BRAIN – MACHINE INTERFACES
Concept of a research framework

Moving Thoughts:
how to control a machine with my thoughts

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Introduction

Motor imagery is a cognitive process in which motor acts are mentally rehearsed without any overt body movements. A fast growing number of studies show that brain areas engaged in the actual performance of movements are for a large part also active during motor imagery. The areas that are activated during execution and imagery are the prefrontal cortex, the premotor cortex, the SMA, the cingulated cortex, the parietal cortex, the cerebellum and the primary motor cortex cerebellum (Porro *et al.* 1996; Roth *et al.* 1996; Luft *et al.* 1998; Lotze *et al.* 1999; Gerardin *et al.* 2000; Porro *et al.* 2000). Furthermore it has been shown that mentally rehearsing a physical exercise induces an increase of muscle strength comparable to that attained by a real exercise (Yue & Cole, 1992).

In an intriguing recent study Ehrsson, Geyer & Naito (2003) showed that imagery of finger, tongue and toe movements activated the somatotopically organized area's of the primary motor cortex in a systematic manner, that is, imagery of finger movement activated the finger area, imagery of toe movements activated the foot zones, whereas imagery of tongue movements activated the tongue region of the primary motor cortex. Thus the imagined body part seems to be reflected directly in the pattern of cortical activation. Fadiga et al (1999) demonstrated that motor imagery influenced the corticospinal excitability and that this influence is specifically related to muscles involved in motor execution. For example, motor imagery of forearm flexion enhances the MEP's of the m. biceps brachialis, an agonist during forearm flexion, whereas this was not the case during imagery of forearm extension, where the m. biceps brachialis acts as an antagonist. So, motor imagery does not lead to an a-specific general increase in arousal but to a very specific activation of neural control structures also involved in the actual execution of (the same) movements.

Gallese & Lakoff (in press) argue that when a given action is planned, its expected motor consequences are forecast. This is possible because these predictions are based on an internal simulation process. Imagining or observing an action is to a large extent equivalent to internally simulating it and it is this internal simulation process that is recordable. Hence, cognitive activities such as imagination are far from being disembodied but make use of the activation of sensory-motor brain regions.

These results form the background for a project which is focused on the question whether it is possible to use the activity elicited by motor imagery in certain areas of the brain for controlling external devices (e.g. a robot arm). When the activity is specific and highly correlated to the imagined movement, it is argued that this activity may be used for the execution of that movement by an external agent. Would the imagination of a grasping movement lead to an actual grasping movement performed by a machine?

In a clinical context it may be asked whether the imagination of a movement by a paralyzed patient can be "recorded" and used for the control of external devices. Recent studies have shown that monkeys are able to control the trajectory of a cursor on a computer-screen without showing any overt behavior. Musallam *et al.* (2004) provided the first demonstration of the feasibility of employing high-level cognitive signals from the parietal and premotor cortex for driving a neural prosthesis. These brain signals reflect the goal of the intended movement and the value of the reward the subject expects to receive for successfully completing a task.

How to record a cognitive state

Available brain recording/imaging techniques for use in BCI are PET, MRI, MEG, EEG, LPF (local field potentials), and single-cell (multi-unit) recording. For technical and practical reasons, however, PET, MRI, and MEG are presently not suitable for application in a neuroprosthesis. Multi-unit recording and LPF, both involving intracranial insertion of electrodes, have produced intriguing and promising results in recent animal studies (e.g. Andersen, Musallam, & Pesaran, 2004). Apart from technical, but perhaps solvable, problems related to the limited useful 'life time' of intracranial electrodes, usage of intracranial recording techniques in humans is beset with other practical and ethical problems. From a purely technical and practical perspective, this leaves EEG as the most viable technique to provide on-line information on brain activity and mental state to be used in (non-invasive) neuroprosthesis.

