Towards a POMDP-based Control in Hybrid Brain-Computer Interfaces

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***Abstract*—Brain-Computer Interfaces (BCI) provide a unique communication channel between the brain and computer systems. After extensive research and implementation on ample fields of application, numerous challenges to assure reliable and quick data processing have resulted in the hybrid BCI (hBCI) paradigm, consisting on the combination of two BCI systems. However, not all challenges have been properly addressed (e.g. re-calibration, idle-state modelling, adaptive thresholds, etc) to allow hBCI implementation outside of the lab. In this paper, we review electroencephalography based hBCI studies and state potential limitations. We propose a sequential decision-making framework based on Partially Observable Markov Decision Process (POMDP) to design and to control hBCI systems. The POMDP framework is an excellent candidate to deal with the limitations raised above. To illustrate our opinion, an example of architecture using a POMDP-based hBCI control system is provided, and future directions are discussed. We believe this framework will encourage research efforts to provide relevant means to combine information from BCI systems and push BCI out of the laboratory.**

***Index Terms*—EEG, Hybrid BCI, POMDP**

I. Introduction

A brain-computer interface (BCI) enables communication with a computerized environment without the need for muscular engagement [1]. Among the three categories of BCIs (active, reactive, and passive [2]), the first two types are aimed at transforming cerebral activity into commands to voluntarily control distant artifacts (e.g., mouse cursor) whereas the last type supports implicit interaction by adapting the human-machine interaction according to the user's mental state (e.g. fatigue). In 2010, Pfurtscheller et al. [3] coined the term *hybrid BCI* (hBCI) to refer to the combination of at least two different BCI systems [4]–[15]. This umbrella term includes numerous modalities that are not limited to the use of brain data as the integration of physiological measures can be considered (see [16] for a detailed taxonomy and [17] for a more in-depth review).

The objective of this paper is to review hBCI systems since the seminal work of [4] and to outline their persistent limitations (see section II). Then a flexible and generic architecture for hBCI control (see section III) based on Partially Observable Markov Decision Process (POMDP) is proposed and future work plans are discussed.

II. Hybrid Brain-Computer Interfaces

Hybrid BCI have allowed to mesh active and reactive BCI as well as reactive and passive BCI. While electroencephalography (EEG) based BCI has been successfully "hybridated" with functional near infrared spectroscopy [18], [19] or peripheral sensors [16], we will focus our review on EEG based hBCI.

A. Combination of Multiple Reactive and Active BCI systems

One of the main motivations of hBCI was to improve the quantitative performance of BCI systems, i.e. the classification accuracy [11], [15], [20], the number of classes [5], [6], [10], [14], and the information transfer rate (ITR) [10], [15]. For example, Allison et al. [5] implemented a system using both motor imagery (MI, active BCI) and Steady State Visual Evoked Potential (SSVEP, reactive BCI) to control the vertical and horizontal axis of a computer cursor, respectively (see Fig. 1(a)). Long, Li, Tianyou and Gu [6] implemented a similar system using P300 and MI, and also included an hybrid feature to accept or reject a target once the cursor was on top of it, akin to clicking on a computer mouse. This was done by combining the feature vectors from the MI and P300 classifiers into a hybrid vector (see Fig. 1(b)) to select or reject the target.

Another primary motivation of hBCI systems was to overcome qualitative limitations of feature extraction methods. A notorious example is the lack of an *idle state* on SSVEP paradigms (i.e., the need for the user to decide when to issue commands from the system) [4], [7], [8], [12], [13]. Interestingly, Pfurtscheller [4] designed a MI BCI system (active) that was used to *switch* a SSVEP-based BCI (reactive) dedicated to control an orthosis (see Fig. 1(c)). The *idle state* issue has also been addressed in a parallel fashion in other use cases such as wheelchair control [7] (see Fig. 1(b)). This later study tackled this problem by integrating scores from two BCI systems and implementing a threshold in order to prevent false positives.

These two main approaches for implementing hBCI systems (sequential and parallel) are what Choi et al., [16] called "mode of operation" in their taxonomy.

Another key component of hBCI is how to approach the integration of several decisions or scores from each BCI system. A naive approach is to take both BCIs' outputs and issue a command from the system if both agreed on a predetermined target. This approach was implemented in early hBCI studies, e.g., the implementation of a mental switch to activate SSVEP recognition on wheelchair control required both a particular SSVEP and MI target to be detected at the same time [8]. Early multi-dimensional systems, that used each BCI system to detect a different feature of the control system in parallel, simply operated decisions for each system independently [5], [6].

