FLEXIBILITY AND PRACTICALITY: GRAZ BRAIN–COMPUTER INTERFACE APPROACH

Reinhold Scherer,*,† Gernot R. Müller-Putz,* and Gert Pfurtscheller*

*Institute for Knowledge Discovery, Laboratory of Brain–Computer Interfaces, Graz University of Technology, Graz, Austria
†Computer Science and Engineering, University of Washington, Seattle, Washington, USA

"Graz brain–computer interface (BCI)" transforms changes in oscillatory electroencephalogram (EEG) activity into control signals for external devices and feedback. Steady-state evoked potentials (SSEPs) and event-related desynchronization (ERD) are employed to encode user messages. User-specific setup and training are important issues for robust and reliable classification. Furthermore, in order to implement small and thus affordable systems, focus is put on the minimization of the number of EEG sensors. The system also supports the self-paced operation mode, that is, users have on-demand access to the system at any time and can autonomously initiate communication. Flexibility, usability, and practicality are essential to increase user acceptance. Here, we illustrate the possibilities offered by now from EEG-based communication. Results of several studies with able-bodied and disabled individuals performed inside the laboratory and in real-world environments are presented; their characteristics are shown and open issues are mentioned. The applications include the control of neuroprostheses and spelling devices, the interaction with Virtual Reality, and the operation of off-the-shelf software such as Google Earth.

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I. Introduction

A brain–computer interface (BCI) is a communication system that allows the user to bypass the efferent pathways of the central nervous system and thus to directly link the human brain with the machine. The motivation for the development of this nonmuscular communication channel is to replace, or at least to somewhat enhance, the lost motor functions of physically disabled persons with intact cortical signals. These include individuals suffering from strokes, spinal cord injuries, or with degenerative diseases like amyotrophic lateral sclerosis. Able-bodied individuals may find BCI-based communication inaccurate and slow compared to their intact motor control abilities. The disabled, however, learned to deal successfully with this technology in their familiar surroundings and to operate spelling devices (Neuper *et al.*, 2006) or neuroprostheses (Müller-Putz *et al.*, 2005a; Pfurtscheller *et al.*, 2003). Under circumstances or in environments where the body behaves differently than under usual conditions, for example, as in space, such an additional "hands-free" communication channel, however, can be advantageous also for able-bodied users.

Here, we give an overview of Graz-BCI research and illustrate, by means of different practical applications, the possibilities this kind of technology offers at the present time. One major aim of our research is to enhance usability, practicality, and flexibility of BCI-based interaction. Important issues in this context are the simplification of the hardware and sensor technology, the reduction of the user training period, and the increased robustness and reliability of the signal processing methods employed.

II. Graz BCI

Graz BCI is based on the real-time detection and classification of transient changes in the ongoing electroencephalogram (EEG) (Pfurtscheller *et al.*, 2006). The EEG signal is in the range of microvolts and consequently is very sensitive to artifacts, that is, to electromagnetic signals not generated by the brain. The most frequent artifacts are muscle activity (electromyogram), eye movements (electrooculogram), and artificial noise generated by nearby electronic devices (e.g., power line interference). Besides artifacts, the nonstationarity and inherent variability of the EEG signal makes a reliable classification of the underlying brain activity difficult.

Steady-state evoked potentials (SSEPs) and event-related desynchronization (ERD) (Pfurtscheller and Lopes Da Silva, 1999) are two neurophysiological phenomena used to encode control messages. SSEPs occur when external sensory stimuli are presented in such a rapid sequence that the resulting individually evoked potentials are overlapping and thus reflecting the stimulation frequency (Regan, 1989). We used visual and somatosensory (tactile) stimuli to evoke detectable brain responses. ERD and event-related synchronization (ERS) (Pfurtscheller and Lopes Da Silva, 1999) describe transient changes in on-going oscillatory EEG activity. ERD means a relative power decrease and ERS means a power increase in specific spectral components over defined brain areas. Motor imagery, that is, the mental simulation of movements, is used to induce ERD and/or ERS in sensorimotor rhythms and is the basis of the ERD–BCI method.