Even in the best of circumstances (using spatial filtering and multivariate modeling techniques to enhance the spatial resolution of the EEG signal), EEG measures the synchronous (average) activity of millions of neurons. Thus, EEG provides a macroscopic measure of brain activity, at a scale that most likely exceeds the magnitude that is assumed by population-vector theories of neural information processing. The implications of the relative lack of specificity of the EEG signal for application in

neuroprostheses should be clearly acknowledged. For instance, while the EEG might well be used to reliably differentiate between left-hand and right-hand motor intentions (due to the well-known lateralization of manual motor systems), it seems questionable whether it can usefully differentiate between more specific intentions to engage in functionally distinct and meaningful actions, such as grasping versus releasing.
Informational states and transactions at mesoscopic and microscopic levels of brain activity, arguably the levels at which mental (e.g., motor) representation and processing is realized, are unlikely to be assessable by means of EEG recording. Thus, when the goal is to develop a neuroprosthetic system that allows the user to control an artificial effector by 'natural' ideomotor means, i.e. by imagining specific, punctuated actions (or action goals), EEG seems intrinsically ill-suited and cortical implants should be considered to provide the only feasible technology. However, an EEG-based neuroprosthesis does remain a highly viable alternative, for reasons to be discussed next.

Multichannel EEG represents a highly complex signal. Time-frequency analysis in conjunction with experimental manipulation and multivariate signal analytical techniques, such as Independent Component Analysis, has been used to uncover a range of underlying components, defined in terms of frequency signature, spatiotemporal properties, and associations with mental state. Moreover, neurofeedback research has provided ample evidence that humans can be trained to acquire some degree of control over many of these components. In principle, then, the EEG signal should provide ample degrees of freedom to represent and communicate a variety of basic motor intentions. However, realization of this potential may well require extensive training in order to teach users to translate (by more of less 'natural' means) motor intentions into distinct EEG signatures.

An elegant and compelling demonstration of the potential of this approach is provided by the recent research of Wolpaw and McFarland (2004). These investigators capitalized on the fact that manual responses (and associated intentions) are associated with strongly lateralized and quite specific power changes in the alpha (mu) band (10 Hz) and the beta band (20 Hz) in the EEG recorded over precentral motor cortex, and that humans can be trained to control the power in these frequency bands (by mentally simulating left-hand or right-hand actions). Using a simple adaptive classifier to translate linear combinations of the various spectral powers into horizontal and vertical cursor movements, these investigators reported good control of two-dimensional cursor movement, comparable, with respect to precision, accuracy, and movement time, to that obtained with invasive BCIs. Interestingly, whereas subjects reported using explicit motor imagery strategies early in training, such strategies tended to become less important and performance more automatic as training progressed.

As this example illustrates, the success of EEG-based BCI critically relies on two integral parts. First, a range of potentially useful EEG features or components must be preselected. This selection jointly depends on the accuracy (and speed) with which components can be identified and measured at a single-trial level (requiring prior information and suitable techniques for signal preprocessing – on-line time-frequency analysis and spatial filtering), and on the quality of control that users (can be trained to) have over these components (relevant prior information from motor imagery and neurofeedback literature, to be complemented with development of suitable training tasks). Second, adaptive classifier algorithms are needed that can focus on those EEG features each user is best able to control and that can guide and promote further improvement in control, thereby interlocking the user and computer into a process of mutually dependent adaptation in order to find a robust and high bit rate BCI.

Pattern classification in multichannel recordings of brain activity

Although the point can be made that not enough is known about neural coding of information in the brain or about the nature of neural-information processing, a number of concrete experiments in biomedical engineering and in cognitive neuroscience have demonstrated that with the currently available methods in signal processing and pattern recognition more intended-Shannonian bits can be derived from brain activity than was considered possible until very recently. The early results, both by groups using invasive methods as well as by groups using non-invasive EEG recordings have stimulated a new wave of multidisciplinary research. In 2003, the first open Brain-Computer Interfacing competition was held, organized by the following researchers:

Albany (USA):	Theresa M. Vaughan, Gerwin Schalk, Jonathan R. Wolpaw
Berlin (DE):	Benjamin Blankertz, Gabriel Curio, Klaus-Robert Müller
Graz (AU):	Alois Schlögl, Christa Neuper, Gernot Müller, Bernhard Graimann, Gert Pfurtscheller
Tübingen (DE):	Thilo Hinterberger, Michael Schröder, Niels Birbaumer

Numerous results have been published, e.g. Mensh et al. (2004). Other work in BCI concerns the (invasive) electrode arrays for restoring motor control by John Donoghue at Brown University and Nicholas Hatsopoulos (1998) in macaque monkey, following the seminal work of Georgopoulos. Recent work by Carmena et al. (2003) Again, in the domain of invasive methods, there is the exploratory work of Richard Norman, University of Utah towards restoration of vision.