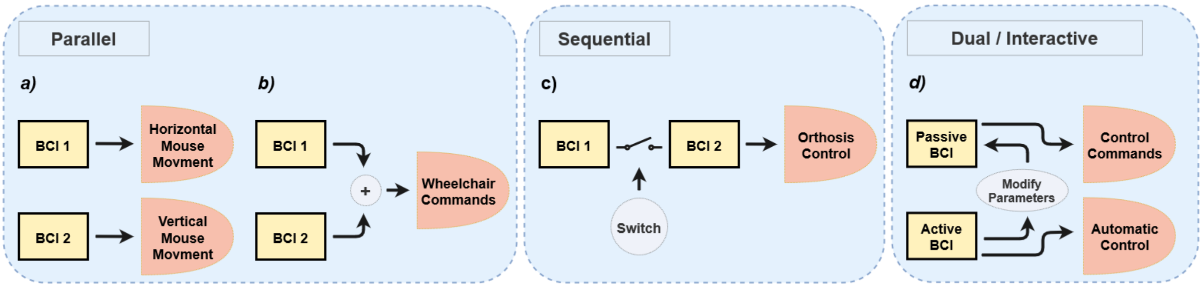

Fig. 1. Main hybrid active/reactive BCI systems, based on diagrams from [3]. *a)* Parallel hBCI for multi-dimensional system control. *b)* Parallel hBCI with aggregated / fused metric. *c)* Sequential hBCI with 'brain switch' implementation.

Later systems started integrating information to create hybrid features and scores. For example, Yin et al. [11] used maximum probability estimation (MPE) with the scores from P300 and SSVEP classifiers to estimate the probability of a target based on both BCI systems. Another study conducted by Yu et al. [12] leveraged hybrid features by linearly combining the features of SSVEP and MI. Notably, the combined feature vector allowed them to calculate an 'offset' corresponding to the base activity of the SSVEP (i.e., the output of the classifier when the participant is not paying attention to any target) and subtract it from the final score, thus achieving a control/idle state for the SSVEP.

B. Combination of Passive and Re/Active BCI systems

Surprisingly, passive BCI has attracted very few research interest in the hBCI community. It is an issue since a recent review [21] showed that affective and mental state estimation still remain a big challenge especially in out of the lab settings [22]. One approach has been to combine frequency features and temporal domain features (i.e. event related potential) to account for the user's cognitive states [23], [24]. Also one relevant direction is to take advantage of the mental state detection of passive BCI to inform the re/active BCI. Indeed, it is well admitted that degraded cognitive states (eg. fatigue, mental workload) can negatively impact re/active BCI accuracy [25]. To that end, Cotrina et al. [9] used a passive BCI to estimate user's mental workload to adjust the recognition characteristics of SSVEP-BCIs. Alternatively, a recent study implemented a dual reactive-passive BCI that enabled bi-directional interaction between a pilot and the flight deck [26]. The pilots were using the reactive part of the BCI to operate some actuators in the flight deck, while the passive BCI was triggering adaptive automation when the user's level of attention was too low. The way the scores were handled was similar to early works with active hBCI (as Fig. 1(a)), where two BCI systems work in parallel to control different aspects of the interaction.

C. Current limitations and challenges of hybrid BCI systems

Thanks to great research efforts, several improvements on feature extraction methods and decoding algorithms for brain signals were reported [27], [28], as well as the optimization of presentation methods, like joint frequency-phase modulation (JFPM) [29]. SSVEP-based BCIs now present high performance (i.e high accuracy, number of targets and ITR). These improvements have also been achieved to an extent for P300-based BCI systems, with methods such as triple rapid serial visual presentation (RSVP) [30], and have also been addressed by the hybridation of SSVEP and P300 [7], [10], [15]. With recent methods being able to detect brain signals quickly and reliably, the focus has shifted to bring BCI systems outside of the lab. Issues like high variability in the signal, the difficulty of managing noisy data, and BCI illiteracy are still pressing against the validity of BCI in more ecological environments.