To convey messages, the user generally changes their brain activity either in response to a cue from the BCI (cue-based BCI) or voluntarily with free will, when an interaction is required (self-paced BCI). While cue-based BCI follow a fixed time scheme and accept messages only within a predefined time window following the cue, self-paced BCIs must continuously analyze the ongoing EEG in order to autonomously detect these messages (Mason *et al*., 2007).

To reach a high level of classification accuracy, training with the BCI is necessary for two reasons: first, to obtain enough EEG-trials in order to set up the classifier, and second, to enable the user to find the best control strategy (this is crucial for motor imagery). The standard training procedure employed is to first adapt the computer to the user's brain activity by applying machine learning algorithms to samples of different EEG patterns. Usually statistical classifiers such as Fisher's linear discriminant analysis (Duda *et al*., 2001) are employed. Next feedback training is performed to enhance and activate these patterns. Finally, the feedback data are again analyzed and if necessary the classifier is updated. In this way the brain and the BCI are mutually adapting (Pfurtscheller and Neuper, 2001; Vidaurre *et al*., 2006). To make this technology affordable and thus also accessible to patients, the requirements during optimization and adaptation are not only accuracy and robustness, but also the reduction of the number of EEG sensors. BCI training may last for hours, weeks, or even longer and requires ongoing interaction between user and researcher. To facilitate user training Graz BCI uses telemonitoring (Müller *et al*., 2003; Neuper *et al*., 2003), that is, it provides remote access, audio/video communication capabilities, and file transfer tools.

Graz BCI is implemented by using Matlab/Simulink-based (MathWorks, Inc., Natick, MA, USA) rapid prototyping (Guger *et al*., 2001). The hardware consists of a commercial biosignal amplifier (Guger Technology, Graz, Austria) connected to a data acquisition card and a standard personal computer or laptop. The Graz-BCI open source software package rtsBCI (Scherer *et al*. 2004b) includes the modules that have been used to successfully realize the results presented here. The package is licensed under the GNU Public License (GPL) and can be downloaded from the BIOSIG homepage that is hosted by the Sourceforge Web site (http://biosig.sourceforge.net).

III. Applications

A. Operating a (Neuro)Prosthetic Hand—Part I

When individuals gaze at a flickering light source, steady-state visual evoked potentials (SSVEPs) are evoked over the visual cortex. In our first feasibility study, four lights, each flickering at a different rate, were used to encode control messages for an electromechanical hand prosthesis (Müller-Putz and Pfurtscheller, 2008). 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 and 13 Hz) represented the commands for opening and closing the hand (Fig. 1A). Four naïve able-bodied subjects followed a given grasping sequence at will. Three out of the four subjects successfully performed the predefined sequence. Erroneous selections had to be undone. The fourth subject was not able to obtain SSVEP control. Two bipolar EEG channels were recorded from four electrodes placed on predefined positions over the visual cortex. The goal of a recent paper of Müller-Putz *et al.* (2008) was to investigate optimal electrode positions by evaluating classification accuracies from a set of 21 electrode positions placed over the entire occipital cortex. Results based on data from 10 able-bodied subjects show that the classification accuracy of individually selected electrode positions is significantly higher than those obtained with the "default" electrode positions used in the previous study. Furthermore, a comparison of different signal processing (Müller-Putz 2005a, 2008) methods suggests that it is possible to detect SSVEPs after a very short training period—basically it is possible to operate a self-paced BCI after a short calibration period of 1 min (Scherer *et al.*, 2007a).

B. Haptic Stimulation: Steady-State Somatosensory-Evoked Potentials

For real-world applications ongoing acoustic stimulation is not practical. Haptic (sensorimotor) stimulation seems reasonable and thus we researched the usefulness of tactile stimulation in the resonance-like frequency range of the somatosensory system (Müller *et al.*, 2001). The right index finger of the user was stimulated with the individual specific frequency f_{T1} (range 25–31Hz). The left index finger was stimulated at $f_{\mathrm{T2}} = f_{\mathrm{T1}} - 5$ Hz. A sinusoidal waveform was used to produce a weak tapping stimulation (Fig. 1B). Subjects were asked to focus their attention on the finger indicated by a visual cue and to count the intermittent amplitude twitches of the stimulation signal. The purpose of the counting task was to force the participants to focus on the cued stimulation. Four subjects

