Adaptive Brain Interfaces—ABI: Simple Features, Simple Neural Network, Complex Brain-Actuated Devices

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Abstract

This paper reports results with ABI, a portable non-invasive brain-computer interface. It uses 8 scalp electrodes to measure spontaneous EEG signals from which we extract simple power spectral features. The features are fed to a simple local neural network that recognizes reliably 3 different mental states. We compare the performance of this local classifier to more complex time-processing neural networks. We also illustrate the control of a complex brain-actuated device; i.e., a robot moving along smooth and safe paths between rooms.

1 Introduction

There is a growing interest in the use of physiological signals for communication and operation of devices for the severely motor disabled as well as for able-bodied people. Over the last years evidence has accumulated to show the possibility to analyze brainwaves on-line 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 [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. This alternative communication and control channel is called a *brain-computer interface (BCI)*.

A BCI may monitor a variety of brainwave phenomena. Some groups exploit evoked potentials generated in response to external stimuli (see [1] for a review). Evoked potentials are, in principle, easy to pick up but constrain the subject to get synchronized to the external machinery. A more natural and practical alternative is to rely upon components associated with spontaneous mental activity. Thus, [4] measures slow cortical potentials of the EEG over the top of the scalp, which indicate the overall preparatory excitation level of a cortical network. Other groups look at local variations of EEG rhythms. The most used of such rhythms are related to the imagination of movements and are recorded from the central region of the scalp overlying the sensorimotor cortex [3], [6]. But, in addition to motor-related rhythms, other cognitive mental tasks are being explored [5], [7] as a number of neurocognitive studies have found that different mental tasks—such as imagination of movements, arithmetic operations, or language—activate local cortical areas at different extents. In this latter case, rather than looking for predefined EEG phenomena as in the previous paradigms, the approach aims at discovering EEG patterns embedded in the continuous EEG signal associated with different mental states. Finally, another kind of spontaneous signals is the direct activity of neurons in the motor cortex [8], [9], [10].

[3] and [4] have demonstrated that some subjects can learn to control their brain activity through appropriate, but lengthy, training in order to generate fixed EEG patterns that the BCI transforms into external actions. Other groups follow machine-learning approaches to train the classifier embedded in the BCI [5], [6], [7], [11]. Most of these approaches are based on a mutual learning process where the user and the brain interface are coupled together and adapt to each other [5], [6], [7]. This should accelerate the training time. Thus, [7] has allowed subjects to achieve good performances in just a few hours of training in the presence of feedback.

Most of these works deal with the recognition of just 2 mental states [3], [4], [5], [6] or report classification errors bigger than 15% for 3 or more tasks [6], [11]. An exception is the approach called *Adaptive Brain Interface (ABI)* [7] that achieves error rates below 5% for 3 mental tasks, while correct recognition is 70%. Contrarily to almost all other BCIs, ABI relies upon an *asynchronous* protocol where the subject makes self-paced decisions on when to stop doing a mental task and start immediately the next one[1]. This makes ABI very flexible and natural to operate, and yields rapid response times—the system tries to recognize what mental task the subject is concentrated on every 1/2 second.

ABI has a simple local neural classifier where every RBF unit represents a prototype of one of the mental tasks to be recognized. Experimental results have shown that this local network performs much better than

[1] In the case of *synchronous* protocols, the subject must follow a fixed repetitive scheme to switch from a mental task to the next [3], [4], 6]. A trial consists of two parts. A first cue warns the subject to get ready and, after a fixed period of several seconds, a second cue tells the subject to undertake the desired mental task for a predefined time. The EEG phenomena to be recognized are time-locked to the last cue and the BCI responds with the average decision over the second period of time. In these synchronous BCI systems, a trial lasts from 4 to 10 or more seconds.

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more sophisticated approaches such as support vector machines and equally well (or slightly better) than temporal-processing neural networks such as time-delay neural networks (TDNN) [12] and Elman-like recurrent networks [13]. This is achieved by simply averaging the outputs of the network for 8 consecutive EEG samples (and still yielding a global response every 1/2 seconds). The first part of this paper summarizes the results of this comparative study among these three common strategies to incorporate temporal dynamics of brain activity into the classifier.