The hBCI paradigm itself also currently faces its own set of challenges. A potential disadvantage for the widespread use and adoption of hBCI systems is that an *ad hoc* scoring fusion approach needs to be created (i.e. specifically for the particular experiment and combination of BCI systems used), which limits their scalability and transferability to different paradigms or BCI modalities. This is also the case when the system requires some kind of threshold, as it is often the case with SSVEP and the called *Midas' touch effect* (i.e. regular outputs commands even if the user is not actively controlling the system), but is also interesting for P300 in order to limit the number of repetitions needed to achieve a decision. Several studies have implemented thresholding in some fashion that was either heuristically decided by the researchers or needed additional calibration in order to find the value for each participant or group [7], [8], [11], [14].

Additionally, hBCI research has shown that the integration of the systems can achieve more than the mere combination of two classification outputs. To the knowledge of the authors, hBCI implementations where the individual BCIs interact with or influence each other have not been reported in the literature (although it has been proposed in [9]). Designing systems where one BCI can influence the other could open a new field of research that would allow for more nuanced implementations to exist and potentially improve the user experience. Such systems could be designed to modify each other based on hypothesis or cognitive models of how certain cognitive processes can influence others, like how visual attention can be influenced by arousal [31] or mental workload [32].

To address these challenges, a general framework that can integrate a wide range of BCI systems is needed. Such a framework should be able to adapt its characteristics to each specific problem, while at the same time maintaining a general structure in order to allow modification of the involved BCIs or to be applied to a different participant or type of experiment. This general framework could also include a mechanism that allows the BCI components to influence each other. As previously suggested, this framework could be able to modify the time it takes for an active BCI to make a decision based on the fatigue level of the user, detected by a second, passive BCI. And, at the same time this second BCI could take care of managing parts of the control system that can be operated automatically when the user is fatigued (see Fig. 1(d)). Moreover, the system could keep track of the confidence of the classifier outputs and trigger re-calibration or halt of the BCI if needed, which would greatly reduce the impact of noisy environments.

In this work, we advocate that such a framework could be achieved using a mathematical model often used for optimally control automated systems under uncertainty and partial observability. This framework is named Partially Observable Markov Decision Process (POMDP) [33].

III. A New Framework for managing Brain-Computer Interfaces

The following section introduces the motivation to apply POMDP to BCI research, and how it can help to address the current challenges of hBCI paradigms. Next, a formal definition of the framework is provided, and finally, a detailed example of a POMDP-based hBCI system architecture is discussed.

A. Why POMDPs?

POMDP is dedicated to model sequential decision processes under uncertainty. It relies on the belief state (i.e the environment/system state estimation) to compute actions that maximize expected long-term rewards. A BCI, similarly, leverages different brain markers that reflect (but do not give direct knowledge of) a particular brain state, and use that information to send commands to a computer system. In this context, the targeted mental state of the system (e.g., left hand vs right hand MI, fatigue, mental workload, etc.) can be seen as the hidden true state of the user's brain. We access these brain states through brain markers (observations) that wish to use as a basis to the commands we will send to the system of our choice. This similarity in their conceptual structure make POMDPs a natural fit for BCI implementations. Moreover, the formulation of a POMDP model allows to easily integrate additional BCI systems with different state variables that influence the commands sent to the system.

To the very best knowledge of the authors, only one paper has implemented a POMDP model based BCI system [34], though several studies have been conducted on the the more broad field of human-machine interaction (HMI). Specifically, some work has been conducted on implementing mixed-observability MDP (MOMDP) systems to model the collaboration between a human agent and autonomous machines, while considering the cognitive state of the human in search and rescue [35] or target search [36] scenarios. In these studies, the cognitive state of the human agent is considered as partially observable state which is continuously estimated through the belief state.

Additionally to this key advantage of estimating human cognitive state through the belief state [37], POMDPs could be a promising approach to the aforementioned thresholding problem. As discussed, some BCI systems suffer to establish an 'idle' state. In detail, the POMDP model naturally manages this limitation thanks to the belief state. The belief state is a probability distribution over states, and is updated taking an action and receiving a reward. To take a decision (to choose an action), the POMDP computes a policy which defines to each belief state an optimal action to be performed. This policy depends on the reward function, which assigns a specific reward value to each possible action in each possible state. This allows the experimenter to set a cost (negative reward) for any incorrect action and a reward for correct ones. Instead of arbitrarily choosing a numerical threshold for the decision function, this approach allows for a more generic manner of determining actions preferences, and the POMDP solution (policy) will determine the confidence (probability of a given state) that the system needs to achieve in order to take a given action.

