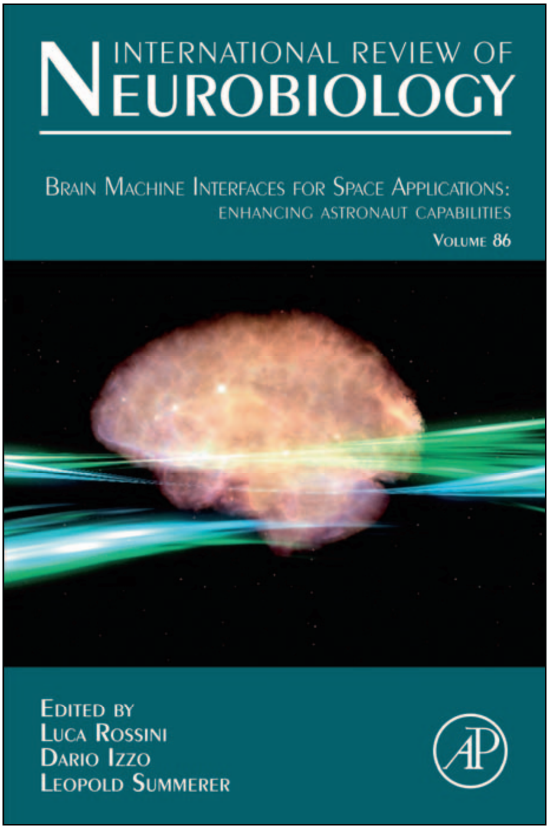

From: F. Babiloni, F. Cincotti, M. Marciani, S. Salinari, L. Astolfi, F. Aloise, F. De Vico Fallani and D. Mattia, On the Use of Brain–Computer Interfaces Outside Scientific Laboratories: Toward an Application in Domotic Environments.
In Luca Rossini, Dario Izzo and Leopold Summerer, editors: International Review of Neurobiology, Vol. 86, Burlington: Academic Press, 2009, pp. 133-146.
ISBN: 978-0-12-374821-8

ON THE USE OF BRAIN–COMPUTER INTERFACES OUTSIDE SCIENTIFIC LABORATORIES: TOWARD AN APPLICATION IN DOMOTIC ENVIRONMENTS

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Brain–computer interface (BCI) applications were initially designed to provide final users with special capabilities, like writing letters on a screen, to communicate with others without muscular effort. In these last few years, the BCI scientific community has been interested in bringing BCI applications outside the scientific laboratories, initially to provide useful applications in everyday life and in future in more complex environments, such as space. Recently, we implemented a control of a domestic environment realized with BCI applications. In the present chapter, we analyze the methodological approach employed to allow the interaction between subjects and domestic devices by use of noninvasive EEG recordings. In particular, we analyze whether the cortical activity estimated from noninvasive EEG recordings could be useful in detecting mental states related to imagined limb movements. We estimate cortical activity from

DOI: 10.1016/S0074-7742(09)86010-8

0074-7742/09 $35.00

high-resolution EEG recordings in a group of healthy subjects by using realistic head models. Such cortical activity was estimated in a region of interest associated with the subjects' Brodmann areas by use of depth-weighted minimum norm solutions. Results show that the use of the estimated cortical activity instead of unprocessed EEG improves the recognition of the mental states associated with limb-movement imagination in a group of healthy subjects. The BCI methodology here presented has been used in a group of disabled patients to give them suitable control of several electronic devices disposed in a three-room environment devoted to neurorehabilitation. Four of six patients were able to control several electronic devices in the domotic context with the BCI system, with a percentage of correct responses averaging over 63%.

I. Introduction

Brain–computer interfaces (BCI) is an area of research that is rapidly growing in the neuroscience and bioengineering fields. One popular approach to the generation of a BCI system consists of the recognition by a computer of the patterns of electrical activity on the scalp gathered from a series of electrodes. One of the problems related to the use of surface EEG is the blurring effect owing to the smearing of the skull on the transmission of the potential distribution from the cerebral cortex toward the scalp electrodes. This happens since the skull has very low electrical conductivity compared with the scalp or the brain. The blurring effect makes the EEG data gathered from the scalp electrodes rather correlated, a problem not observed in the cortical EEG data recorded from the invasive implants in monkeys and people. Such correlation makes the work of classifiers problematical, since the features extracted from the different scalp electrodes tend to be rather similar and this correlation is hard to disentangle with blind methods like principal component analysis.

