an average spelling rate of 2.0 letters per minute.

Another efficient selection strategy is the Hex-O-Spell application,[24] which combines asynchronous two-class BCI control and divides the alphabet into six parts. Participants achieved an average spelling rate of nearly 6.0 letters per minute using this application.

Both these spelling systems are based on rhythmic EEG activity, using an ERD BCI. The use of evoked potentials, such as the P300[5] or the SSVEP[6] BCI lets patients reliably and quickly discriminate four and more classes and so increases the possible spelling rate.

STROKE REHABILITATION

Motor impairment after stroke is the leading cause of permanent physical disability. Strokes frequently result in some form of hemiparesis or hemiplegia, usually contralateral to the stroke site. Rehabilitation methods based on neuroscience seek to stimulate spontaneous functional motor recovery by exploiting the brain's potential for plastic reorganization after a stroke.

One post-stroke therapy—constraint-induced movement therapy (CIMT)—encourages goal-directed movement with the impaired hand while constraining the unaffected limb. The idea is to activate the lesional

Figure 6. Feedback training using virtual hands. The participant's task is to imagine left- and right-hand movements. The BCI generates opening and closing movements of the right or left (virtual) hand according to classified brain patterns.

hemisphere (through forced repetitive practice with the affected limb) and simultaneously deactivate (inhibit) the intact hemisphere by constraining the unaffected limb.

Typically, physical therapy aimed at post-stroke motor recovery focuses on active movement training. Some patients, however, are so severely disabled that they cannot engage in movement without assistance. New rehabilitative strategies seek to extend CIMT to serve these patients. Newly developed protocols based on mentally rehearsing movements (like motor imagery) represent an intriguing backdoor approach to accessing the motor system because they can activate sensorimotor networks that the lesions affected.[25]

One study showed that unilateral hand motor imagery results in a simultaneous contralateral ERD and ipsilateral ERS after some training sessions. Hence, an ERD BCI based on movement imagery can provide some measure of attempted activity in the motor regions and reinforce a patient's sensorimotor experience during post-stroke motor recovery.

Feedback from the BCI can be solely visual, as in the movement of a virtual hand in Figure 6, or it can occur through a prosthetic device, such as an orthotic hand attached to the patient's own.[11] In both cases, not only can positive feedback reinforce the motor imagery process, but the act of observing the hand movement can itself lead to an activation of the sensorimotor areas.

An important question is whether or not stroke patients produce reliable EEG changes during hand motor imagery that are detectable in a single trial and suitable for use as a trigger to induce assisted movements. One study showed that imagery of movement not only with the nonparetic but also with the paretic hand can be objectified in single EEG trials with a clear preponderance of beta ERD in the nonlesioned hemisphere. The study found a similar ERD pattern during hand movement when such movement was possible. The BCI system discriminated the cue-based EEG reactivity patterns from rest with 70 to 80 percent classification accuracy.

Clearly, BCI technology is a relatively new, fast-growing field of research and applications with the potential to improve the quality of life in severely disabled people. To date, several BCI prototypes exist, but most work only in a laboratory environment.

Before a BCI can be used for communication and control at home, research must solve several problems. An important next step is to establish protocols for easily setting up and using BCI systems in a practical environment. Many features, such as electrode positions and frequency components, must be automatically selectable for particular motor imagery. The system must use the fewest number of recording electrodes possible, striving for the optimal single EEG channel. Finally, training time must decrease, perhaps through game-like feedback and automatic detection of artifacts, such as uncontrolled muscle activity.

With these improvements, which are on the horizon, we expect to see practical BCI systems for a wide range of users and applications. ■

Acknowledgments

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References

1. J.R. Wolpaw et al., "Brain-Computer Interfaces for Communication and Control," *Clinical Neurophysiology*, June 2002, pp. 767-791.
2. N. Birbaumer et al., "Potentials of the Cerebral Cortex and Behavior," *Physiology Rev.*, Jan. 1990, pp. 1-41.
3. N. Birbaumer et al., "A Spelling Device for the Paralyzed," *Nature*, 25 Mar. 1999, pp. 297-298.
4. A. Kübler et al., "Brain-Computer Communication: Unlocking the Locked In," *Psychology Bull.*, May 2001, pp. 358-375.
5. E. Donchin, K.M. Spencer, and R. Wijesinghe, "The Mental Prosthesis: Assessing the Speed of a P300-Based Brain-Computer Interface," *IEEE Trans. Neural Systems and Rehabilitation Eng.*, June 2000, pp. 174-179.
6. M. Cheng et al., "Design and Implementation of a Brain-Computer Interface with High Transfer Rates," *IEEE Trans. Neural Systems and Rehabilitation Eng.*, Oct. 2002, pp. 1181-1186.
7. G. Pfurtscheller and F.H. Lopes da Silva, "Event-Related EEG/MEG Synchronization and Desynchronization: Basic Principles," *Clinical Neurophysiology*, Nov. 1999, pp. 1842-1857.
8. G. Pfurtscheller et al., "15 Years of BCI Research at Graz University of Technology: Current Projects," *IEEE Trans. Neural*

