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Adaptive Brain Interfaces for Communication and Control

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Abstract

This paper describes our work on a portable non-invasive brain-computer interface (BCI), called Adaptive Brain Interfaces (ABI), that analysis online the user's spontaneous electroencephalogram (EEG) signals from which a neural classifier recognizes 3 different mental states. The outputs of the classifier are used as mental commands to operate communication and control devices. Although still at a research stage, BCIs offer the possibility to augment human capabilities in a natural way and are particularly relevant as an aid for paralyzed humans.

1 Introduction

There is a growing interest in the use of physiological signals as an alternative interaction channel for physically-disabled as well as able-bodied people. In particular, recent experiments have shown the possibility to use the brain electrical activity for communication and control. This requires the on-line analysis of brainwaves to derive information about the subjects' mental state that is then mapped into some external action such as selecting a letter from a virtual keyboard or moving a robotics device (Birbaumer et al., 1999; Kennedy et al., 2000; Millán, 2002; Millán et al., 2002b; Pfurtscheller & Neuper, 2001; Renkens & Millán, 2002; Serruya et al., 2002; Taylor, Helms Tillery, & Schwartz, 2002; Wolpaw & McFarland, 1994). This alternative communication and control channel, which does not require the user to perform any kind of physical action, is called a *brain-computer interface (BCI)*. In this paper we give an overview of one of such non-invasive portable BCIs, called Adaptive Brain Interface (ABI), and discuss some brain-actuated applications.

BCI may monitor a variety of brainwave phenomena. Most BCIs use electroencephalogram (EEG) signals; i.e., the brain electrical activity recorded from electrodes placed onto the scalp. The main source of the EEG is the synchronous activity of thousands of cortical neurons. Measuring the EEG is a simple non-invasive way to monitor brain electrical activity, but it does not provide detailed information on the activity of single neurons that could be recorded from microelectrodes surgically implanted in the cortex (Kennedy et al., 2000; Serruya et al., 2002; Taylor, Helms Tillery, & Schwartz, 2002). In this paper we will not discuss further invasive techniques, since only in very exceptional cases it is motivated to implant electrodes into the human brain. Some groups exploit evoked potentials; i.e., the automatic responses of the brain to external stimuli. Evoked potentials are, in principle, easy to pick up but constrain the subject to synchronize themselves to the external machinery. A more natural and suitable alternative for controlling devices is to analyze components associated with spontaneous mental activity. In our case, we look at local variations of EEG rhythms over several cortical areas related to different cognitive mental tasks such as imagination of movements, arithmetic operations, or language. The approach aims at discovering mental-specific EEG patterns embedded in the continuous EEG signal associated. We also apply machine learning techniques to train the classifier and follow a mutual learning process where the user and the brain interface are coupled and adapt to each other. This accelerates the training process. For instance, in our case subjects achieve good performance in just a few hours of training in the presence of feedback. Also, analysis of learned EEG patterns confirms that for a subject to operate satisfactorily his/her personal BCI, the latter must fit the individual features of the former (Millán et al., 2002a; Millán et al., 2002b).

2 Asynchronous BCI and Experimental Protocol

Most EEG-based BCIs are based on synchronous protocols where the subject must follow a fixed repetitive scheme to switch from a mental task to the next (Birbaumer et al., 1999; Pfurtscheller & Neuper, 2001; Wolpaw & McFarland, 1994). In these synchronous BCI systems, the EEG phenomena to be recognized are time-locked to a cue and a trial lasts from 4 to 10 or more seconds. On the contrary, our approach, as a few other systems (Birch & Mason, 2000), relies on asynchronous protocols where the subject makes voluntary self-paced decisions on when to stop doing a mental task and start immediately the next one. This makes the system very flexible and natural to operate, and yields rapid response times (e.g., 0.5 second in our case).

After a short evaluation, every user selects the 3 mental tasks that s/he finds easier out of the following: "relax", imagination of "left" and "right" hand (or arm) movements, "cube rotation", "subtraction", and "word association". The tasks consist on getting relaxed, imagining repetitive self-paced movements of the limb, visualizing a spinning cube, performing successive elementary subtractions by a fixed number (e.g., 64–3=61, 61–3=58, etc.), and concatenating related words. Relax is done with eyes closed, whereas the other tasks are performed with eyes opened. But the recognition of the task "relax" is *not* based on the detection of eye movements.