In this last decade, high-resolution EEG technologies have been developed to enhance the spatial information content of EEG activity (Gevins *et al.*, 1990; Nunez, 1995). Furthermore, since the ultimate goal of any EEG recording is to provide useful information about the brain activity, a body of mathematical techniques, known as inverse procedures, has been developed to estimate the cortical activity from raw EEG recordings. Examples of these inverse procedures are dipole localization, distributed source, and cortical imaging techniques (Babiloni *et al.*, 2001; Dale and Sereno, 1993; Gevins *et al.*, 1990; Nunez, 1995). Inverse procedures can use linear and nonlinear techniques to localize putative cortical sources from EEG data, by using mathematical models of the head as volume conductors.

More recently it has been suggested that with the use of the modern high-resolution EEG technologies it could be possible to estimate the cortical activity associated with the mental imagery of the upper limb movements in humans better than with the scalp electrodes (Babiloni *et al.*, 2001; Cincotti *et al.*, 2002). We currently use the approach to estimate the cortical current density in a particular region of interest (ROI) on the modeled brain structures from high-resolution EEG recordings to provide high-quality signals for the extraction of the features useful for a BCI system.

In this chapter, we would like to illustrate how with the use of such advanced high-resolution EEG methods for estimating cortical activity it is possible to run a BCI system able to drive and control several devices in a domotic environment. In particular, we first describe a BCI system used on a group of healthy subjects in which the technology of the estimation of the cortical activity is illustrated. Then we demonstrate use of the BCI system to command several electronic devices within a three-room environment designed for neurorehabilitation. The BCI system was tested by a group of six patients.

II. Methodology

A. Subjects

Two groups of subjects were involved in training on the BCI system. One was composed of healthy subjects while the second one was composed of disabled persons who used the BCI system to attempt to drive electronic devices in a three-room facility at the laboratory of the Fondazione Santa Lucia in Rome. The first group was composed of 14 healthy subjects who voluntarily participated in the study. The second group of subjects comprised six patients affected by Duchenne muscular dystrophy. According to the Barthel index score (BI) for daily activity, all patients depended almost completely on caregivers, having a BI score <35. In general, all patients were unable to walk since they were already adolescent, and their mobility was possible only by means of a wheelchair. This latter was electric in the cases of all (except two) patients and it was driven by a modified joystick which could be manipulated by either the residual "fine" movements of the first and second fingers or the residual movements at wrist. As for the upper limbs, all patients had a residual muscular strength either of proximal or distal arm muscles that was insufficient for carrying on any everyday life activity. The neck muscles were so weak as to require a mechanical support to maintain the posture in all of them. Finally, eye movements were substantially preserved in all of them. At the moment of the study, none of the patients was using technologically advanced aids.

B. Patients' Preparation and Training

Patients were admitted for a neurorehabilitation program that also included the use of a BCI system on a voluntary basis. Caregivers and patients gave informed consent for the recordings in agreement with the ethical committee rules adopted for this study. The rehabilitation programs aimed to allow patients the use of a versatile system for the control of several domestic devices by using different input devices, tailored to the disability level of the final user. One of the possible inputs for this system was the BCI through EEG modulation.

The first step of the clinical procedure consisted of an interview and physical examination performed by the clinicians, wherein several levels of the variables of interest (and possible combinations) were addressed as follows: the degree of motor impairment and of reliance on the caregivers for everyday activities, as assessed by the current standardized scale, that is, the BI for ability to perform daily activities; familiarity with transducers and aids (sip/puff, switches, speech recognition, joysticks) that could be used as input to the system; the ability to speak or communicate and be understood by an unfamiliar person; the level of informatics alphabetization, measured by the number of hours/week spent in front of a computer. Information was structured in a questionnaire administered to the patients at the beginning and end of the training. A level of system acceptance by the users was schematized whereby users were asked to indicate with a number ranging from zero (not satisfactory) to five (very satisfactory) their degree of acceptance relative to each of the controlled output devices. The training consisted of weekly sessions over 3–4 weeks, in which the patient and (when required) patient's caregivers were practicing with the system. During the whole period, patients had the assistance of an engineer and a therapist in their interaction with the system.