With this embedded local network, ABI is being used to operate several brain-actuated devices; namely, a virtual keyboard, a computer game and a mobile robot (see [2] for a brief discussion). In the second part of this paper, we briefly describe this latter application.

2 Experimental Protocol

In the comparative study, five volunteer healthy subjects concentrate on 3 mental tasks out of a set of 5 possible. These are: "relax", imagination of "left" and "right" hand movements, "cube rotation", and "subtraction". The tasks consist on getting relaxed, imagining repetitive movements of the hand, visualizing a cube rotating around one of its axis, and performing successive elementary subtractions by a fixed number (e.g., 64–3=61, 61–3=58, 58–3=55, etc.). In a recording session, the subject performs the selected task during 10 to 15 seconds, and he/she chooses when to stop doing it and the next to be undertaken. For the training and testing of the classifier, the user tells an operator which task is going to perform so that the operator can label the corresponding sequence of EEG samples. Each recording session lasts about 5 minutes.

During the sessions users receive feedback as follows. There are three buttons on the computer screen, each of a different color and associated to one of the mental tasks to be recognized. A button lights up when an arriving EEG sample is classified as belonging to the corresponding mental task.

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. We use the *Welch* periodogram algorithm to estimate the power spectrum of each channel over the last second. Epochs are 0.5 seconds long. 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). In separate studies we have found that these simple power spectral features lead to better or similar performances than more elaborated features such as parameters of autoregressive models and wavelets [14].

In the case of the brain-controlled mobile robot, a volunteer healthy subject concentrates on the 3 mental tasks "relax", imagination of "left" hand movements and "cube rotation". The subject was moderately trained during a few consecutive days, around 1/2 daily. After that, the subject tried to control mentally the mobile platform described below for 2 days.

3 Temporal Processing of Brain Activity

In this section we compare three neural network architectures in the recognition of 3 mental tasks from spontaneous EEG signals for five subjects. The performance of the different networks have been measured in a hard experimental setup; namely, generalization over different sessions while analyzing short-time windows. The difficulty lies in that brain activity changes from a session (with which data the classifier is trained) to the next (where the classifier is applied).

Subjects MJ, MJR and CGS are advanced users of the interface, while subjects FM and MC are beginners. The performance is measured by the *accuracy*, defined as the number of correct classifications divided by the total number of samples, and the *error*, defined as the number of incorrect classifications divided by the total number of samples. It is worth noting that accuracy and error do not always sum to 100% because the networks may give "unknown" responses to uncertain samples. 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 frustrate and stop utilizing the interface.

Table 1 gives, for each of the subjects, the performances of TDNN, Elman and local networks that average the response to 8 consecutive EEG samples. In this case, we use a confidence probability threshold, as the output of these networks is the posterior probability distribution for a sample to belong to the different classes. For each subject, the first row gives the accuracy while the second row reports the error, for the corresponding probability threshold (from 0.70 to 0.95). Averaging is a simple method to combine consecutive responses and, in our case, yields similar or better results than other techniques (e.g., product combination). Space limitations prevent the discussion of these alternatives. [5] and [11] report significant improvements in the classification of EEG signals when averaging over several seconds (from 2.5 to 5 seconds).

Regarding the TDNN and Elman networks, we have explored architectures with different numbers of hidden units. It seems that networks with in between 10 and 50 units perform equally well. In the case of TDNN the time delay is 8 samples, for compatibility with the averaging technique. As for the local networks, they have a small number of prototypes per mental task, namely 4 units. Thus the classifier consists of just 12 units. Interestingly, Table 1 points out that these simple local networks achieve lower relative errors than TDNN and Elman networks and even better accuracy.

Table 1. Performances of TDNN, Elman and local networks for different probability thresholds. Shadowed figures indicate the best performance for each network. The response of the networks is the average of 8 consecutive EEG samples. For each subject, the first row gives the accuracy and the second reports the error.