In a training session, subjects participate in several consecutive training trials (normally four), each lasting 5 minutes approximately and separated by breaks of 5-10 minutes. The subject is seated and switches randomly every 10-15 seconds between the three tasks. Subjects receive feedback online through three colored buttons on a computer screen. Each button is associated to one of the mental tasks to be recognized. A button flashes when the local neural classifier embedded in the BCI recognizes the corresponding mental task. After each training session, or training trial depending on the subjects, the local neural classifier is optimized offline.

Once the subject has reached a sufficient control of the interface, what normally takes from 3 to 5 days, s/he may proceed to the operation of the brain-actuated applications described in Section 4. It must be noted that not all the subjects we have worked with have undertaken this second phase, although all of them have achieved good results at the end of the training phase. While operating a brain-actuated application, the subject does essentially the same as during the training trial, the only difference being that now s/he switches to the next mental task as soon as the desired action has been carried out (instead of keeping that mental task for 10-15 seconds).

EEG potentials are recorded at the 8 standard fronto-centro-parietal locations F3, F4, C3, Cz, C4, P3, Pz, and P4. The sampling rate is 128 Hz. The raw EEG potentials are first transformed by means of a surface Laplacian (SL) computed globally by means of a spherical spline of order 2. This spatial filtering yields new potentials that should represent better the cortical activity due only to local sources below the electrodes. Then, we use the Welch periodogram algorithm to estimate the power spectrum of each SL-transformed channel over the last second. We average 3 segments of 0.5 second with 50% overlap, what gives a frequency resolution of 2 Hz. The values in the frequency band 8-30 Hz are normalized according to the total energy in that band. Thus an EEG sample has 96 features (8 channels times 12 components each). The periodogram, and hence an EEG sample, is computed every 62.5 ms (i.e., 16 times per second).

3 Local Neural Classifier

Usually, EEG-based BCIs make binary decisions as they seek to recognize 2 different mental tasks and reach accuracy levels that, in general, are around 90%. Our BCI achieves error rates below 5% for 3 mental tasks, while correct recognition is 70% (or higher). In the remaining cases (around 20-25%), the classifier does not respond, since it considers the EEG samples as uncertain. The incorporation of rejection criteria to avoid making risky decisions is an important concern in BCI. From a practical point of view, a low classification error is a critical performance criterion for a BCI, for otherwise users would be frustrated and stop utilizing the interface.

ABI achieves this performance using a local neural network trained to classify EEG samples as mental task #1, #2, #3 or "unknown". The classifier is such that every unit represents a prototype of one of the mental tasks to be recognized (Millán et al., 2002b). The output of the classifier gives an estimation of the posterior class probability distribution for an EEG sample, based on the Mahalanobis distance from the sample to the different prototypes. Then the output of the classifier is the task with the highest posterior probability provided that it is above a given confidence threshold (otherwise the response is "unknown"). Finally, ABI responds every 0.5 seconds by averaging the outputs of the network for 8 consecutive EEG samples.

Normally, people reach the above-mentioned performances at the end of a few days of moderate training (around 1/2 hour daily). But other subjects have also reached them in a single day of intense training. It is worth noting that one of these latter subjects is a physically impaired person suffering from spinal muscular atrophy.

4 Brain-Actuated Devices for Communication and Control

We have developed several demonstrators that illustrate the wide range of systems that can be linked to ABI. Thus, the brain interface can be used to select letters from a *virtual keyboard* on a computer screen and write a message. Initially, the whole keyboard (26 English letters plus the space to separate words, for a total of 27 symbols organized in a matrix of 3 rows by 9 columns) is divided in three blocks, each associated to one of the mental tasks. The association between blocks and mental tasks is indicated by the same colors as during the training phase. At this first level each block contains an equal number of symbols, namely 9 (3 rows by 3 columns). Then, once the neural classifier recognizes what the subject is concentrated on, the corresponding block is split in 3 smaller blocks, each having 3 symbols this time (1 row). As one of this second-level blocks is selected (the neural classifier recognizes the corresponding mental task), it is again split in 3 parts. At this third and final level, each block contains 1 single symbol. Finally, to select the desired symbol, the user concentrates in its associated mental task as indicated by the color of the symbol. This symbol goes to the message and the whole process starts over again. Thus, the process of writing one letter requires three decision steps.