C. Experimental Task

Both healthy volunteers and patients were trained in using the BCI system to control the movement of a cursor on the screen on the base of the modulation of their EEG activity. A description of the experimental task performed by all of them during the training follows. Each trial consisted of four phases:

1. *Target appearance*: a rectangular target appeared on the right side of the screen, covering either the upper or the lower half of the side.
2. *Feedback phase*: one second after the target, a cursor appeared in the middle of the left side of the screen and moved at a constant horizontal speed to the right. Vertical speed was determined by the amplitude of sensorimotor rhythms (see Section II.G). A cursor sweep lasted about 3 s.

3. *Reward phase*. If the cursor successfully hit the target, the latter flashed for about 1 s. Otherwise, it just disappeared.
4. *Intertrial interval.* The screen stayed blank for about 2 s, in which the subject was allowed to blink and swallow.

Subjects were aware that the increase or decrease of a specific rhythm in their EEG produced a movement of the cursor toward the top or the bottom of the screen. They were advised to concentrate on kinesthetic imagination of upper limb movements (e.g., fist clenching) to produce a desynchronization of the mu rhythm on relevant channels (cursor up), and to concentrate on kinesthetic imagination of lower limb movements (e.g., repeated dorsiflexion of ankle joint) to produce a contrasting pattern (with possible desynchronization of mu/beta rhythm over the mesial channels, cursor down). With this simple binary task as a performance measure, training is meant to improve performances from 50–70 to 80–100% of correct hits.

D. Experimental Training

The BCI training was performed using the BCI2000 software system (Schalk *et al.*, 2004). An initial screening session was used to define the ideal locations and frequencies of each subject's spontaneous mu- and beta-rhythm activity. During this session, the subject was provided with any feedback (any representation of her/his mu rhythm), and she/he had to perform motor tasks just in open loop. The screening session consisted of the alternate and random presentation of cues on opposite sides of the screen (either up/down-vertical or left/right-horizontal). In two subsequent runs, the subject was asked to execute (first run) or to image (second run) movements of her/his hands or feet upon the appearance of top or bottom targets, respectively. This sequence was repeated three times. From the seventh run on, the targets appeared on the left or right side of the screen, and the subject was asked to move (odd trials) or to image (even trials) his/her hands for a total of 12 trials. The off-line analysis based on pairs of contrasts for each task was aimed at detecting two, possibly independent, groups of features, which would be used to train the subject to control two independent dimensions in the BCI. Analysis was carried out by replication of the same signal conditioning and feature extraction that was also used in the online processing (training session). Data sets were divided into epochs (usually 1 s long) and spectral analysis performed by means of a maximum entropy algorithm, with a resolution of 2 Hz.

Differently from the online processing, when the system only computes the few features relevant for BCI control, all possible features in a reasonable range were extracted and analyzed simultaneously. A feature vector was extracted from each epoch, composed of the spectral value at each frequency bin between 0 and 60 Hz, for each spatially filtered channel. When all features in the two data sets under comparison had been extracted, a statistical analysis was performed to assess significant differences in the values (epochs) of each feature in the two conditions. Usually a r^2 analysis is performed, but in the case of 2-level independent variables (as in this case: Tasks = {T1, T2}), *t*-test, ANOVA and other test provide analogous results. At the end of this process, the results were available (channel-frequency matrix and head topography of r^2 values) and evaluated to identify the most promising set of features to be enhanced with training.

Using information gathered from the off-line analysis, the experimenter set the online feature extractor so that a "control signal" was generated from the linear combination of the time-varying value of these features and then passed to a linear classifier. The latter's output controlled how the position of the feedback cursor was updated. During the following training sessions, the subjects were thus fed back with a representation of their mu-rhythm activity, so that they could learn how to improve its modulation.

Each session lasted about 40 min and consisted of eight 3-min runs of 30 trials. The task was increased in difficulty during the training, so two broadly different task classes could be defined.