Subject	TDNN						Elman						Local					
	0.70	*0.75*	*0.80*	*0.85*	*0.90*	*0.95*	*0.70*	*0.75*	*0.80*	*0.85*	*0.90*	*0.95*	*0.70*	*0.75*	*0.80*	*0.85*	*0.90*	*0.95*
MJ	52.4	47.6	41.8	35.3	30.5	16.8	63.4	60.3	41.4	36.3	29.8	18.2	65.8	61.6	57.8	53.7	48.6	40.1
	10.6	08.6	06.8	02.4	01.0	00.7	11.6	08.2	07.5	04.5	02.7	00.7	11.3	09.6	08.2	06.2	05.5	02.7
MJR	75.6	71.5	65.6	68.9	62.2	43.3	73.3	69.6	65.2	64.4	60.7	44.4	71.5	67.8	64.1	60.4	55.9	51.5
	14.8	12.6	09.6	06.3	04.1	02.6	14.8	11.8	09.3	05.5	03.7	02.2	10.4	07.1	05.5	03.7	02.6	02.2
CGS	61.2	64.0	45.0	33.7	19.7	05.5	68.6	64.0	47.9	36.9	26.5	17.2	58.8	56.8	54.2	52.3	50.7	48.7
	08.7	06.5	04.2	02.3	00.6	00.0	14.9	11.3	09.1	07.8	04.9	01.3	08.2	06.9	04.7	03.0	02.1	01.5
FM	28.6	19.8	15.9	14.3	08.7	06.3	27.8	22.2	16.7	13.5	11.1	03.2	54.8	51.6	47.6	43.7	39.7	33.3
	12.7	11.1	06.3	03.2	00.8	00.0	15.1	11.1	07.1	01.6	00.0	00.0	10.3	08.7	06.3	06.3	04.8	02.4
MC	15.8	09.8	05.5	04.5	03.4	01.8	21.4	13.7	08.4	04.7	03.7	01.6	42.0	38.3	33.5	28.2	21.9	16.6
	10.3	04.2	00.8	00.3	00.3	00.0	15.0	05.8	01.8	00.8	00.3	00.0	20.8	17.4	15.6	11.3	06.3	03.4

These experiments illustrate that neither the advanced users nor the beginners achieve high recognition rates. However, the modest accuracy figures achieved by advanced users (MJ, MJR and CGS) are compensated by the low percentages of wrong decisions. For the best networks and probability thresholds, the accuracy is 60% for MJR, 52% for CGS, 40% for MJ, while the error is always below 4%. Thus, errors are, at least, 15 times smaller than the classification accuracy. These absolute and relative classification errors are also achieved by the beginner users (FM and MC) who, however, reach lower accuracies (33% and 17%, respectively). In addition to the appealing property of low classification errors, the system exhibits another key feature. Since it makes decisions every 1/2, a modest classification accuracy (in combination with low errors) does not preclude practical operation. In fact, recognition of a desired mental task takes in between 1 and 1.5 seconds on average. It is worth noting that 1 second is the shortest time necessary for recognition as EEG samples are derived from sequences that are 1-second long—and so subjects must stay concentrated on the task during that time to obtain a good codification.

4 Brain-Actuated Control of a Mobile Robot

The task is to drive a mobile robot among different rooms in a house-like environment (see Figure1). The robot is a Khepera mobile platform. This mobile platform closely mimics the operation of a motorized wheelchair. The robot moves at a speed of one-third its diameter per second, similar to the speed of a wheelchair in indoor environments.

To make the robot move along a given trajectory it is necessary to determine the speed of the motors controlling the wheels at each time step. Obviously, this is impossible by means of just three mental commands. The key idea is that the user's mental states are associated to high-level commands that the robot executes autonomously using the readings of its on-board sensors. Also, once a mental state is recognized and the associated high-level command is sent to the mobile platform, the subject does not need to keep that mental state (which would be exhaustive). Another critical aspect for the continuous control of the robot is that subjects can issue high-level commands at any moment as the operation of the BCI is self-paced and does not require waiting for external cues (as compared to synchronous approaches). The robot will continue executing a high-level command until the next is received or the intended goal is reached. In this way a given mental state, for instance "left", will be associated to make the robot turn left and cross a doorway.