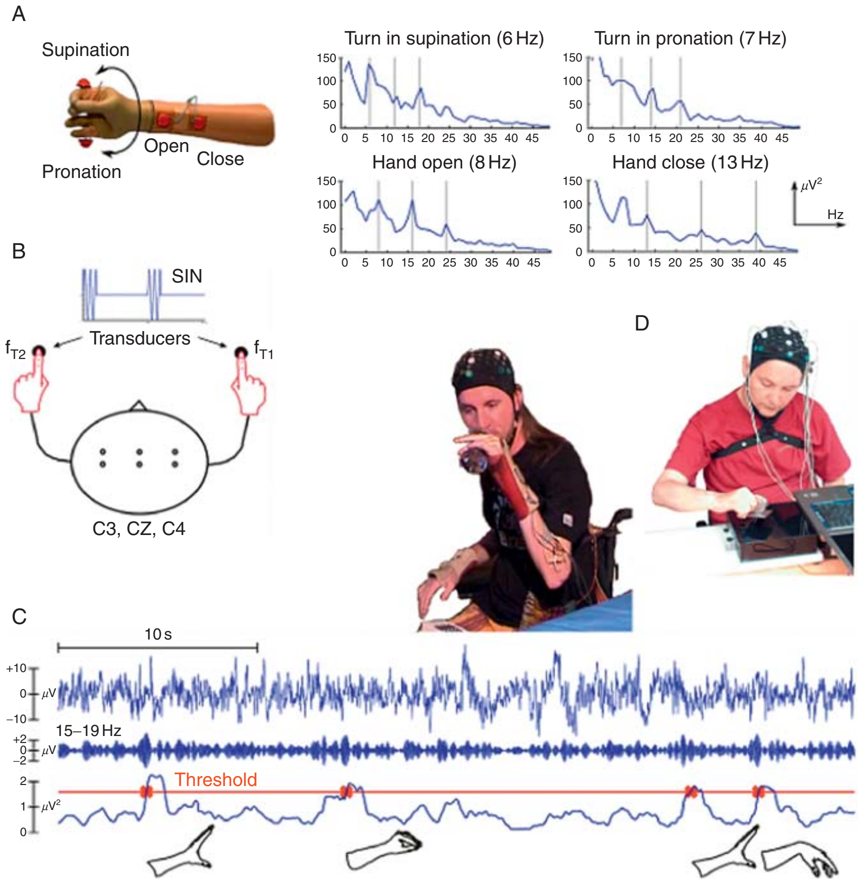

FIG. 1. (A) Hand prosthesis with four light emitting diodes, each associated with a control command. The curves show typical 1-s SSVEP power spectra from one bipolar EEG channel recorded over visual areas. Gray lines indicate the stimulation frequency and the second and third harmonic. (B) The principle of SSSEP-based BCIs—modified from Müller-Putz *et al.* (2006). (C) Spinal cord injury (SCI) patient grasping a glass by means of surface functional electrical stimulation (FES). The curves show (from above) one EEG channel recorded bipolarly over sensorimotor foot representation area, the 15–19 Hz band pass filtered EEG, and the power of the filtered signal averaged over the past 1-s period. A threshold detector (horizontal gray line) is used to switch between grasp sequences. (D) SCI patient with implanted neurophrosthesis during a grasp-release performance test.

participated in these feedback experiments. Two of them were unable to focus their attention for the entire duration of an experimental session (usually 160 trials). A selection of their runs with good performance, however, leads to off-line classification accuracies of about 73%. The performance of the two remaining subjects was better. One subject increased performance from session to session.

The online accuracy after three sessions was 71.7%. The last subject was able to focus attention from the very beginning. Online performances ranged between 79.4 and 83.1% (Müller-Putz *et al.*, 2006). These results suggest that the evoked responses are stable and can be used to encode control messages.

