Endowing the Machine with Active Inference: A Generic Framework to Implement Adaptive BCI

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ENDOWING THE MACHINE WITH ACTIVE INFERENCE: A GENERIC FRAMEWORK TO IMPLEMENT ADAPTIVE BCI

ABSTRACT Recent developments in computational neuroscience gave rise to an efficient generic framework to implement both optimal perceptual (Bayesian) inference and choice behaviour. This framework named Active Inference rests on minimizing free energy or surprise [3]. We suggest it could be used to implement efficient adaptive Brain-Computer Interfaces (BCIs). We briefly illustrate it on a simulated P300-speller task.

INTRODUCTION BCIs still suffer from poor reliability which can be attributed to the highly variable, noisy and incomplete nature of brain signals that need to be interpreted online. However, this challenge is very similar to the one faced by Robotics, or by any Human-Computer Interfaces where an artificial agent has to implement perceptual abilities to interpret its environment and decide how to act optimally. BCI is quite challenging though, because it is also facing the lack of fundamental knowledge to define appropriate features. The precise mappings between the targeted user mental states or intentions and some specific features of brain activity remain unknown. This renders the BCI challenge very acute.
To overcome these limitations, several authors have highlighted the need for adaptive approaches able to cope with noisy brain signals [4, 5, 6, 7, 8]. However, many of these adaptive approaches do not explicit the relationship between the modulation of the brain signals and the factors related to both the task and the user. Yet, the Good Regulator theorem states that "*Every good regulator of a system must be a model of that system*" [1]. In BCI, the system to be regulated is the triplet: {user, task, signal processing pipeline}. Hence to implement an optimal adaptive BCI, this theorem prescribes to use an explicit model of that triplet. The signal processing pipeline is already part of the machine. The tricky part is thus to implement a model of the user and the BCI task.

METHODS The Bayesian modelling framework is a powerful and generic one. A recent Bayesian approach has been proposed to cast human perception and action within a common - Active Inference - framework [2]. In Active Inference, the human brain makes use of a model of its environment, including the task to accomplish. We propose to endow the machine with Active Inference (see Fig. 1.a), hence with adaptive behaviour through optimized perceptual inference and action. We use a discrete formulation of that model, which we exemplify on a simulated P300-speller BCI. The model entails three main components (see Fig. 1.b): **the data likelihood** (prescribed by **matrix A**), that maps the model hidden states s_t to observations o_t at time t; **the priors over hidden states** (prescribed by **matrix B**), which formalize likely state transitions, given the control states (or actions) u_t of the machine; and **the preferences** or prior probabilities that a final outcome will be observed (prescribed by **vector C**). Finally, parameter γ defines the exploration-exploitation tradeoff for action selection. **A**, **B, C** and γ have to be specified beforehand by the BCI designer, so as to estimate s_t and u_t online, from o_t.

RESULTS With the P300-speller, time amounts to trials. Each trial t yields a single action u_t: "*flashing a group of items*" or "*sending the feedback of the chosen item*". Hidden state s_t refers to the user's state of mind one has to infer: "*I just saw my target flashing*", "*the flashed items did not contain my target*" or "*I saw a feedback and now change target*". This simple model already enables to implement two adaptive features: optimal stopping but also optimal flashing. The later refers to moving away from a pseudo-random sequence of flashes (method **M1**) by optimally choosing the group of items to flash next which best reveal the target (method **M2**). Comparing **M1** and **M2** on one hundred simulated spelled items, we could show that **M2** is both more accurate (85.2% vs. 80.6%) and faster (15.8 ± 6 vs. 20.1 $\pm$ 9 flashes).

CONCLUSION These preliminary results demonstrate the face validity of this new approach and further illustrate how it can easily provide additional and new adaptive behaviour, namely optimal flashing. Future work will consider real data while ensuring that the flashing sequence complies with the oddball paradigm.

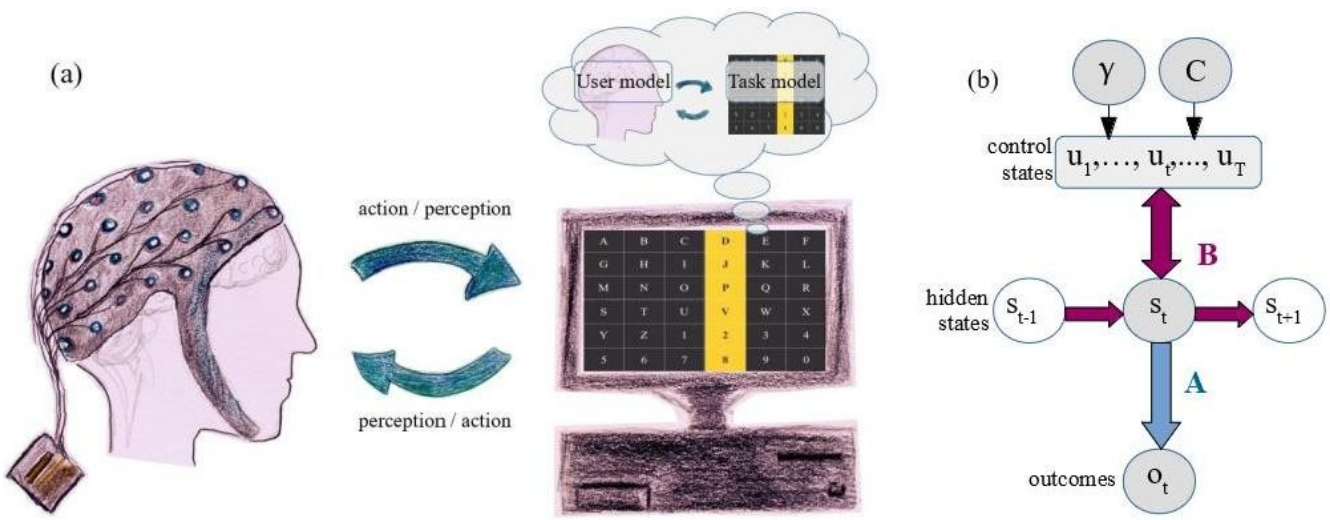

Figure 1: (a) BCI closed-loop where the machine is endowed with a model of the task and the user which subsumes its perception of EEG commands and prescribes its action; (b) Generic form of the (Bayesian) Markov Decision Process implementing Active Inference. (adapted from [2]).

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