Finally, an essential element for the correct control of the robot is to give an appropriate *feedback* to the user to inform him/her of what the robot is doing (or about to do next). This is done by means of three lights on top of the robot, with the same colors as the buttons used during the training phase. This simple feedback, in combination with the user's knowledge of the control system, allows the user to correct rapidly the trajectory of the robot in case of errors in the recognition of the mental states or errors in the execution of the desired behavior (due to the limitations of the robot's sensors). Testing has put forward the essential role of feedback.

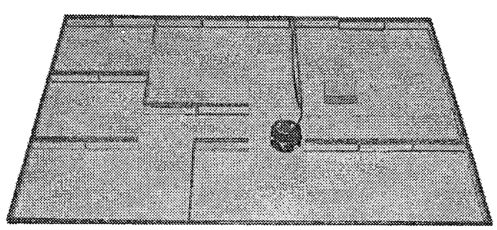

Figure 1. The working environment for the robot made of different connected rooms.

After a few days of consecutive training, less than 4 hours in total, the subject achieved a satisfactory control of his individual brain interface. Correct recognition was around 85% while errors were slightly below 5%. For the remaining 10% of EEG samples, there was no response.

Then, the subject started to use the learned neural classifier to control the mobile robot. This is considerably harder than the problem faced during the first phase of training. Indeed, now the subject has to tackle two tasks: concentration on the desired mental state as before, and determination of the appropriate behavior of the robot to drive it to the target destination. This second task requires, in turn, observing the current situation of the robot (position and active behavior) as well as remembering the how the controller works.

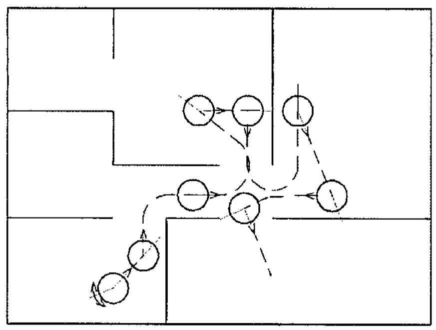

Figure 2. Trajectory followed by the robot under the mental control of the subject. The robot started in the bottom left room and then visited 3 other rooms, top center, top right and bottom right, sequentially.

After two days of practice (around 2 hours in total), the subject was able to drive the robot along a non-trivial trajectory. Figure 2 shows this trajectory that made the robot visit 4 different rooms. This was obtained at the end of the second day of training with the robot. It is worth noting that this was achieved during a public demo, with the corresponding increase of stress for the subject. To generate this trajectory the subject was driving the robot for about 10 minutes continuously. Although the subject brought the robot to the desired rooms each time, there were a few occasions where the robot did not follow the optimal trajectory. This was mainly because the interface took a longer time than usual to recognize the subject's mental state. In other couple of situations, the robot's sensors were not working properly and perceived an object too close, thus making the robot stop to avoid collisions. In this case, the subject needed to turn the robot against the offending wall and then resume the trajectory.

5 Conclusions

In this paper we have explored different neural networks for the classification of 3 mental tasks from spontaneous EEG signals. From these signals we extract simple power spectral features, and the neural classifiers make decisions every 1/2 second. It turns out that a simple local neural classifier, which averages the response to 8 consecutive EEG samples, is to be preferred to more complex time-processing networks. It is then possible, for users with some hours of training, to operate different brain-actuated applications. We have described one of them, namely a brain-controlled robot emulating a motorized wheelchair. This demonstrates the feasibility of controlling non-trivial robotics devices by means of a portable non-invasive BCI.

We have tested the above networks in a hard experimental setup; namely, generalization over sessions while analyzing short-time windows. A current area of research is to adapt on-line the classifier while the subject operates a brain-actuated application. In this respect, the current local neural classifier is better suited than other methods due to its robustness against catastrophic interference and simple learning rule.

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