During the training sessions, subjects were asked to perform the same kinesthetic imagination movement they were asked to do during the screening session. An upward movement of the cursor was associated with the bilateral decrease of mu rhythm over the hand area (which usually occurs during imagination of upper limb movement). Consequently, the (de)synchronization pattern correlated to imagination of lower limb movements made the cursor move downward. On the same principle, the horizontal movement of the cursor to the left (right) was linked to the lateralization of mu rhythm owing to imagination of movement of the left (right).Two different control signals were defined. The vertical control signal was obtained as the sum of the mu rhythm's amplitude over both hand motor areas; the value of the mu rhythm's amplitude over the foot area was possibly subtracted (depending on the individual subject's pattern). The horizontal control channel was obtained as the difference between the mu rhythm's amplitude over each hand's motor area.

During the first 5–10 training sessions, the user was trained to optimize modulation of one control signal at a time, that is, overall amplitude ("vertical control") or lateralization ("horizontal control") of the mu rhythm. Each control channel was associated with vertical or horizontal movement of a cursor on the screen, respectively.

For the training of "vertical" control, the cursor moved horizontally across the screen from left to right at a fixed rate, while the user controlled vertical movements toward appearing targets, justified at the right side of the screen. Similarly, for the training of "horizontal" control, the cursor moved vertically across the screen from top to bottom at a fixed rate, while the user controlled horizontal movements toward appearing targets, justified at the bottom side of the screen.

This phase was considered complete when the healthy subjects reached a performance of 70–80% correct hits (60–65% for patients) on both monodimensional tasks. In the case of bidimensional tasks, performed only by the healthy subjects, the cursor appeared in the center, and its movement was entirely controlled by the subject, using both control channels ("horizontal" and "vertical") simultaneously.

E. Domotic System Prototype Features

The core system that disabled patients attempted to use to drive electronic devices in a three-room laboratory was implemented as follows. It received logical signals from several input devices (including the BCI system) and converted them into commands that could be used to drive the output devices. Its operation was organized as a hierarchical structure of possible actions, whose relationship could be static or dynamic. In the static configuration, it behaved like a "cascaded menu" choice system and was used to feed the feedback module only with the options available at the moment (i.e., current menu). In the dynamic configuration, an intelligent agent tried to learn from use the most probable choice the user would make. The user could select the commands and monitor the system behavior through a graphic interface. The prototype system allowed the user to operate electric devices remotely (e.g., TV, telephone, lights, motorized bed, alarm, and a front door opener) as well as monitoring the environment with remotely controlled video cameras. While input and feedback signals were carried over a wireless communication, so that the mobility of the patient was minimally affected, most of the actuation commands were carried via a powerline-based control system. As described above, the generated system admits the BCI is one possible way to communicate with it, being open to accept command by other signals related to the residual ability of the patient. In this study, however, we report only the performance of the patients with the BCI system in the domotic applications.

F. Estimation of the Cortical Activity from EEG Recordings

For all healthy subjects analyzed in this study, sequential MR images were acquired and realistic head models were generated. For all the patients involved in this study, owing to the lack of their MR images, we used the Montreal average head model. Figure 1 shows a realistic head model generated for a particular experimental subject, together with the high-resolution electrode array that was employed. Scalp, skull, dura mater, and cortical surfaces of the realistic and average head models were obtained. The surfaces of the realistic head models were then used to build the boundary element model of the head as volume

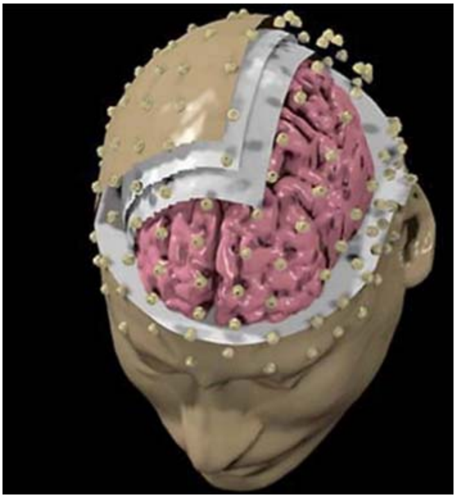

FIG. 1. A realistic head model employed for the estimation of the cortical activity. Three layers are displayed namely representing dura mater, skull, and scalp. Also the electrode positions are visible on the scalp surface.

conductor employed in the present study. Conductivity values for scalp, skull, and dura mater were those reported previously (Oostendorp *et al.*, 2000). A cortical surface reconstruction was accomplished for each subject's head with a tessellation of about 5000 triangles on average, while the average head model had about 3000 triangles.

