Brain–Machine Interfaces: The Perception–Action Closed Loop

A Two-Learner System

by José del R. Millán

A brain–machine interface (BMI) is about transforming neural activity into action and sensation into perception (Figure 1). In a BMI system, neural signals recorded from the brain are fed into a decoding algorithm that translates these signals into motor outputs to control a variety of practical devices for motor-disabled people [1]–[5]. Feedback from the prosthetic device, conveyed to the user either via normal sensory pathways or directly through brain stimulation, establishes a closed control loop.

An important aspect of a BMI is the capability to distinguish between different patterns of brain activity, with each being associated with a particular intention or mental task. Hence, adaptation is a key component of a BMI because, on the one hand, users must learn to modulate their neural activity to generate distinct brain patterns, while, on the other hand, machine-learning techniques need to discover the individual brain patterns characterizing the mental tasks executed by the user. In essence, a BMI is a two-learner system that must engage in a mutual adaptation process [6], [7].

Future neuroprosthetics—robots and exoskeletons controlled via a BMI—will be tightly coupled with the user in such a way that the resulting system can replace and restore impaired limb functions because they are controlled by the same neural signals as their natural counterparts. However, the robust and natural interaction of subjects with prostheses over long periods of time remains a major challenge. To tackle this challenge, we can take inspiration from natural motor control, where

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goal-directed behavior is dynamically modulated by perceptual feedback resulting from executed actions.

Brain signals for a BMI can be recorded from single neurons using microelectrode arrays implanted in the brain (single-unit activity) or as the concerted activity of neuronal populations of different sizes depending on the position of the electrodes—either implanted in the brain (local field potential), on the surface of the brain (electrocorticography), or outside the scalp (electroencephalography). These approaches provide complementary advantages, and a combination of technologies may be necessary to achieve the ultimate goal of controlling neuroprostheses capable of replicating any kind of body movement as easily as able-bodied people control their natural limbs [8].

No matter the origin of the brain signals, current BMIs partly emulate human motor control as they decode cortical correlates of movement parameters—from the onset of a movement to directions to instantaneous velocity—to generate the sequence of movements for the neuroprosthesis. However, a closer look shows that motor control results from the combined activity of the cerebral cortex, subcortical areas, and spinal cord. In fact, many elements of skilled movements, from manipulation to walking, are mainly handled at the brain stem and spinal cord level, with cortical areas providing an abstraction of the desired movement. This hierarchical organization supports the hypothesis that complex behaviors can be controlled using the low-dimensional output of a BMI in conjunction with intelligent devices in charge to perform low-level commands, akin to the role of the subcortical and spinal cord levels in human motor control.

Our brain-controlled wheelchair (Figure 2) illustrates the future of intelligent neuroprostheses that, like our spinal cord and musculoskeletal system, work in tandem with motor commands decoded from the user's brain cortex [9]. Users can drive it reliably and safely over long periods of time thanks to the incorporation of shared-control (or context-awareness) techniques. This relieves users from the need to continuously deliver all the necessary low-level control parameters and, therefore, reduces their cognitive workload and facilitates split attention [10].

A further component that will facilitate intuitive and natural control of motor neuroprosthetics is the incorporation of rich multimodal feedback and neural correlates of perceptual processes resulting from this feedback. Realistic sensory feedback must convey artificial tactile and proprioceptive information—i.e., the awareness of the position and movement—of the neuroprosthesis [11]. This type of sensory information has the potential to significantly improve the control of the prosthesis by allowing the user to feel the environment in cases in which natural sensory afferents are compromised—either through other senses or by stimulating the body or even the brain directly to recover the lost sensation. Furthermore, rich multimodal feedback is essential to promote the user's agency and owernship of the prosthesis.

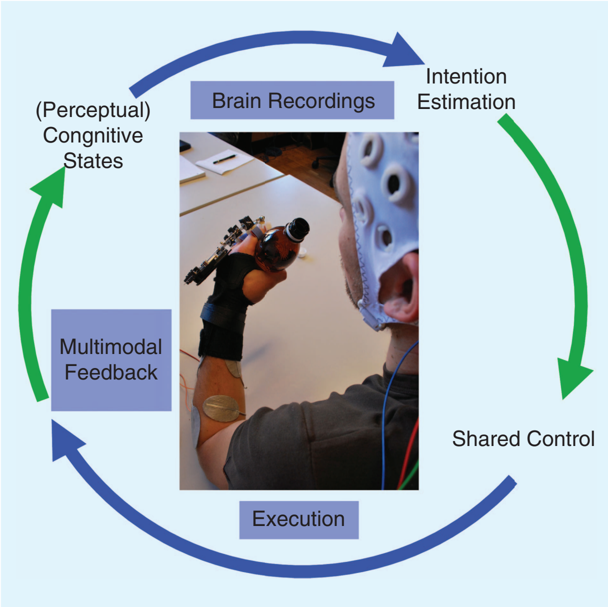

Figure 1. A BMI loop: a BMI transforms brain activity (recorded at the micro-, meso-, or macrolevel) into actions by decoding the user's intention. The estimated intention is enlarged with contextual information (external input plus the internal state of the neuroprosthesis) using shared control. The execution of actions conveys rich multimodal feedback to the user, who makes perceptual cognitive decisions that dynamically modulate his or her goal-directed behavior.

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Finally, we can decode and integrate the prosthetic control-loop information about perceptual cognitive processes of the user that are crucial for volitional interaction, such as awareness to errors made by the device [12], anticipation of critical decision points, and lapses of attention. As in natural motor control, this information is associated with processing feedback and should dynamically modulate interaction.

About the Author

José del R. Millán (jose.millan@epfl.ch) is the Defitech Professor at the École Polytechnique Fédérale de Lausanne, Switzerland, where he explores the use of brain signals for multimodal interaction and, in particular, the development of noninvasive brain-controlled robots and

Figure 2. A brain-controlled wheelchair: users can drive it reliably and safely over long periods of time thanks to the incorporation of shared-control (or context-awareness) techniques.

neuroprostheses. He received his Ph.D. degree in computer science from the Universitat Politècnica de Catalunya, Barcelona, Spain, in 1992. He was a research scientist at the Joint Research Centre of the European Commission, Ispra, Italy, a senior researcher at the Idiap Research Institute in Martigny, Switzerland, and a visiting scholar at the University of Stanford, the University of California at Berkeley, and the International Computer Science Institute in Berkeley. His research on brain–machine interfaces was nominated a finalist of the European Descartes Prize 2001, and he has been named Research Leader 2004 by the journal *Scientific American* for his work on brain-controlled robots. He is the recipient of the IEEE Nobert Wiener Award 2011 and has coordinated a number of European projects on brain–machine interfaces.

An important aspect of a BMI is the capability to distinguish between different patterns of brain activity.

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