In The Netherlands there is an important group around Wim Rutten (UT), working on fundamental aspects of neuron-silicium interfacing. Also at UT, there is the Roessingh institute, working on the development of general prosthesis systems.

The promising results at the level of invasive methods for brain-machine interfacing and the initial results in non-invasive, e.g., EEG-based methods are currently setting a stage for exciting new research in **Groningen**. Rather than focusing on low-level aspects, we want to exploit the available expertise at the level of kinesiology, EEG analysis, and pattern recognition. Apart from the results in the EEG arena, supportive evidence on the ability to detect cognitive states of the brain has been delivered by Tom Mitchell, one of the most important representants of Machine Learning. His group showed that current state-of-the art machine learning methods can be applied very successfully to the classification of fMRI signals into corresponding "cognitive states". In our proposed research, we will use EEG signals to obtain similar results, thereby setting the stage for a more practical application of BCI than would be possible using fMRI.

The type of research in this domain benefits from the participation of multidisciplinary groups. Cognitive psychologists, neuropsychologists and kinesiologists will be able to define experimental conditions, which can be used by neuroscientists or electrophysiologists for the accurate recording of the neural signals, which in turn need to be analyzed by researchers from techological or methodological fields. It seems that all ingredients for success are present at **Groningen University**. For the dept. of Artificial Intelligence, there are three levels of interest within the depicted research area.

The most challenging level concerns our understanding of neural representations at a spatiotemporal scale which is much smaller than is the case with current recording technology. Even the fastest fMRI devices and the EEG-recording setups with the highest attainable spatial resolution will not immediately deliver sufficient information to build a bridge between voxel intensities and neural spiking patterns. However, there are more general questions within computational neuroscience which address the nature of a representation at the level of the signal, the definition of what constitutes the brain system state and the computing mechanism and mathematical transforms that model the essential invariances in the stream of multidimensional time functions.

The second level of interest concerns another bridge, i.e., the connection between the rather abstract concepts in Cognitive Science and the concrete, measurable changes in the state of the brain. The availability of the “BCI” paradigm, as a complementary approach to the ANOVA-driven experimentation in cognitive neuroscience, will allow for a focused and functional testing of theories on motor imagery, intention, action and attention.

The third level of interest concerns the development of methods in machine learning. The presence of high-dimensional time-variant signals for which the class identity of an episode, i.e., its ground truth is known due to the fact that the recordings have been obtained under stringent experimental conditions, provides an exciting breeding ground for the development of algorihms which are able to detect order in chaos. The availability of the Beowulf computing cluster at Groningen University allows for the brute-force analysis of massive amounts of data, in order to hunt for 1) signal transforms, 2) brain areas, and 3) classification methods which are optimal for the derivation of functionally usable and meaningful information brain activity. A specifically challenging notion concerns the bidirectional adaptivity which is needed for a high signal-to-noise ratio in brain-computer interfacing. The user of a BCI needs to learn to control a new end effector, whereas, at the same time, the pattern-recognition and machine learning modules of the interface need to learn incrementally in real time. In fact, it may be argued that the introduction of BCI interfaces in, e.g., patients with peripheral motor disorders, will necessitate a continuous adaptivity on behalf of the biological and technical components of the movement -control system.

Plan for BCI research at RuG

Being aware of the attempts at invasive neural implants and stem-cell research for neural recovery of function, we will first focus on non-invasive “EEG”-based attempts at extracting action intentions in humans.

Three PhD students will be needed, one in Movement Science, one in Experimental Psychology and one in Artificial Intelligence, to perform a joint project which consists of the following stages.

1. Determining experimental and controlled conditions for bringing the brain into several well-defined neural-activation states, allowing for specificity of activation patterns. Attention will be given to both continuous and discrete (symbolic) modes of control.

2. EEG/fMRI localization coordination, determining optimal electrode placement, derivation and signal preprocessing

3. Pattern Recognition and signal processing method development to allow for a reliable classification of brain states.

4. Development of functional tasks, i.e., tasks with a benefit for the user of the BCI system. This may involve control of computer applications but also the control of robotic systems is considered here.

The research will result in three PhD theses under supervision of, respectively, T.Mulder, R. de Jong & L.Schomaker

Related groups in **Groningen**, which may benefit from the results of the proposed research kernel BW/Psy/AI are:

Roerdink (Inf.), Duifhuis (BMT), Robillard

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