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Context-aware brain-computer interfaces

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Systems using brain-generated signals can control complex, smart devices by taking into account information about the situation at hand, as well as the operator's cognitive state.

Developments in neuroscience, signal processing and machine learning are enabling device control using our brain activity. Specifically, current technology allows us to record brain-generated signals in real time, infer the human intention and translate it into control commands for external devices. These brain-computer interfaces (BCIs) can currently control virtual keyboards, games, smart wheelchairs and mobile robots.[1] Most commonly, BCI systems are based on electrical brain activity recorded on the scalp (using electroencephalograms: EEGs). Machine-learning techniques help to classify these signals into pre-defined patterns of activity associated with particular intentions (e.g., imagining moving one's left hand will lead to device motion toward the left). BCI applications have traditionally focussed on subjects suffering from motor handicaps (caused by, for instance, spinal-cord injury, degenerative diseases or locked-in syndrome). Their predominant aim has been restoration or substitution of communication and/or motor capabilities, although recent developments have also explored their use in healthy subjects in applications ranging from games[2] to image browsing[3] and space-system applications.[4]

However, despite their impressive achievements, BCI applications are strongly limited by their low throughput and the small number of commands they can deliver. Designing context-aware interfaces has been proposed as a way to cope with these limitations. Using this approach, the interface collects information about the state of the device, as well as its environment, and combines this with the commands it has decoded from brain activity (see Figure 1). This enables the performance of complex tasks with a reduced number of mental commands (typically two or three) and using the latter to signal high-level instructions while smart devices take care of low-level controlsignals. For instance, we have shown that noninvasive BCIs can be used for real-time control of an intelligent wheelchair in realistic conditions.[5] In this application, BCI commands are limited to general directions of movement (i.e., move forward, turn left or right), which are interpreted by the wheelchair in conjunction with information from the on-board sensors to compute the actual control commands needed for execution (i.e., speed and angle of movement) to travel smooth trajectories and avoid obstacles. Alternative approaches in context-aware BCI robotics applications dynamically change the behaviour corresponding to a particular mental task depending on context. For instance, when controlling a mobile robot, a 'left' command signalled by the BCI would have different meaning depending on whether or not there is a wall on that side of the robot. The robot will either move along the wall or turn to the left on the spot.[6] Either way, this shared-control approach increases the robustness of the overall system, allowing it to perform complex tasks.

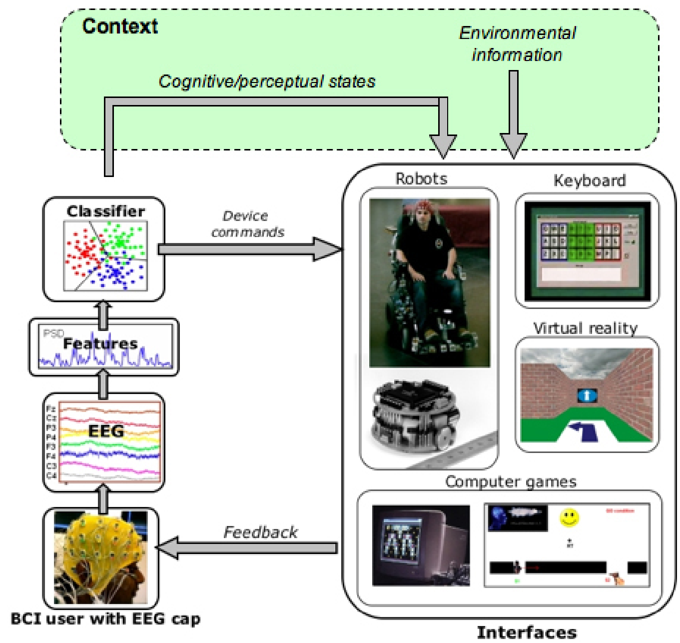

Figure 1. *Context-aware brain-computer interface (BCI). The traditional BCI control loop is enriched by the addition of contextual information describing the environment and the user's cognitive state. EEG: Electroencephalogram.*

The interface can also extract information about the subject's cognitive and perceptual state from the recorded brain activity,

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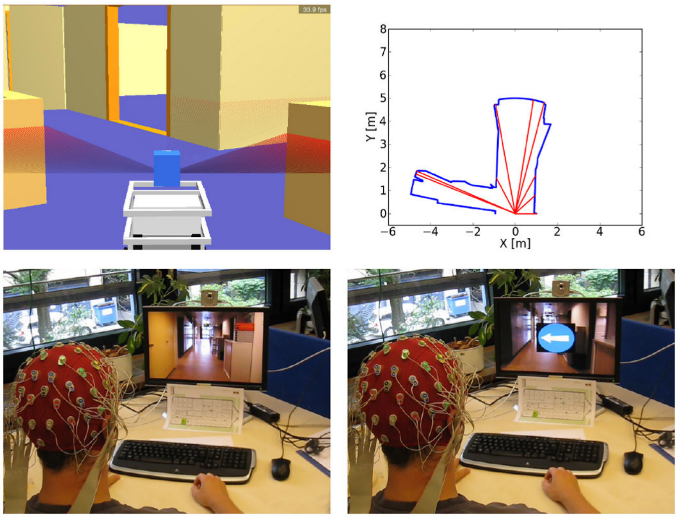

