PhD position

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Robust human operator monitoring through signal processing and machine learning applied to physiological features

Context

Although research on brain-computer interfaces (BCIs) has been increasing dramatically these recent years, passive BCIs, systems that implicitly adapt to the operator based on his/her psychophysiological state, are still far from optimal in terms of accuracy. Yet they provide a means to perform operators' online monitoring in risky settings (e.g. aeronautical context) which is not feasible with subjective and behavioral measurements. Moreover, they enable engineers to build closed-loop systems that not only monitor but take into account this psychophysiological state to modify the interaction and/or the task in order to increase both safety and performance.

The implementation of effective BCIs faces several issues including the following ones: i) The very nature of the signals makes this problem particularly complex. Indeed, the signal-to-noise ratio is very low for physiological signals such as cerebral ones. Also, they are non-stationary and fluctuate over participants, time and experiments; ii) Mental states can interact/overlap, and physiological features too (1; 2); iii) The size of the datasets used for learning is limited since they come from time and money-consuming experiments that involve humans.

Therefore, a need for specific and robust classification pipelines exist, one that would be robust to mental states interaction, features' overlap, settings, participants and sessions. Many promising avenues have emerged to overcome these issues (3). For instance, adaptive classifiers (4) update learning using new data, which improves accuracy when the distribution of data changes over time. Transfer-learning (5) can also be a good solution when available datasets are not close enough to the actual considered data. The improvement of the BCIs has also been made possible by the use of techniques from Riemannian geometry (6), particularly in very noisy contexts (7). Other examples of solutions are control-inspired monitoring (8), dataset improvement with data generation (9; 10), deep learning (11) etc.

Content and Outline

This PhD topic addresses the issue of developing a pipeline to process physiological data in an online manner which would be robust to noise, to the work context and the operator, and which would enable to monitor mental states relevant in risky settings such as workload, fatigue, stress, and error detection. The physiological data of interest would mainly consist of cardiac and oculomotor measures recorded using ECG and eye-tracking devices, but also cerebral measures recorded by electroencephalography (EEG). The PhD would not include any experimental campaigns since the analyses would chiefly be performed on already acquired datasets and publicly available ones.

PhD outline:

- First year: literature review, databases identification and selection, development of state-of-the-art pipelines.
- Second year: benchmarking of signal processing and machine learning methods, proposal of a new pipeline, first scientific publication/proceeding.
- Third year: last comparisons and developments, thesis writing, second scientific publication/proceeding.

The main libraries that will be used:

- Scikit-learn – `https://scikit-learn.org/stable/`
- MNE-python – `https://martinos.org/mne/stable/index.html`
- Pytorch – `https://pytorch.org/`
- EEGLab – `https://sccn.ucsd.edu/eeglab/index.php`
- Gumpy – `http://gumpy.org/`
- PyRiemann – `https://github.com/alexandrebarachant/pyRiemann`

PhD candidate's profile:

- Applied Mathematics, Artifical Intelligence, Signal Processing or Biomedical Engineering background;
- Strong programming skills;
- Autonomous, hard-working, problem-solver;
- Interested in Neuroscience and Cognitive Science.

Additional Information

- Salary: This PhD thesis is financially supported by the ANITI Institute which offers a competitive net salary of 2096 euros per month with some teaching (64 hours per year on average) .
- Starting date: October 2019 (can be delayed for an outstanding candidate).
- Duration: 36 months
- Supervisors: Dr Raphaëlle N. Roy and Dr Nicolas Drougard, ISAE-SUPAERO, Université de Toulouse, France.
- Collaborators: ANITI Chair holder Professor Frédéric Dehais and Dr Caroline Ponzoni Carvalho Chanel.
- Application procedure: Formal applications should include a detailed CV, a motivation letter, at least one reference letter, and transcripts of degrees. Samples of published research by the candidate and reference letters will be a plus.

References

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