Brain-Controlled Robots

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The idea of moving robots or prosthetic devices not by manual control, but by mere "thinking" (i.e., the brain activity of human subjects) has fascinated researchers for the last 30 years, but it is only now that first experiments have shown the possibility to do so. How can brainwaves be used to directly control robots? Most of the hope for brain-controlled robots comes from invasive approaches that provide detailed single neuron activity recorded from microelectrodes implanted in the brain [1]. The motivation for these invasive approaches is that it has been widely shown that motor parameters related to hand and arm movements are encoded in a distributed and redundant way by ensembles of neurons in the motor system of the brain—motor, premotor and posterior parietal cortex. For humans, however, it is preferable to use non-invasive approaches to avoid health risks and the associated ethical concerns. Most non-invasive brain-computer interfaces (BCI) use electroencephalogram (EEG) signals; i.e., the electrical brain activity recorded from electrodes placed on the scalp. The main source of the EEG is the synchronous activity of thousands of cortical neurons. Thus, EEG signals suffer from a reduced spatial resolution and increased noise due to measurements on the scalp. As a consequence, current EEG-based brain-actuated devices are limited by a low channel capacity and are considered too slow for controlling rapid and complex sequences of robot movements. But, recently, we have shown for the first time that online analysis of EEG signals, if used in combination with advanced robotics and machine learning techniques, is sufficient for humans to continuously control a mobile robot [2] and a wheelchair [3]. In this article we will review our work on non-invasive brain-controlled robots and discuss some of the challenges ahead.

1. Spontaneous EEG and Asynchronous Operation

Non-invasive EEG-based BCIs can be classified as "evoked" or "spontaneous". An evoked BCI exploits a strong characteristic of the EEG, the so-called evoked potential, which reflects the immediate automatic responses of the brain to some external stimuli. Examples of such evoked potentials are P300 and SSVEP. Evoked potentials are, in principle, easy to pick up with scalp electrodes. The necessity of external stimulation does, however, restrict the applicability of evoked potentials to a limited range of tasks. In our view, a more natural and suitable alternative for interaction is to analyze components associated with spontaneous "intentional" mental activity. This is particularly the case when controlling robotics devices. Like for driving a car, subjects' attention *must* be focused on driving and *not* on external stimuli.

Spontaneous BCIs are based on the analysis of EEG phenomena associated with various aspects of brain function related to mental tasks performed by the subject at his/her own will. Possible mental tasks are imagination of limb movements (e.g., right or left hand) and cognitive operations (e.g., arithmetic or language). But for steering a wheelchair or a prosthesis, voluntary mental control is not enough. It is also necessary that subjects make self-paced decisions. In such asynchronous protocols the subject can deliver a mental command at any moment without waiting for external cues [2, 4], contrarily to a synchronous interaction where EEG is time-locked to externally paced cues. Only then it is possible to send the appropriate mental command at the right time to make the wheelchair turn and cross the desired doorway while it is moving continuously.

2. The Statistical Machine Learning Way

A critical issue for the development of a BCI is training—i.e., how users learn to operate the BCI. We, as other groups [5, 6], follow a mutual learning approach to facilitate and accelerate the user's training period. This means that the user and the BCI are coupled together and adapt to each other. In other words, we use machine learning approaches to discover the individual EEG patterns characterizing the mental tasks executed by the user while users learn to modulate their brainwaves so as to improve the recognition of the EEG patterns. We use statistical machine learning techniques at two levels, namely feature selection and training the classifier embedded into the BCI. In particular, the statistical classifier achieves error rates below 5% for 3 mental tasks, but correct recognition is 70%. In the remaining cases, the classifier doesn't 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; otherwise users can become frustrated and stop utilizing it. Furthermore, not executing probable wrong commands increases the theoretical bit rate of the BCI and improves the robot's trajectories—the subject will not need to correct wrong turns or bring back the wheelchair to the desired doorway.

3. A Blending of Intelligences

How is it possible to control a robot that has to make accurate turns at precise moments in time using signals that arrive at a rate of about one bit per second? The key element of our brain-actuated robots is to combine the subject's mental capabilities with the robot's intelligence. That is, the subject delivers a few high-level mental commands (e.g., "turn right at the next occasion") and the robot executes these commands autonomously using the readings of its on-board sensors. In other words, the EEG conveys the subject's intent and the robot performs it so as to generate smooth and safe trajectories.

This approach makes it possible to continuously control a mobile robot—emulating a motorized wheelchair—along non-trivial trajectories requiring fast and frequent switches between mental tasks [2]. Two human subjects learned in a few days to mentally drive the robot between rooms in a house-like environment visiting 3 or 4 rooms in the desired order. Furthermore, when later the subjects controlled manually the robot along the same trajectories, manual performance was only marginally better than mental performance.

More recently, we have extended this work to the mental control of both a simulated and a real wheelchair [3]. This has been done in the framework of the European project MAIA (http://www.maia-project.org) and in cooperation with the KU Leuven. In this case, we have incorporated shared control principles to blend the two intelligences [7]. Although our first brain-actuated robot had already some form of cooperative control, shared control is a more principled and flexible framework and provides users with a finer degree of control

4. Challenges and Future Directions of Research

For brain-actuated robots, contrarily to augmented communication through BCI, fast decision-making is critical. In this sense, real-time control of brain-actuated devices, especially robots and neuroprostheses, is the most challenging application for BCI. Certainly, we would like to have a large number of mental commands, but I don't think this is the main priority because, as it has already been shown, three commands is enough to operate complex robotics systems provided they are endowed with shared control.

Delivering fast commands goes hand in hand with another challenge, namely a high robustness, which doesn't necessarily imply perfect accuracy. As discussed before, the critical issue is low errors. One of the main sources of errors is that brain signals are non-stationary and change naturally over time. A solution is online adaptation of the interface to the user to keep the BCI constantly tuned to its owner [8]. Another complementary solution is to exploit users' cognitive capabilities to detect errors directly from their EEG. Recent results have shown satisfactory single-trial recognition of error potentials that arises some milliseconds after users get aware of the erroneous responses of the BCI [9]. Thus, user's commands are executed only if no error is detected in this short time, what leads to significant improvement of the BCI performance. In addition, this new type of error potential provides performance feedback that, in combination with online adaptation, allows improving the BCI while it is being used.

Still, how can subjects deliver fast mental commands naturally? The key is asynchronous analysis of spontaneous EEG, but we will need to increase the speed of current BCI by exploring local components of brain activity with fast dynamics that subjects can consciously control. This challenge is, in a nutshell, *the* BCI challenge—the multidisciplinary cooperation of neuroscience, bioengineering and computer science.

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