The estimation of cortical activity during the mental imagery task was performed in each subject by use of the depth-weighted minimum norm algorithm (Babiloni *et al.*, 2000, 2003). Such estimation returns a current density estimate for each one of the thousand dipoles constituting the modeled cortical source space. Each dipole returns a time-varying amplitude representing the brain activity of a restricted patch of cerebral cortex during the entire task time-course. This rather large amount of data can be synthesized by computation of the total average of all the dipole magnitudes belonging to the same cortical ROI. Each ROI was defined according to each subject's cortical model adopted in accordance with its Brodmann areas (BAs). Such areas are regions of the cerebral cortex whose neurons share the same anatomical (and often also functional) properties. Actually, such areas are largely used in neuroscience as a coordinate system for sharing cortical activation patterns found with different neuroimaging techniques. In the present study, the activity in the following ROI was taken into account: the primary left and right motor area, related to the BA 4, the left and right primary somatosensory and supplementary motor areas.

G. Online Processing

Digitized EEG data were transmitted in real time to the BCI2000 software system (Schalk *et al.*, 2004), which performed all necessary signal processing and displayed feedback to the user. The processing pipe can consist of several stages, which process the signal in sequence. Only the main ones will be mentioned below: spatial filter, spectral feature extraction, feature combination, and normalization.

Spatial filter. A general linear combination of data channels was implemented by defining a matrix of weights multiplied by each time sample of potentials (vector). This allowed implementation of different spatial filters, such as the estimation of cortical current density waveforms on the cortical ROIs, by use of weights derived as explained in Section II.

Spectral feature extraction was performed every 40 ms, using the latest 300 ms of data. An autoregressive spectral estimator, based on the maximum entropy algorithm, yielded an amplitude spectrum with resolution of 2 Hz. Maximum frequency was limited to 60 Hz.

Feature selection and combination. A small subset of those spectral features (frequency bins $\times$ EEG channels or ROIs) that were significantly modulated by the motor imagery tasks was linearly combined to form a single control signal. Selection of responsive channels and frequency bins, and determination of combination weights, took place before each online session (see Section II.H). In general, only two or three spectral amplitude values (depending on individual patterns) were generally used to obtain the control signal.

Normalization. The control channel was detrended to avoid cursor bias, and scaled so that the resulting vertical deflection of the feedback cursor was visible but not saturated. In fact, the vertical position of the cursor was updated every 40 ms by a number of pixels (positive or negative) equal to the output by this stage. Normalization was adaptive, and based on the estimate of the moving average and standard deviation of the control signal. During the very first session of each subject (screening session), since no off-line analysis was available to guide feature selection and combination, the subject was given no online feedback (targets only).

H. Off-line Analysis

After artifact rejection, the EEG intervals corresponding to the feedback phase were binned into two classes—up or down, depending on the target appearing in each trial. The spatial filtering and feature extraction stages of the online processing were replicated. Since no feedback delay issue had to be considered during the off-line analysis, spectral estimation was computed on

1-s-long epochs, overlapped by 50% (i.e., only five spectral estimates had to be computed for each 3-s-long trial, yielding about 600 spectral estimates per class for the whole session).

For each of the EEG channels or ROI waveforms employed, and for each one of the 30 frequency bins in which the EEG spectral interval was divided, a contrast was performed, to assess statistically significant modulations induced in a specific feature. To this end, we computed for each feature (dependent variable) the coefficient of determination (r^2), that is, the proportion of the total variance of the feature samples accounted for by target position. This index had been previously utilized in literature for similar experimental setups (Wolpaw *et al.*, 2002) and allows direct comparison with published results. A fictitious independent variable was created, using values $+1$ or -1 in correspondence of "down" or "up" epochs, respectively. A negative sign was attributed to the r^2 value when dependent and independent variables were contravariant. If we look at statistical results from a different perspective, features characterized by a high r^2 value are those that maximize prediction of the current target. Higher values of r^2 indicate that the subject has gained steadier control of EEG rhythms (in fact they generally increase during the training, from values below 0.1 to values above 0.3).

