Tools for affective, cognitive and conative states estimation from both EEG and physiological signals

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Introduction

Research on electroencephalography (EEG)-based brain-computer interfaces (BCIs) has become vastly more democratic in recent decades (Nam 2018). This technology enables transfer of information from the human brain to a machine via EEG, and can notably enable people with severe motor impairments to send commands to assistive technologies such as a wheelchair, e.g., by imagining left or right hand movements to make the wheelchair turn left or right. Such BCIs are called active BCIs since users are actively sending commands to the system by performing mental imagery (Zander 2011). However, the lack of robustness of BCIs limits the development of the technology outside of research laboratories, and current active BCIs cannot be controlled by 10 to 30% of its users. However, another type of BCIs proved particularly promising: passive BCIs (Zander 2011). Such BCIs are not used to directly control an application, but to monitor in real-time users' mental states in order to adapt an application accordingly. Note that passive BCIs can be coupled with physiological signals: they are called "hybrid BCIs" (Pfurtscheller et al., 2010).

Among these mental states, passive BCIs could estimate cognitive (process of coming to know and understand), conative (personal, intentional and motivational drives to process the information) and affective states (emotional interpretation of perceptions, information, or knowledge). Such states can be used to study human learning, which is a crucial research endeavour: how can humans learn and what are their motivations to keep building-up knowledge? Indeed, every human is permanently learning to adapt to his environment and current generations now have to learn to use rapidly evolving technologies. The Cognitive Load Theory (CLT) perfectly illustrates the relationship between a cognitive state, here the cognitive load, and learning (Sweller 1998), as many researchers have been using it to analyze the effect of cognitive load on learning (Paas 2010). Concerning affective states and learning, Damasio's work enabled us to understand the strong link between emotions and certain cognitive processes such as attention or memorization, that are strongly involved in learning (Damasio 1994). Finally, epistemic curiosity is an important conative state that is associated with spontaneous exploration, active learning, facilitated memorization and sustained engagement (Oudeyer 2016). Being able to estimate such mental states from EEG and/or physiological signals, using passive BCIs, would improve the understanding of individual users' capabilities and motivations to learn.

However, being able to do so is no easy task. Indeed, this requires psychological models and protocols to induce and manipulate such mental states, as well as machine learning algorithms and software tools to robustly estimate them from EEG signals. In this work, we summarize some of our recent research works with passive BCIs to address these issues. In particular we present 1) machine learning algorithms we designed and/or studied to classify cognitive and affective states from EEG; 2) BioPyC, an open-source python toolbox for easy classification of EEG and physiological signals; and 3) a protocol and study demonstrating that a conative state can be newly estimated from EEG: curiosity.

1. Machine learning algorithms to estimate cognitive and affective states

In order to estimate such mental states, we explored recent machine learning algorithms that have shown to be promising for oscillatory-based BCIs, but that have been scarcely tested on oscillatory mental states estimation, proposed new variants of them, and benchmarked them with classical methods to estimate both mental workload and affective states (Valence/Arousal) from oscillatory-based EEG signals. We studied these approaches with both subject-specific and subject-independent calibration, to go towards calibration-free systems (Appriou 2020a). Our results suggested that a Convolutional Neural Networks (CNN) obtained the highest mean accuracy, although not significantly so, in both calibration conditions for the mental workload study, followed by our proposed Riemannian Geometry Classifier (RGC), namely the Filter Bank Minimum Distance to Mean (FBMDM) classifier. However, this same CNN underperformed in both conditions for the affective states study, where fewer training data was available, when our proposed Filter Bank Tangent Space RGC (FBTSC) performed the best.

2. BioPyC: an open-source Python toolbox for easy EEG and physiological signal classification

In order to perform such machine learning algorithm comparisons, and enable anyone - including non-engineers - to easily run such studies, we developed the free and open-source BioPyC Python library (Appriou 2021). This toolbox, available at https://gitlab.inria.fr/biopyc/BioPyC, enables anyone to easily compare and benchmark both Signal Processing algorithms and Machine Learning algorithms for offline EEG and physiological signals decoding. Based on an intuitive and well-guided graphical interface, the user can follow the standard steps of the BCI process without any programming skills, in just a few clicks: 1) reading different neurophysiological signal data formats 2) filtering and representing EEG and physiological signals 3) classifying them 4) automatically visualizing and performing statistical tests on the results.

3. Estimating curiosity from neurophysiological signals

Finally, we performed a study to estimate curiosity levels from EEG and physiological signals. In particular, we first designed a protocol to induce participants into different states of curiosity, using trivia question and answer chains about more-or-less interesting topics. Then, we ran an experiment in which we used EEG, Heart Rate (HR), breathing and Electrodermal Activity (EDA) signals to measure the neurophysiological activity of participants using this protocol. Results from the within-participant study attempting to classify EEG signals into low versus high curiosity levels, with five-fold stratified cross-validation, revealed classification accuracies oscillating around 60% (63.09% for FBTSC) (Appriou 2020b). We also attempted to classify curiosity levels from physiological signals (ECG, EDA and breathing): we obtained a classification accuracy of 58.45% when classifying breathing signals features with a Linear Discriminant Analysis classifier (Appriou 2020c).

Conclusion

Altogether, our work contributed tools, namely machine learning algorithms, a software toolbox (BioPyC), a protocol and studies to estimate cognitive (workload), affective (arousal and valence) and conative (curiosity) states from EEG and physiological signals. In the longer term, this should contribute to a better understanding of learning-related mental states and their use to design adaptive training systems.

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