Brain-Computer Interfaces for Communication and Rehabilitation

Brain-computer interfaces (BCIs) translate neural recordings into signals that may be used for communication and/or the control of neuroprosthetic devices. Research in this domain poses interesting challenges to machine learning, as data is typically scarce, noisy, and non-stationary [8]. Furthermore, good decoding algorithms are contingent on domain knowledge that is not readily available and difficult to obtain with traditional statistical methods. Accordingly, we employ machine-learning methods to study neural processes involved in BCI-control and use these insights to develop novel decoding algorithms and enhance experimental paradigms.

One example of this research agenda is our work on the neural causes of performance variations in BCIs. Utilizing causal-inference methods, we could provide evidence that the neural substrate of distributed γ-range oscillations exerts a causal influence on the sensorimotor-rhythm (SMR) [6]. We localized the origins of these oscillations to fronto-parietal networks that are believed to regulate attention, and could show that activity in these networks predicts a subject's ability to operate a SMR-BCI on a trial-to-trial basis [5]. These insights have far-reaching consequences for the design of BCI-systems, as acknowledged by the *Annual BCI Research Award 2011* that we were awarded for this project.

Besides investigating the neural causes of performance variations, we further study the effect of experimental design on BCI-performance. For instance, our work indicates that the design of visual stimuli has a profound effect on decoding accuracy in visual P300-based speller systems [9] and that the perceived level of control over a BCI influences a subject's performance [1].

It remains controversial, however, whether severely paralyzed subjects, e.g. those in late stages of amyotrophic lateral sclerosis (ALS), are capable of utilizing BCIs that depend on signals generated by the motor system. We thus also explore novel BCI paradigms that are independent of motor signals. This is exemplified by our work on auditory BCIs that utilize attention shifts to concurrent streams of auditory stimuli for transmitting information [7].

A further crucial aspect of our work, that is closely intertwined with the projects discussed so far, is the development of novel algorithms for decoding brain states. Building upon our experience in Bayesian inference, we have developed a graphical model decoding framework for ERP-based visual speller systems [10]. This framework incorporates prior information on letter frequencies into the decoding process, thereby enhancing decoding performance. Furthermore, we were the first to successfully apply the framework of multi-task learning to the domain of BCIs [12]. As the signal characteristics used by subjects to control a BCI share common aspects, the incorporation of data from previously recorded subjects substantially decreases calibration time and enhances overall decoding performance. Other prior information, that can be utilized to improve decoding performance, is provided by the homogeneous spatial organization of the human cortex. For instance, we have shown that beamforming is a feasible approach to utilize prior information on brain areas relevant for a certain experimental paradigm, which is particularly useful when dealing with noisy data recorded outside of well-controlled laboratory environments [3].

While BCIs were initially conceived as communication devices for the severely disabled, they have recently also attracted attention in the context of stroke rehabilitation. We have constructed an experimental setup that combines a seven degrees-of-freedom robotic arm with a BCI (Figure 1). This system enables us to detect the movement intent of severely impaired stroke patients in real-time, and translates this intent into actual movements through haptic feedback provided by the robotic arm [2]. As we have argued in a recent review article on the use of BCIs for rehabilitation [4], this artificial re-connection of the sensorimotor loop may support processes of cortical plasticity involved in post-stroke recovery.

Finally, BCI-systems may also prove to be useful as augmentative devices for healthy subjects. For instance, BCIs can detect aspects of user state not readily available in traditional human-machine interaction. In a proof of concept study, we presented experimental evidence that BCIs can be used to detect a perceived loss of control over a system, which may be used to adapt the human-machine interface accordingly [11].

Figure 0.1: A stroke patient attached to the BCI-robotics system.

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