C. Operating a (Neuro)Prosthetic Hand—Part II

Functional electrical stimulation (FES) can be applied to paralyzed limbs and restore motor function. By placing surface electrodes near the motor point of the muscle, or by implanting subcutaneous electrodes and applying stimulation pulses, action potentials are elicited which lead to the contraction of the innervated muscle fibers. In two case studies with spinal cord injury (SCI) patients, we successfully realized self-paced motor imagery-controlled operation of a neuroprosthesis. The grasp function of the left hand of the first patient (29 year, male, SCI at level C5) was restored with FES using surface electrodes. During a 4-month ERD–BCI-training period, the patient learned to induce 17-Hz oscillations by means of foot motor imagery which became sufficiently dominant that a threshold detector could be used for the realization of a binary control signal (Pfurtscheller *et al.*, 2003). This trigger signal was used to switch sequentially between grasp phases implemented using the stimulation unit (Fig. 1C). With this grasp the patient was again able to hold for example, a drinking glass. The second patient (42 year, male, SCI sub-C5) had a Freehand® system (Peckam *et al.*, 2001) implanted in his right hand and arm. Within 3 days of feedback training, he learned to reliably induce an ERD pattern during left-hand motor imagery and thus to generate a binary control signal (Müller-Putz *et al.*, 2005a). In this case, the self-paced BCI system emulated the shoulder joystick which is usually used to operate the Freehand® system. With the BCI-controlled Freehand® system, the patient successfully executed parts of a hand-grasp performance test (Fig. 1D). In the first case, one single bipolar EEG channel, and in the second case, two bipolar EEG channels were recorded from sensorimotor foot and hand representation areas.

D. The Virtual Keyboard Spelling Device

For practical applications, however, one binary control signal might not be sufficient. An increase of the number of brain patterns that can be equally reliably detected also increases the communication speed. To this end a 3-class self-paced ERD–BCI was designed and used to operate the "Virtual Keyboard (VK)" spelling device (Scherer *et al.*, 2004a). Users can write text messages by scrolling through the alphabet and choosing symbols arranged on either side of the screen. Left hand, right hand, and foot motor imagery were used to move the cursor to the left, to the right, and to browse the alphabet, respectively. Figure 2A illustrates such a selection process. Three bipolar EEG channels were recorded over sensorimotor hand and foot representation areas. Results of three able-bodied subjects operating the VK, two successfully, showed an improvement of the number of correctly spelled letters per minute σ (spelling rate) up to $\sigma = 3.38$ (average $\sigma = 1.99$). In the previous 2-class cue-based version of the VK the ability to use the VK varied between $\sigma = 0.5$ and $\sigma = 0.85$ (Obermaier *et al.*, 2003). This performance increase already suggests the inherent potential of BCI technology. Despite the limited information transfer bandwidth, the use of well-designed human–computer interfaces and optimized selection techniques allowed user to significantly speed up communication.

E. Navigation in Virtual Environments

The 3-class self-paced ERD–BCI allowed users to reliably switch among three different motor imagery tasks. The classifier, however, was not optimized to reduce the number of erroneous detections (false positive) during periods when BCI control was not needed. To this end an additional classifier was trained to discriminate among the three motor imagery-induced EEG patterns and continuously recorded EEG without motor imagery. Each time the new classifier detected motor imagery, the class identified by the 3-class classifier was the output of the BCI; otherwise the output was "0" and no action was triggered. To further increase the robustness, online methods for eye movement reduction and muscle artifact detection were incorporated (Scherer *et al.*, 2007b).

To evaluate the new system, a virtual environment that consisted of a number of labyrinthine arranged hedges with a tree positioned in the middle was created (Fig. 2B). Objects were initially positioned on fixed locations inside the park and users had the task of navigating through the virtual world and collecting them within a time limit. Users could explore the park by moving forward (foot motor imagery) and turning to the left/right (left-/right-hand motor imagery). No directions were given; the subjects could freely choose their trajectory. Three naïve users participated in online experiments. After about 5 h of cue-based, 3-class feedback training, the classification accuracy for each subject reached 80% among the three mental tasks with 17% false positive detections during longer periods when no messages had to be sent. Two out of three subjects succeeded in collecting all three objects; one subject succeeded in collecting only two out of three objects. Figure 2B shows an example of a user chosen trajectory. Because there were no approved performance measures for self-paced operation, the participants were asked to self-report their ability to operate the BCI. The interviews revealed that the ERD–BCI usually detected the control messages correctly (Scherer *et al.*, 2008).

