Naturally controlling a MI BCI-driven mobile robot

Background

Non-invasive Brain-Computer Interface (BCI) technology allows to circumvent natural human neuromuscular pathways and, consequently, enables people suffering from severe motor disabilities to successfully control a new generation of neuroprostheses. In such BCI systems, neural signals are recorded by non-invasive techniques (e.g., Electroencephalography, EEG) and features that are strictly related to the mental task performed by the user are extracted and continuously classified by means of machine learning algorithms. Then, the resulting probabilistic output is translated into commands for the brain-actuated neuroprosthesis.

In this framework, BCI systems based on Motor Imagery (MI) have been largely exploited by the scientific community. MI BCIs rely on the detection of self-paced brain patterns (sensorymotor rhythms) associated to specific motor imagination tasks performed by the user (e.g., imagination of the movement of right or left hand) without the need of any exogenous—visual or auditory—stimulation. Thus, the BCI system translates user's intentions in predefined actions for the robotic device (e.g., make a mobile robot turn right or left).

However, state-of-the-art MI BCI driven neuroprostheses still suffer from a major shortcoming: most of the MI BCI systems provide—de facto—a discrete control strategy. Indeed, the estimated probabilities carrying information about user's intention are often too noisy to be directly exploited as a control signal. Thus, most of the systems implement decision making algorithms considering several seconds in the past in order to improve the reliability and robustness of the detection. Once enough evidences are accumulated (i.e., a predefined threshold or timeout is reached), the command is sent to the device (e.g., in the case of a mobile robot to make it turn right or left). This approach results in discrete commands delivered with an average bit-rate of 0.3 command/second. Obviously, this is not the best solution for fine operations with complex robotic devices where a continuous control would rather be desirable. In this project, students will explore a BCI approach that allows continuous control of a mobile robot and will compare it to a classical discrete approach.

Protocol

Students will to participate in 3 recording sessions (up to 120 minutes, including the setup). Each session is split in 3 phases: calibration, online and control. In the first two sessions, they are asked to control a feedback bar with two motor imagery tasks (Figure 1A). A classifier will be trained based on the data of the first phase (calibration) and then, evaluated in the second phase (online). During the third session, students are asked to mentally drive a mobile robot in order to reach five different targets (Figure 1B). By default the robot moves forward and the two motor imagery tasks are used to make it turn left or right. In this phase, students will evaluate two control modalities: discrete (the robot turns by a fixed angle only when the feedback bar reaches a predefined threshold) and continuous (the robot turns accordingly to the position of the feedback bar). Optionally, students will have the possibility to run their own code to decode motor imagery tasks and control the robot.

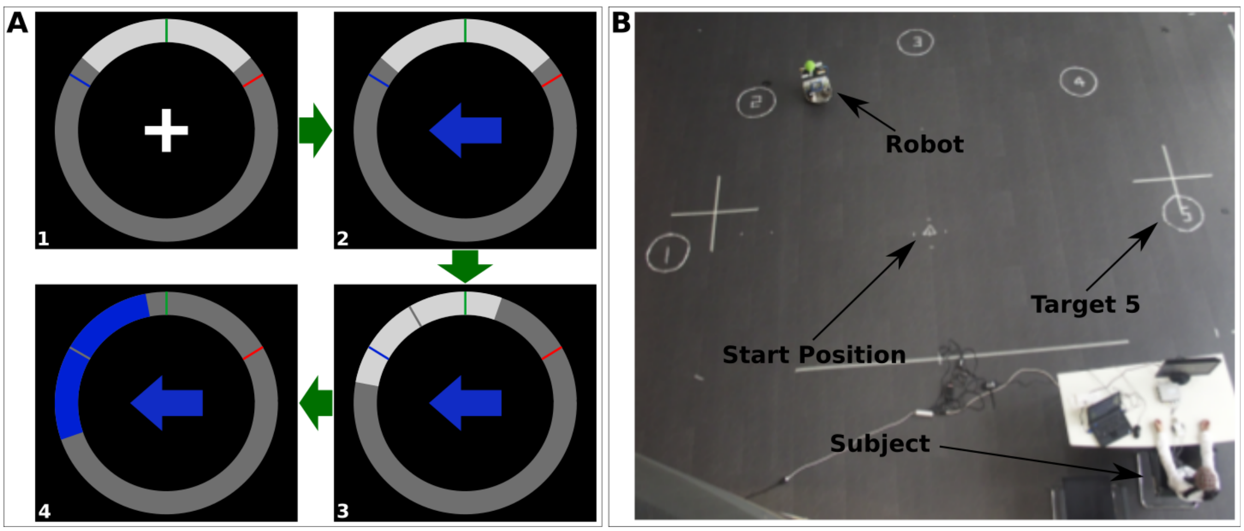

Figure 1: A) The visual feedback provided to the subject. The bar moves accordingly to the BCI output. Thresholds are marked in blue and red. B) Experimental setup. The subject is driving the robot from the start position to the target 2.

Learning Objective:

- Get a hands-on experience with EEG equipment and setup
- Familiarize with EEG signal
- Learn to process EEG data (artifact removal, feature extraction)
- Learn EEG correlates to motor imagery task
- Apply machine learning to EEG for solving classification problems
- Write a scientific report about your findings