The idea of implementing dynamic thresholds for SSVEP BCI has already been explored by [38], where Bayesian-based methods were employed to estimate the likelihood that a prediction made by a classifier is correct. This idea uses methods that are conceptually similar to how the POMDP framework manage the update of the belief state, but is much more computationally expensive, as the posterior probabilities for each pair of targets needs to be updated several times during every trial. Note, the POMDP framework could provide an unified framework to apply similar methods to any categories of BCI system (hybrid or otherwise). Moreover, the POMDP solution (policy) defining when an action should be performed given the current belief state only needs to be computed once, at the beginning, similar to how BCI systems often need to be calibrated before its use.

Moreover, the reward function could potentially be adapted for every participant so as to capture individual differences, (e.g. their signal-to-noise-ratio) and could be updated in an online fashion using reinforcement learning, similarly to [34]. Another potential advantage of the reward function is to assign different rewards (or costs) to actions operating in different parts of the system. For example, in the case of aviation, incorrectly activating the front lights using a SSVEP BCI could have a much minor cost than unintentionally operating the flaps, since this latter action may jeopardize safety.

B. What are POMDPs?

Formally, a POMDP is a tuple $\langle S, A, \Omega, T, O, R, \gamma, b_0 \rangle$, where: S is the set of states; A is the set of actions; Ω is the set of observations; $T : S \times A \times S \rightarrow [0; 1]$ is the transition function denoting the probability $T(s', a, s) = p(s'|a, s)$ of reaching state $s' \in S$ given the action $a \in A$ is performed in state $s \in S$; $O : \Omega \times S \rightarrow [0; 1]$ is an observation function such that $O(o, s) = p(o|s)$, denoting the probability of observing $o \in \Omega$ given state $s \in S$; $R : S \times A \rightarrow \mathbb{R}$ is the reward function associated with pair of actions and states; γ is the discount factor; and b_0 is the initial probability distribution over states such that $b_0(s) = p(s_0 = s)$, with $b_0(s) \in \Delta$, the belief state space.

At each decision time step t, the agent takes an action $a \in A$, receives an observation $o \in \Omega$ and updates its *belief state* $b \in \Delta$ using the Bayes' rule:

$$b_a^o(s') = \eta^{-1} p(o|a, b) = \eta^{-1} p(o|s') \sum_{s \in S} p(s'|s, a) b(s) \quad (1)$$

where $\eta = \sum_{s'} p(o|s') \sum_s p(s'|s,a)b(s)$ is the normalization factor. The belief state can be seen as a complete information history, as it concatenates all the action-observation sequences such as $b_t(s) = p(s_t = s|o_t, a_{t-1}, o_{t-1}, ..., a_0)$.

In order to act efficiently, the POMDP solving step entails finding a policy $\pi : \Delta \rightarrow A$, which maximizes a performance criterion, the Value Function, generally defined as the expected discounted sum of rewards:

$$V^\pi(b) = \max_\pi \mathbb{E}^\pi \left[\sum_{t=0}^{\infty} \gamma^t r(b_t, \pi(b_t)) \middle| b_0 = b \right]. \quad (2)$$

Thus, the optimal policy π^* is the policy that maximizes the value function (Eq. 2). Interestingly, V^{π^*} satisfies the Bellman equation ($V^{\pi^*} = V^*$):

$$V^*(b) = \max_{a \in A} \left[r(b,a) + \gamma \sum_{o \in \Omega} p(o|a,b) V^*(b_a^o) \right], \quad (3)$$

where $r(b,a) = \sum_{s \in S} R(s,a)b(s)$. As $r(b,a)$ can be see as the average gain. The optimal policy π^* can be extracted from Eq. 3 when it converges for all belief states. In practice, the exact optimal solution of an infinite horizon POMDP is hard to be achieved. However, POMDPs solving algorithms, as PBVI [39], HSVI2 [40] and SARSOP [41] are able to approximate the ϵ-optimal value function (i.e., a value function ϵ close to the optimal one) in reasonable time (see [40], [41] for more details on POMDP solving).