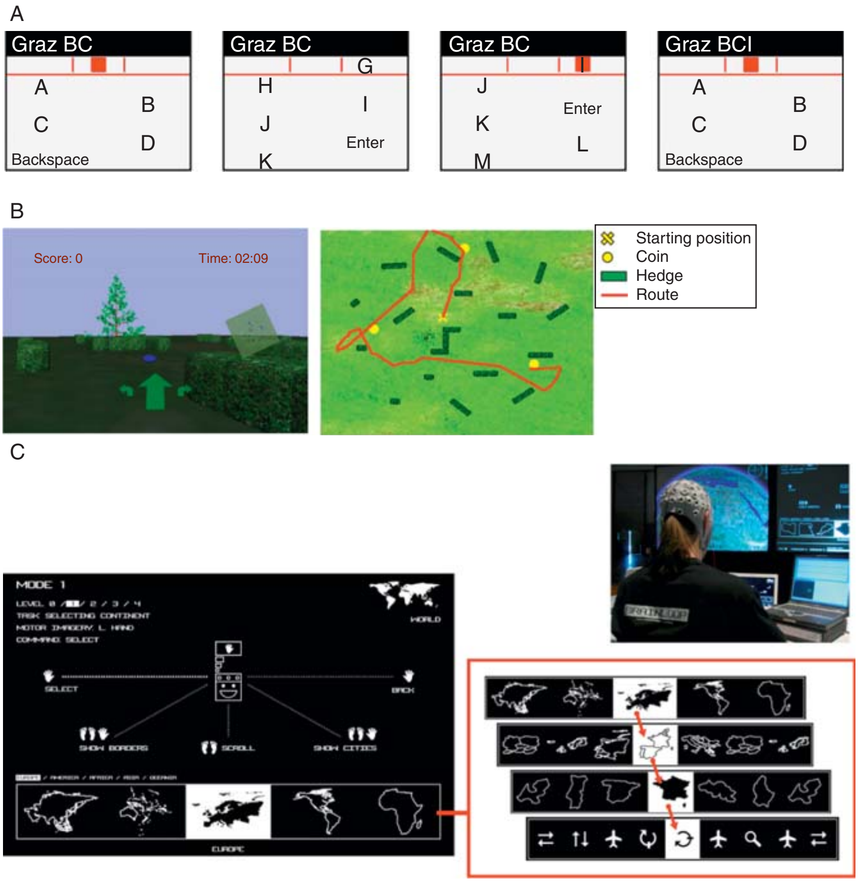

FIG. 2. (A) Virtual keyboard letter selection process (left to right): User scroll through the alphabet (symbols move from the bottom to the top of the screen) and pick, by moving the feedback cursor, the desired symbol (letter or control command) shown on the left or on the right half of the screen. This example shows the insertion of the letter "I" in order to spell the word "BCI." Modified from Scherer *et al.* (2004a). (B) Screenshot of the virtual environment consisting of a tree and several hedges. The arrows show the current navigation command (here move forward). The trajectory taken by one subject is shown in the map on the right side. Modified from Scherer *et al.* (2008). (C) Screenshot of the GUI used to operate Google Earth. The user is represented by an icon positioned in the center of the display. The commands at the user's disposal are placed around this icon and can be selected by moving the feedback cursor (dashed line) into the desired direction. A hierarchical four-level selection procedure allows the user to select the continent, the continental area, the country, and finally to manipulate the virtual camera. The picture shows the experimental setup during a public performance. Modified from Scherer *et al.* (2007b).