Figure 2. *EEG error-based navigation.*[9] *(top) The robot moves autonomously using sensory information about its surroundings. (bottom) Wherever it cannot take a reliable decision, it proposes an action using visual feedback. Error-related signals are decoded from the elicited EEG activity to confirm or reject this proposal.*

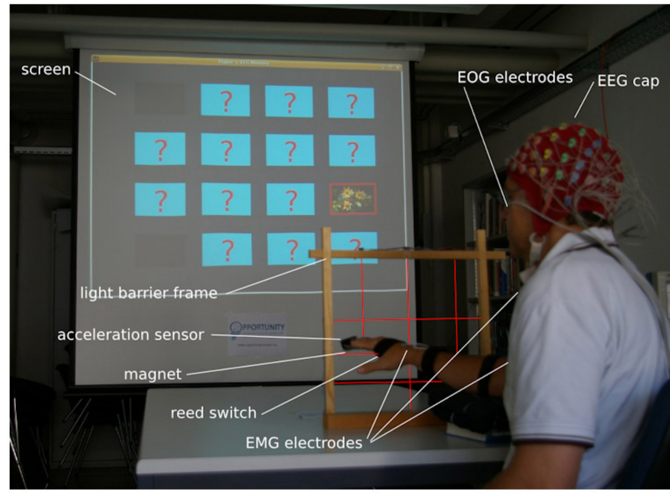

Figure 3. *Self-adaptation in human-computer interaction.*[10] *The computer game is controlled by motion-based gesture recognition while EEG-decoded error-related activity is used for self-adaptation. EMG: Electromyographic. EOG: Electrooculographic.*

such as awareness of erroneous decisions, either taken by the subject itself or by an external agent. We have shown that it is possible to detect error-related EEG activity in real time in single trials and use this as corrective or learning signals for BCI systems.[7,8] In addition, in the framework of semi-autonomous navigation (similar to our wheelchair experiment), we tested a tele-operated robot platform that navigates autonomously in indoor environments using its on-board sensors until it reaches a decision point (because it does not know the target destination). At this location, it uses visual feedback to propose a possible action (see Figure 2). That action is either selected or discarded based on online detection of error-related EEG potentials. A user remotely commands the robot while observing a video stream provided by an on-board camera. The visual feedback is superimposed onto the video image.[9] Online experiments on one subject using both real and simulated robots show that it is possible to successfully guide the robot while providing a natural approach to brain-machine interaction that reduces the user's cognitive load (the system behaves autonomously 82% of the time).

Error-related EEG signals can also be used to adapt the interface's behaviour. We recently explored whether similar potentials can be used to assess and improve the system's performance. We designed a hybrid approach for human-computer interaction that uses human gestures to send commands to a computer and exploits brain activity to provide implicit feedback about the degree of recognition of such commands (see Figure 3). Using a simple computer game controlled by wearable motion sensors, we showed that EEG activity evoked by erroneous gesture recognition can be classified in single trials at well above random levels. Thus, the gesture-recognition system becomes self-aware of its performance.[10] Moreover, we designed a simple adaptation mechanism which uses the EEG signal to label newly acquired samples that can be used to recalibrate the gesture-recognition system in a self-supervised fashion. Offline analysis shows that this technique can significantly improve the accuracy of independent gesture recognition for most subjects tested.

In summary, the field of BCI has experienced astonishing recent developments, highlighting the feasibility of using brain activity to efficiently control complex devices despite existing limitations in terms of reliability and number of commands. We have shown that enriching the interface with contextual information yields more robust results. Robotic applications can collect information about their environments by employing on-board sensors and use this information to better interpret the user's intentions based on the BCI, thus allowing the user and device to share the responsibility of control. EEG signals can also provide information about the subject's assessment of the device's performance. In particular, error-related activity can be

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used to identify erroneous system decisions. This information can then be used to trigger corrective actions or adapt the system in a self-supervised manner.

Our future research efforts include studies of mechanisms to change the level of the system's autonomy, depending on the context or expected reliability (e.g., giving more or less responsibility to the system depending on whether the environment is well known). Other mental states decoded from brain activity (such as fatigue, attention or alarm) can also be included to better meet the user's needs.

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