C. *How to use POMDPs in Hybrid BCIs?*

When defining a POMDP model, one needs to define every possible state for the particular application. This is formulated by the use of different *state variables*, each taking a number of different values. Using this type of formulation, the possible stimuli or cognitive states that the BCI systems target can be easily defined. For example, let's imagine a hBCI system that operates using SSVEP stimuli and a passive BCI system to estimate mental workload of the user. In this context, the POMDP model would have an 'SSVEP target' state variable, indicating which SSVEP stimulus the user is looking at, and a 'mental workload' state variable, indicating the possible states (mental workload levels) that the user could currently be in. The Figure 2 shows a graphic representation of the such POMDP elements and their relationships. The POMDP model would then use that formulation to create a state space with every possible combination of the state variables' values. Previous works have used POMDP models in order to integrate information from behavioral and physiological features, such as eye tracking (ET) and electrocardiogram (ECG), among others [42] [43]. This integration of state variables also means that the POMDP model can seamlessly integrate the outputs of several BCI systems into a single metric (the belief state), without the need for the experimenter to create a specific combined metric, as it has been done previously in hBCI literature [11], [12].

A POMDP model can be defined such as one state variable depends on the other and affects how they are processed thorough the right definition of transition and observation functions expressing Bayesian dependencies between variables. Following with the previous SSVEP and mental workload

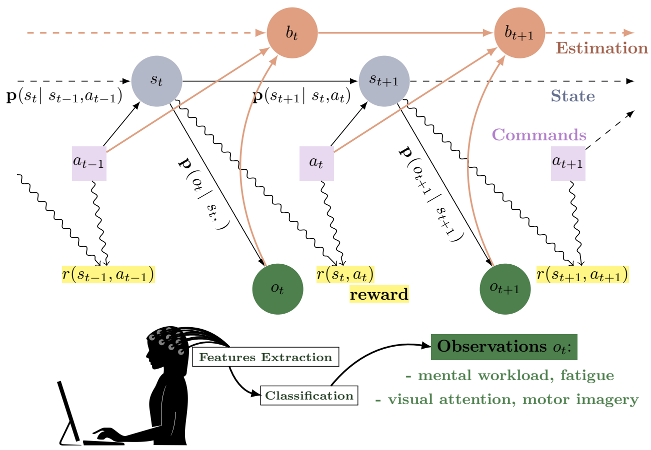

Fig. 2. General POMDP illustration for hybrid BCI control.

estimation, one can define the corresponding POMDP model such as, when the mental workload is high, the threshold for the SSVEP decision increases, and thus classification accuracy [27], [28], [38].

In order to address the challenge of subject variability, a POMDP model can be tuned to each individual signal-to-noise, by dynamically updating the reward function and with the creation of the observation function. The observation function is the part of the model that determines the number of possible observations (usually finite), and their related probability value. Two solutions have been proposed in the literature in order to translate the otherwise continuous physiological measurements into a set of discrete observations. One solution is to take the feature vectors (observations) from the classifiers and implement a sort of clustering to regroup all the possible measurements that result in the same change in the belief state [34]. Another solution is to use the confusion matrix provided by the classifier as the observation function, since it describes the probability of correctly 'observing' (predicting) a particular 'state' (class) given labeled data [36], [44]. However, another issue arises in high-noise naturalistic environments, since EEG data is sensitive to movement and muscular activity. It is possible to include a state variable describing the confidence of the system on its own accuracy. This can indeed prompt the model to re-calibration (using a preferred action) or halt of the BCI systems if it believes it is no more reliable in the current conditions.

Additionally, this framework would allow to potentially introduce other signal modalities like ECG, electromyogram (EMG) and ET. Measures like EMG could provide ground-truth information about the state of the muscles for orthosis control, which would be integrated with BCI markers for more nuanced interactions. Also, context or present information about the system being controlled (e.g. whether there is an alarm currently being presented to the pilot in the cockpit) could be considered in order to modify the BCI behavior. In essence, the POMDP framework can act as a decision unit that takes into account all the information in the system and integrates it to optimize the best course of actions.

D. Example of POMDP-based Hybrid BCI system

We propose a detailed example of a POMDP-based hBCI that is composed by two different BCIs: a reactive BCI, and a passive BCI that detects mental workload. The reactive BCI that we will use to activate arbitrary buttons on a control panel. For the passive BCI, mental workload could be estimated with frequency band features and used to trigger the automation of some control elements when the user is under high workload. Additionally, detecting high workload could modify the amount of data used to analyze the SSVEP, which is expected to increase classification accuracy.