F. Operating off-the-Shelf Software

Google Earth (Google Inc., Mountain View, CA, USA) is a popular virtual globe program that allows easy access to the world's geographic information. In contrast to the previously presented applications, the range of functions needed to comfortably operate the software is much higher and, since users have to wait an undefined period of time for the response of the software (e.g., the download of satellite images), a minimization of false positive events is crucial for reasonable operation. Figure 2C shows a screen shot of the specially designed graphical user interface and illustrates the principle of interaction. The user, represented by an icon in the center of the interface, is surrounded by the available commands which can be selected by moving the cursor toward the desired icon for a predefined time. The command "Scroll" (foot motor imagery) was used to browse the available options. As long as this command is enabled, that is, the user continuously performed motor imagery, the options were scrolling from the right to the left side of the screen. The available options were arranged in four levels. These were continent (five options), subcontinent (3–5 options), country (3–18 options), and camera movement (seven options). This means that first the users have to select the country and then they can position the camera over the desired location. The commands "Select" (left-hand imagery) and "Back" (right-hand imagery) were used to select the current option and to go back to the previous level, respectively. After each selection, Google Earth's virtual camera moved to the selected position. For more details about this interface see http://www.aksioma.org/brainloop.

After about 6 h of feedback training, one subject, previously participating in the virtual environment experiment, successfully operated the application in the lab, as well as in public (Scherer, 2008; Scherer *et al.*, 2007b). The average time required to get from level 1 to level 4 and thus to select one out of 201 available options was about 20 s (minimum 12 s).

IV. Discussion

The presented studies document the advancement of Graz BCI and demonstrate that the system is functioning properly in real-life conditions. The developed system is small, lightweight, robust, and relatively inexpensive because the system complexity has been minimized. On the basis of its open system architecture and rapid prototyping environment, it is highly customizable and incorporating new algorithms is relatively easy. This flexibility and the possibility to remotely adjust parameters and to change the setup allow fast corrections due to unforeseen circumstances (e.g., by suddenly appearing electrical interference caused by a new artificial ventilation system at the patient's home). It is also easy to combine SSVEPs and ERD/ERS to create a hybrid system, or to measure and process additional biosignals like the electrocardiogram (Pfurtscheller *et al.*, 2008; Scherer *et al.*, 2007a).

SSEP-based systems are fast and easy to handle, however, external stimuli are needed. Under some circumstances (e.g., during repair work in outer space which requires the full visual attention or in situations where the user is unable to move) it may not be possible to perceive the required stimulus. On the other hand, motor imagery-based BCIs (ERD–BCI), do not need external stimulation, but the information-transfer-rate is low and reliable classification is difficult. Whether SSEP or ERD is best for a given application must be decided on a case-by-case basis.

Robustness and on-demand operability are extremely important issues. Proper artifact handling is mandatory to ensure that the classifier output is based on voluntary brain activity. So are self-paced operation and self-initiation, that is, the ability of BCI user to autonomously switch the system on and off (Scherer *et al.*, 2007a). The effort to reduce the number of channels may cause an increase in the training period. The presented feedback studies, however, prove that the selected "minimalistic" approach achieves satisfactory results within a limited time period. A larger number of channels potentially result in increased classification performances; however, also the probability of electrode failures or of electrode-related error increases. A recent study by Scherer (2008) has shown that the reduction of the number of EEG sensors from 30 to 5 decreases the median classification accuracies, for example, for left hand versus foot motor imagery from 87.1 to 83.2%, that is, only by 4%. Of course higher accuracies result in better performances. The operation of the Virtual Keyboard spelling application and Google Earth, however, clearly indicates the potential of incorporating concepts of the fields' human–computer interaction and usability. A sound design of the user interface and a sophisticated evaluation of the BCI output may help overcome inaccuracies originated from misclassification and thus supports users and help them to reduce erroneous selections.

Once the EEG patterns have been established and the ERD–BCI has been trained, we have found that our system can work reliably for years without the need for any updates. In the case of our first SCI patient, the oscillations have been stable for 9 years; Our Google Earth user's oscillations have been stable for two years. The long-term stability of trained brain patterns significantly contributes toward the creation of a more reliable communication.