Systems and Rehabilitation Eng.*, June 2006, pp. 205-210.
9. B.B. Blankertz et al., "The Berlin Brain-Computer Interface: Accurate Performance from First-Session in BCI-Naive Subjects," *IEEE Trans. Biomedical Eng.*, to be published in 2008.
10. R. Scherer, "Towards Practical Brain-Computer Interfaces: Self-Paced Operation and Reduction of the Number of EEG Sensors," PhD dissertation, Computer Science Faculty, Graz Univ. Technology, 2008.
11. N. Birbaumer and L.G. Cohen, "Brain-Computer Interfaces: Communication and Restoration of Movement in Paralysis," *J. Physiology*, Mar. 2007, pp. 621-636.
12. G. Pfurtscheller, J. Kalcher, and D. Flotzinger, "A New Communication Device for Handicapped Persons: The Brain-Computer Interface," *Proc. 1st Technology Insertion, Demonstration, and Evaluation (TIDE) Congress*, IOS Press, 1993, pp. 123-127.
13. G. Pfurtscheller et al., "Walking from Thought," *Brain Research*, 3 Feb. 2006, pp. 145-152.
14. R. Leeb et al., "Self-Paced (Asynchronous) BCI Control of a Wheelchair in Virtual Environments: A Case Study with a Tetraplegic," *Computational Intelligence and Neuroscience*, 2007, ID 79642; http://dx.doi.org/doi:10.1155/2007/79642.
15. A. Chatterjee et al., "A Brain-Computer Interface with Vibrotactile Biofeedback for Haptic Information," *J. Neuroengineering and Rehabilitation*, Oct. 2007.
16. J. Müller-Gerking, G. Pfurtscheller, and H. Flyvbjerg, "Designing Optimal Spatial Filters for Single-Trial EEG Classification in a Movement Task," *Clinical Neurophysiology*, May 1999, pp. 787-798.
17. G.R. Müller-Putz et al., "Brain-Computer Interfaces for Control of Neuroprostheses: From Synchronous to Asynchronous Mode of Operation," *Biomedizinische Technik/Biomedical Eng.*, 2006, pp. 57-63.
18. G. Müller-Putz and G. Pfurtscheller, "Control of an Electrical Prosthesis with an SSVEP-Based BCI," *IEEE Trans. Biomedical Eng.*, Jan. 2008, pp. 361-364.
19. T.A. Kuiken et al., "Targeted Reinnervation for Enhanced Prosthetic Arm Function in a Woman with a Proximal Amputation: A Case Study," *The Lancet*, Feb. 2007, pp. 371-380.
20. A. Kübler et al., "The Thought Translation Device: A Neurophysiological Approach to Communication in Total Motor Paralysis," *Experimental Brain Research*, Jan. 1999, pp. 223-232.
21. C. Neuper et al., "Clinical Application of an EEG-Based Brain-Computer Interface: A Case Study in a Patient with Severe Motor Impairment," *Clinical Neurophysiology*, Mar. 2003, pp. 399-409.
22. J. del R. Millán and J. Mouriño, "Asynchronous BCI and Local Neural Classifiers: An Overview of the Adaptive Brain Interface Project," *IEEE Trans. Neural Systems and Rehabilitation Eng.*, June 2003, pp. 159-161.
23. R. Scherer et al., "An Asynchronously Controlled EEG-Based Virtual Keyboard: Improvement of the Spelling Rate," *IEEE Trans. Biomedical Eng.*, June 2004, pp. 979-984.
24. K-R. Müller and B. Blankertz, "Toward Noninvasive Brain-Computer Interfaces," *Signal Processing*, Sept. 2006, pp. 125-128.
25. N. Sharma, V.M. Pomeroy, and J-C. Baron, "Motor Imagery: A Backdoor to the Motor System after Stroke?" *Stroke*, July 2006, pp. 1941-1952.

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