III. Results

A. Experimentation with Healthy Subjects

By applying the aforementioned signal processing techniques in the context of the proposed BCI setup, we used the r^2 as an index of reliability of the recognition of subjects' mental activity. The comparisons between the maximum values of the r^2 that takes into account the best usable feature (frequency/ROI or scalp channel) were performed for the unprocessed EEG data as well as for the estimated cortical activity by use of the procedure already described above. Mean r^2 is 0.20 ± 0.114 SD for the unprocessed EEG case, 0.55 ± 0.16 SD for the cortical current density estimation case. The differences are relatively constant across the subjects, and a paired Student's t test returned a highly significant difference between the two conditions ($p < 10–5$). Once all the healthy subjects had completed the training, we chose the two with the best performance and trained them to use a different BCI application, namely the old game of electronic ping-pong.

Figure 2 shows a sequence with two subjects who played a ping-pong game with the use of the BCI system realized through the guidelines provided above. The subjects are able to control the movement of the vertical cursors while the white cursor, simulating the ball, moves across the screen. The sequence reads

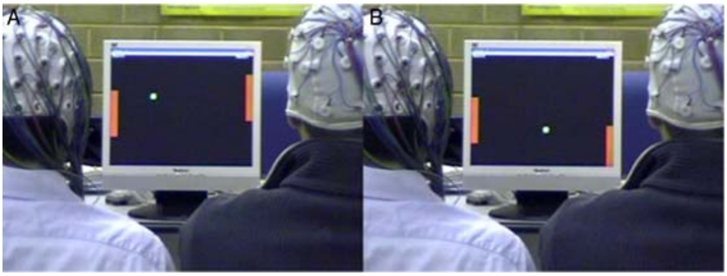

FIG. 2. Sequence of two healthy subjects that play the ping-pong with the use of the BCI described in the text. Subjects control the cursor movement along the vertical directions. Sequence from (A) to (B).

from A to B. The two subjects are able to control the device by performing 95 and 96% of successful hits during a game lasting several minutes, with a rate of about five correct hits per minute per subject.

B. Experimentation with the Patients

As described previously in Section II, all the patients underwent a standard BCI training. In 8–12 sessions of training, four out of six patients were able to develop a sensorimotor reactivity sufficiently stable to control the cursor with performance in excess of 63%. They could image either foot or hand movements and the related sensorimotor modulation was mainly located at midline centro-parietal electrode positions. Two patients were not able to control the cursor with a percentage superior to 55% and were not taken into consideration further here in the context of the use of the BCI system. At the end of the training, the four patients were able to control the several system outputs, namely the domotic appliances. According to the early results of the questionnaire, these patients were independent in the use of the system at the end of the training and they experienced (as they reported) "the possibility to interact with the environment by myself." A schematic evaluation of the degree of system acceptance revealed that among the several system outputs, the front door opener was the most accepted controlled device. Such an application that controls the access to the domotic environment in the three-room rehabilitation laboratory is illustrated in the first row of Fig. 3. In particular, the figure shows two sequences of commands realized through the BCI system. In the first row, with (A) and (B) there is a sequence in which the BCI system was able to open a door. The red circles of the first row highlight a person entering through the door that was opened by the successful modulation of the EEG mu rhythm. The second row shows the