Lets consider now that participants would perform a wheelchair control experiment. Each participant would move through a path consisting on a straight line, followed by a 90 degree turn, and another straight line. At the end, the user is asked to stay in a designated goal zone for two minutes without moving the wheelchair. All participants would repeat the circuit twice, on two different difficulty variations: No obstacles (as described above) and one obstacle in each straight line. The two variations would modulate mental workload (task difficulty).

For the POMDP part, let us describe the different components of the system. Assuming six possible flickers $S_f : \{s_{f_1}, \ldots, s_{f_6}\}$ and two possible mental states $S_m : \{s_{lw}, s_{hw}\}$. The combined total number of states in $\mathcal{S} : S_f \times S_m$ is in this example case 12.

Regarding the possible actions ($a \in A$), let's suppose one command a associated to each of SSVEP buttons, as well as one action that will trigger adaptive automation when the user is facing overload. When this is the case, the speed of the wheelchair could be automatically set to a medium setting and the user would not have to control it manually. We also suppose a *wait* action for which the system does not send any command. Note, we assume that all actions are applicable in any state. Concerning the transition function, we assume that the underlying state remains the same (i.e. the transition function is set to identity) until a button-related action or any automatic task-mode action is played (i.e. then the transition function enables to re-initialize the system - all states are considered as possible next states).

For the reward function R, we assume a type of reward function that would push the POMDP agent to ensure the necessary confidence on state estimation for any action to be high, with the loss from a potential mistake being much higher than the gains for a correct answer [45]. The initial belief b_0 should be considered as uniformly distributed.

After training the respective classifiers for the two BCI systems, we retrieve the confusion matrices and use them to specify the observation model such as: $O_f(o_f|s_f, s_m) = p(o_f|s_f, s_m), \quad \forall (s_f, s_m) \in S, \quad \forall o_f \in \Omega_f$, and $O_m(o_m|s_f, s_m) = p(o_m|s_f, s_m), \ \forall (s_f, s_m) \in S, \forall o_m \in \Omega_m$. Following the literature, one may assume a high classification accuracy (e.g. 0.9 and 0.7) [21], [38], and a uniform spread on the probabilities of incorrectly classifying each class. Note, this leaves us with as many possible observations as classes (ten for SSVEP, two for mental workload), such as $\Omega : \Omega_f \times \Omega_m$.

We could then proceed to solve the POMDP problem using, for example, the SARSOP [41] algorithm, which is a fast and efficient algorithm to approximate the solution of a POMDP model. Once the optimal value function approximated, a policy mapping belief states to actions is obtained and no further calculations are needed online during the operation, except the belief update step (see Eq. 1).

Then, for the experiment, we start with a decision step of 50ms for the POMDP model (i.e, an action will be taken every 50ms). For the reactive BCI, following the literature [38], we will start with an epoch of 200ms of EEG data, and add further steps until a decision is taken or the total length of the epoch reaches 1s. For the passive BCI, we determine a sliding window of 2s of EEG data, following [21]. Each action and observation modifies the belief state of the POMDP system (i.e, a belief update is performed), and successive observations of the same class would take the belief closer to the threshold specified by the policy. When the belief reaches a level of confidence for which a button-related action is preferred following the policy, the associated command is send to the computer system and the cycle repeats again. Data from the mental workload estimation can be carried over from trial to trial in order to keep a continuous estimation.

IV. Conclusion and future work

In this paper, we presented some of the current limitations of both single modality and hBCI paradigms, and proposed a novel approach for hBCI control based on the POMDP framework. This framework has already been explored by neighbouring research fields, and sports many attractive features for BCI implementations. Some of these properties include dynamic thresholds, opposed to the arbitrary and static solutions currently implemented in the literature. POMDP models could pave the way for more nuanced hBCI systems, including the estimation of the user's mental state via passive BCI to dynamically adapt the control systems to their intended application and thus bring them closer to more realistic environments.

Future directions include the offline assessment of performance of the proposed POMDP framework and posterior online implementation of a system as the one described in section III-D. Since the work from [34], notorious advancements in feature extraction and stimulus presentation have been made. Because of that, we believe the first step towards the implementation of this framework is to benchmark a SSVEP-POMDP BCI implementation using state-of-the-art feature extraction and stimulus presentation methods. Once offline performance of the proposed framework has been assessed, the next step would be to proceed with the implementation of a hybrid passive/reactive BCI system using POMDP as a decision framework.

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