The actual selection of a block incorporates some additional reliability measures (in addition to the statistically-based rejection criteria) for the purpose of increasing the likelihood of correct functioning, especially during the different public demonstrations we have given (including live

TV programs). In particular, a part of the keyboard is only selected when the corresponding mental task is recognized three times in a row. Also, in the case of an eventual wrong selection, the user can undo it by concentrating immediately on one of the mental tasks of his/her choice. Thus the system waits a short time after every selection (3.5 seconds) before going down to next level. The mental task used to undo selection is that for which the user exhibits the best performance. For our trained subjects, it takes 22.0 seconds on average to select a letter. This time includes recovering from eventual errors (Millán, 2003). Despite all these additional checks before the actual selection of a block, this time compares favorably with some other brain-actuated virtual keyboards requiring 1 minute (Pfurtscheller & Neuper, 2001) or 2 minutes (Birbaumer et al., 1999) per letter.

ABI makes it also possible the continuous control of a mobile robot (emulating a motorized *wheelchair*) generating non-trivial trajectories among different rooms in a house-like environment. A key idea is that the user's mental states are associated to high-level commands (e.g., "turn right at the next occasion") that the robot executes autonomously using the readings of its on-board sensors. Another critical aspect is that subjects can issue high-level commands at any moment. This is possible because the operation of the BCI is asynchronous and does not require waiting for external cues, unlike synchronous approaches. The robot relies on a behavior-based controller to implement the high-level commands that guarantees obstacle avoidance and smooth turns. In this kind of controller, on-board sensors are read constantly and determine the next action to take. The mapping from the user's mental states to the robot's behaviors is not simply one-to-one, but, in order to achieve a more flexible control of the robot, the mental states are just one of the inputs for a finite state automaton with 6 states (or behaviors). The transitions between behaviors are determined by the 3 mental states (#1, #2, #3) and 6 perceptual states of the environment determined from the robot's sensory readings (left wall, right wall, wall or obstacle in front, left obstacle, right obstacle, and free space). The interpretation of a mental state depends on the perceptual state of the robot. Thus, in an open space the mental state #2 means "left turn" while the same mental state is interpreted as "follow left wall" if a wall is detected on the left-hand side. Similarly, mental state #3 means "right turn" or "follow right wall"; mental state #1 always implied "move forward". The robot will continue executing a behavior until the next mental state is received. Two subjects have mentally driven the robot along non-trivial trajectories in an office environment visiting 3 or 4 rooms in the desired order. Furthermore, experimental results, partially reported in (Renkens & Millán, 2002), show that mental control of the robot is only marginally worse than manual control.

5 Discussion

Despite recent progress, EEG-based BCIs are still limited by a low channel capacity (number of bits that can be sent in a second). The main reason is that EEG suffers from a reduced spatial resolution. On the contrary, recent experiments with invasive BCIs (where microelectrodes were implanted in the cortex of monkeys and measured the activity of single neurons) show the possibility to use the brain electrical activity to directly control in real time devices such as a computer cursor or a prosthetic limb (Serruya et al., 2002; Taylor, Helms Tillery, & Schwartz, 2002). The challenge is to achieve similar results with non-invasive technologies. In this sense, recent progress in EEG analysis suggests that a sufficient number of mental states could be recognized to operate devices faster and more naturally. In cooperation with the Functional Brain Mapping Laboratory of the Geneva University Hospital, we are exploring the use of one of their techniques that transforms scalp potentials (recorded with a sufficiently high number of electrodes—32, 64 or more) to brain maps to get detailed information on the activity of small cortical areas (Michel et al., 2001). The neural classifier embedded in the BCI would work upon selected parts of these brain maps instead of using EEG features.

Another key concern is to keep the BCI constantly tuned to its owner. This requirement arises because, as subjects gain experience, they develop new capabilities and change their brain activity patterns. In addition, spontaneous brain signals changes naturally over time. Hence it is critical to adapt on-line the neural classifier while the subject operates the brain interface.

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