Astronauts potentially benefit from BCI-based control of devices in situations where mobility is limited such as during periods of heavy acceleration or during maintenance repairs in outer space. In the former case the self-paced 3-class ERD–BCI could be used to browse through several menus and check the status of the spaceship or execute predefined program sequences; in the latter case a binary brain-switch—as developed for neuroprothesis control—could be employed to sequentially flip through a repair manual. Recently it has been shown that the detection accuracy of such a brain switch can be increased when including the post-imagery beta rebound (Pfurtscheller and Solis-Escalante, 2009). Due to the timing of the post-imagery phenomenon, however, the information transfer rate is limited to about 15 bits/min. SSVEP–BCIs may be useful to operate the gripper arm in order to move it closer to the workspace before taking over manual control for fine-tuning. The required visual stimuli, again, could be switched on/off by means of a brain switch.

Another potential field of application for BCI technology is neuromonitoring. Fatigue, stress, increased work load or other mental states which may make individuals error-prone could be detected and used to exemplarily adapt the complexity of the current task or to alert the central station.

For any space application, Graz-BCI system already contains a series of methods—both signal processing and experimental strategies—that can be used immediately and can be adapted very easily. The system was engineered so that at the bedside of a patient, the different options can be tested so that the most promising can be applied. Equipped with the experience gained during several months of telemonitoring-based BCI training, a new user can easily be guided through this process. The analogous remote training from a base station on Earth to the International Space Station follows directly.

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References

Duda, O. R., Hart, P. E., and Stork, D. G. (2001). "Pattern Classification." 2nd ed. Wiley Interscience, New York.

Guger, C., Schlögl, A., Neuper, C., Walterspacher, D., Strein, T., and Pfurtscheller, G. (2001). Rapid prototyping of an EEG-based brain-computer interface (BCI). *IEEE Trans. Neural Syst. Rehabil. Eng.* **9**(1), 49–58.

Mason, S. G., Bashashati, A., Fatourechi, M., Navarro, K. F., and Birch, G. E. (2007). A comprehensive survey of brain interface technology designs. *Ann. Biomed. Eng.* **35**(2), 137–169.

Müller, G., Neuper, C., and Pfurtscheller, G. (2001). Resonance-like frequencies of sensorimotor areas evoked by repetitive tactile stimulation. *Biomed. Tech.* **46,** 186–190.

Müller, G. R., Neuper, C., and Pfurtscheller, G. (2003). Implementation of a telemonitoring system for the control of an EEG-based brain-computer interface. *IEEE Trans. Neural. Syst. Rehabil. Eng.* **11**(1), 54–59.

Müller-Putz, G. R., and Pfurtscheller, G. (2008). Control of an electrical prosthesis with an SSVEP-based BCI. *IEEE Trans. Biomed. Eng.* **55**(1), 361–364.

Müller-Putz, G. R., Scherer, R., Pfurtscheller, G., and Rupp, R. (2005a). EEG-based neuroprosthesis control: A step towards clinical practice. *Neurosci. Lett.* **382**(1–2), 169–174.

Müller-Putz, G. R., Scherer, R., Brauneis, C., and Pfurtscheller, G. (2005b). Steady-state visual evoked potential (SSVEP)-based communication: Impact of harmonic frequency components. *J. Neural Eng.* **2**(4), 123–130.

Müller-Putz, G. R., Scherer, R., Neuper, C., and Pfurtscheller, G. (2006). Steady-state somatosensory evoked potentials: Suitable brain signals for brain-computer interfaces? *IEEE Trans. Neural Syst. Rehabil. Eng.* **14**(1), 30–37.

Müller-Putz, G. R., Eder, E., Wriessnegger, S. C., and Pfurtscheller, G. (2008). Comparison of DFT and lock-in amplifier features and search for optimal electrode positions in SSVEP-based BCI. *J. Neurosci. Methods* **168**(1), 174–181.

Neuper, C., Müller, G. R., Kübler, A., Birbaumer, N., and Pfurtscheller, G. (2003). Clinical application of an EEG-based brain-computer interface: A case study in a patient with severe motor impairment. *Clin. Neurophysiol.* **114**(3), 399–409.

Neuper, C., Müller-Putz, G. R., Scherer, R., and Pfurtscheller, G. (2006). Motor imagery and EEG-based control of spelling devices and neuroprostheses. *In* "Progress in Brain Research" (C. Neuper and W. Klimesch, Eds.), Vol. **159**, pp. 403–419. Elsevier, Amsterdam.