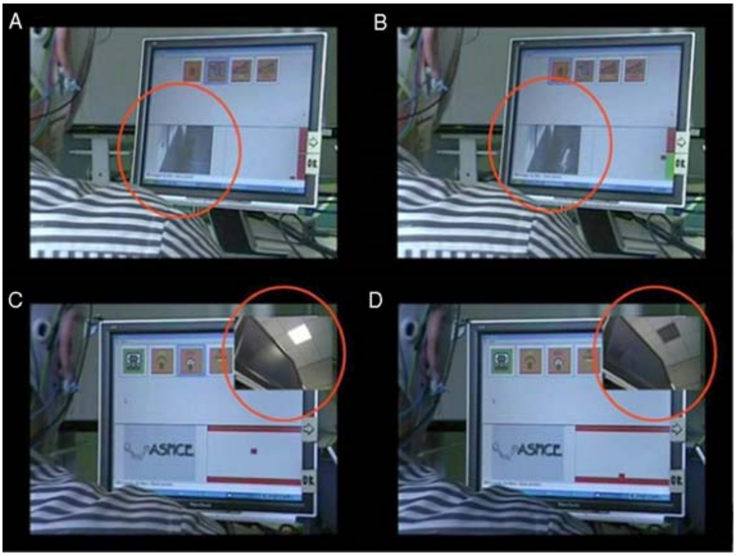

FIG. 3. Two sequences of commands realized through the BCI systems at the Fondazione Santa Lucia in Rome. In the first row, with (A) and (B) there is a sequence with the BCI system that opens a door. In the red circles of the first row a person enters through a door that was opened with the use of the BCI based on the EEG mu rhythm. The second row (C and D) shows the closure of a light with the use of the same BCI system. The BCI system is controlled with the cursor at the right of the screen.

switching-off of a light with the use of the same BCI system. The feedback from the BCI system is displayed on the screen with the cursor positioned at the lower right of the screen.

IV. Discussion

The data reported here suggest that it is possible to retrieve the cortical activity related to mental imagery by using sophisticated high-resolution EEG techniques, obtained by solving the inverse linear problem with the use of realistic head models. Of course, the analysis of the distribution of the potential fields associated with the motor imagery in humans has already been described (Babiloni *et al.*, 2001; Cincotti *et al.*, 2002; Wolpaw *et al.*, 2002). In the context of the brain–computer interface, however, it assumes importance if the activity related to the imagination of arm movement could be better detected by the use of such high-resolution EEG techniques than that of unprocessed EEG. It is worth noting that the cortical estimation methodology illustrated above is suitable for the online applications needed for the BCI device. In fact, despite the use of sophisticated realistic head models for scalp, skull, dura mater, and cortical surface, the estimation of the instantaneous cortical distribution from the acquired potential measures required a limited amount of time for a matrix multiplication. Such multiplication occurs between the vector data gathered and the pseudoinverse matrix, which is stored off-line before the start of the EEG acquisition process. In the pseudoinverse matrix is enclosed the complexity of the geometrical head modeled with the boundary element or with the finite element modeling technique, as well as the a priori constraints used for the minimum norm solutions.

The described methodologies were applied in the context of the neurorehabilitation of a group of six patients affected by Duchenne muscular dystrophy. Four out of six were also able to control with the BCI system several electronic devices disposed in the three-room facility we described previously. The devices guided by them with an average percentage score of 63% are (i) a simple TV remote commander, with the capabilities to switch the device on and off as well as the capability to change a TV channel, (ii) the switching of the light in a room on and off, and (iii) the switching on and off of a mechanical engine for opening a door of the room. These devices can, of course, also be controlled by different inputs signals that eventually use a residual degree of muscular control of patients. This experiment was reported here because it demonstrates the potential for the patient to accept and adapt themselves to the use of the new technology for the control of their domestic environment.

There is a large trend in the modern neuroscience field to move toward invasive electrode implants to record cortical activity in both animals and humans for the realization of an efficient BCI device (Donoghue, 2002; Kennedy *et al.*, 2000; Taylor *et al.*, 2002). In this chapter, we have presented evidence to suggest an alternative methodology for the estimation of such cortical activity in a noninvasive way, by using the possibilities offered by an accurate modeling of the principal head structures involved in the transmission of the cortical potential from the brain surface to the scalp electrodes.

Acknowledgments

This work was supported by the Minister for Foreign Affairs and the Department for Scientific and Technological Development in the framework of a bilateral project between Italy and China (Tsinghua University), and by the European Union through COST Action BM0601 NEUROMATH. We acknowledge two other institutions as the FP7 projects TOBI and SM4ALL. It was also supported in part by a grant from NIH (EB006356) in the USA and from a grant of the Fondazione Banca Nazionale Comunicazioni (BNC), Rome. This chapter reflects only the authors' views, and funding agencies are not responsible for any use that may be made of the information contained herein.

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