Obermaier, B., Müller, G. R., and Pfurtscheller, G. (2003). "Virtual keyboard" controlled by spontaneous EEG activity. *IEEE Trans. Neural Syst. Rehabil. Eng.* **11**(4), 422–426.

Peckham, P. H., Keith, M. W., Kilgore, K. L., Grill, J. H., Wuolle, K. S., Thrope, G. B., Gorman, P., Hobby, J., Mulcahey, M. J., Carroll, S., Hentz, V. R., and Wiegner, A. (2001). Efficacy of an implanted neuroprosthesis for restoring hand grasp in tetraplegia: A multicenter study. *Arch. Phys. Med. Rehabil.* **82**(10), 1380–1388.

Pfurtscheller, G., and Lopes Da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: Basic principles. *Clin. Neurophysiol.* **110**(11), 1842–1857.

Pfurtscheller, G., and Neuper, C. (2001). Motor imagery and direct brain-computer communication. *Proc. IEEE* **89,** 123–134.

Pfurtscheller, G., and Solis-Escalante, T. (2009). Could the beta rebound in the EEG be suitable to realize a "brain switch"? *Clin. Neurophysiol.* **120**(1), 24–29.

Pfurtscheller, G., Müller, G. R., Pfurtscheller, J., Gerner, H. J., and Rupp, R. (2003). "Thought"–control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia. *Neurosci. Lett.* **351**(1), 33–36.

Pfurtscheller, G., Müller-Putz, G., Schlögl, A., Graimann, B., Scherer, R., Leeb, R., Brunner, C., Keinrath, C., Lee, F. Y., Townsend, G., Vidaurre, C., and Neuper, C. (2006). 15 years of BCI research at Graz University of Technology: Current projects. *IEEE Trans. Neural Syst. Rehabil. Eng.* **14,** 205–210.

Pfurtscheller, G., Leeb, R., Friedman, D., and Slater, M. (2008). Centrally controlled heart rate changes during mental practice in immersive virtual environment: A case study with a tetraplegic. *Int. J. Psychophysiol.* **68,** 1–5.

Regan, D. (1989). "Human Brain Electrophysiology: Evoked Potentials and Evoked Magentic Fields in Science and Medicine." Elsevier, Amsterdam.

Scherer, R. (2008). Towards practical brain-computer interfaces: Self-paced operation and reduction of the number of EEG sensors, Ph.D. dissertation. Computer Science Faculty, Graz University of Technology, Austria.

Scherer, R., Müller, G. R., Neuper, C., Graimann, B., and Pfurtscheller, G. (2004a). An asynchronously controlled EEG-based virtual keyboard: Improvement of the spelling rate. *IEEE Trans. Biomed. Eng.* **51**(6), 979–984.

Scherer, R., Schlögl, A., Müller-Putz, G., and Pfurtscheller, G. (2004b). Inside the Graz-BCI: rtsBCI. *In* "Proceedings of the 2nd International Brain-Computer Interface Workshop and Training Course 2004." Biomedical Technik, Vol. **49**(1), pp. 81–82.

Scherer, R., Müller-Putz, G. R., and Pfurtscheller, G. (2007a). Self-initiation of EEG-based brain-computer communication using the heart rate response. *J. Neural Eng.* **4**(4), L23–L29.

Scherer, R., Schlögl, A., Lee, F. Y., Bischof, H., Grassi, D., and Pfurtscheller, G. (2007b). The self-paced Graz brain-computer interface: Methods and applications. *Comput. Intell. Neurosci.* **2007,** 79826.

Scherer, R., Lee, F., Schlögl, A., Leeb, R., Bischof, H., and Pfurtscheller, G. (2008). Towards self-paced brain-computer communication: Navigation through virtual worlds. *IEEE Trans. Biomed. Eng.* **55**(2), 675–682.

Vidaurre, C., Schlögl, A., Cabeza, R., Scherer, R., and Pfurtscheller, G. (2006). A fully online adaptive BCI. *IEEE Trans. Biomed. Eng.* **53**(6), 1214–1219.