Decodable anticipation from prestimulus activity

[Isabelle Hoxha[1,2,3,4], Sylvain Chevallier[3], Arnaud Delorme[4], Arnaud Boutin[1,2], Michel-Ange Amorim[1,2]]

[[1]CIAMS, Université Paris-Saclay, 91405 Orsay, France]

[[2]CIAMS, Université d'Orléans, 45067 Orléans, France]

[[3]LISV, UVSQ, Université Paris-Saclay, 78140 Vélizy-Villacoublay, France]

[[4]CerCo, CNRS, Université Toulouse III - Paul Sabatier, Toulouse, France]

Correctly anticipating external stimuli allows for shorter reaction times, and is relevant in many real-life situations, such as driving, sports, and playing a musical instrument. While it is common in everyday life, perceptual anticipation is difficult to observe in a laboratory setting, as these processes are mainly unconscious (Trevena and Miller, 2002; Barik et al., 2019) and hence difficult to study. In particular, asking participants to report what they anticipated implies for them the elucidation of unconscious processes, which in itself is a form a decision-making and is thus likely to change brain activation patterns (Eriksen, 1960; Koch and Preuschoff, 2007). This makes the identification and analysis of anticipatory activity difficult, and its use in brain-computer interface paradigms impractical. However, reaction times can be helpful to infer on the class of the stimulus (Petro et al., 2019). While previous EEG studies have shown the impact of pre-stimulus alpha band (8-13Hz) activity on reaction (Petro et al. 2019) and encoding performances (Lou et al., 2014), the predictive power of this spectral feature is still to be investigated. In particular, brain-computer interface applications decoding anticipation should be able to answer the question "what is the participant anticipating next?".

The goal of this preliminary study was therefore to classify anticipatory activity in a two-alternative forced-choice task at the single-trial level, with the classes representing the type of the stimulus that is presented subsequently. We assumed that longer response times are symptomatic of incorrect expectations from the participant in order to obtain the class of anticipation.

Participants (N=9) had to categorize a random series of stimuli into two categories, either "face" if they saw the sketch of a face, or "number+sound" if they saw a number and heard a sound simultaneously. While performing this task their brain activities were recorded by a 32-electrode EEG device. Pre-stimulus alpha activity (8-13Hz) in temporal and occipital electrodes was used as feature for classification. Each trial was then classified using a Support Vector Machine whose kernel and regulation parameter were tuned specifically for each participant through grid search. We performed the classification twice using the same features but different labels. In one case the labels corresponded exactly to the class of the stimulus presented subsequently to the participant ("stimulus labels"), while in the other case the labels of trials with response times larger than the fourth quartile of all response times were inverted ("inverted labels"). In that case, the inversion algorithm translates our hypothesis on long response times.

We showed that above-chance classification accuracies (60%) are achieved for some participants when taking into account behavioral observations, whereas stimulus labels yield chance-level classification performance. The level of chance has been determined for each participant by permutation testing (Figure 1). To test group-level trends while taking into account the small sample size, we performed a Wilcoxon Signed-Rank test (critical W=8 for $p<0.05$), which showed a significant increase of accuracy when using the inverted labels compared to the stimulus labels (W=6, mean difference: 0.05).

Our finding paves the way towards a better understanding of the unconscious processes of anticipation and decision-making. Further investigation of these processes is necessary for designing brain-machine interfaces that are faster and more user-friendly. This goes through two complementary paths: first, creating a paradigm where the true class of anticipation can be inferred without biasing the decision task, and second, knowing better the neural correlates behind anticipation.

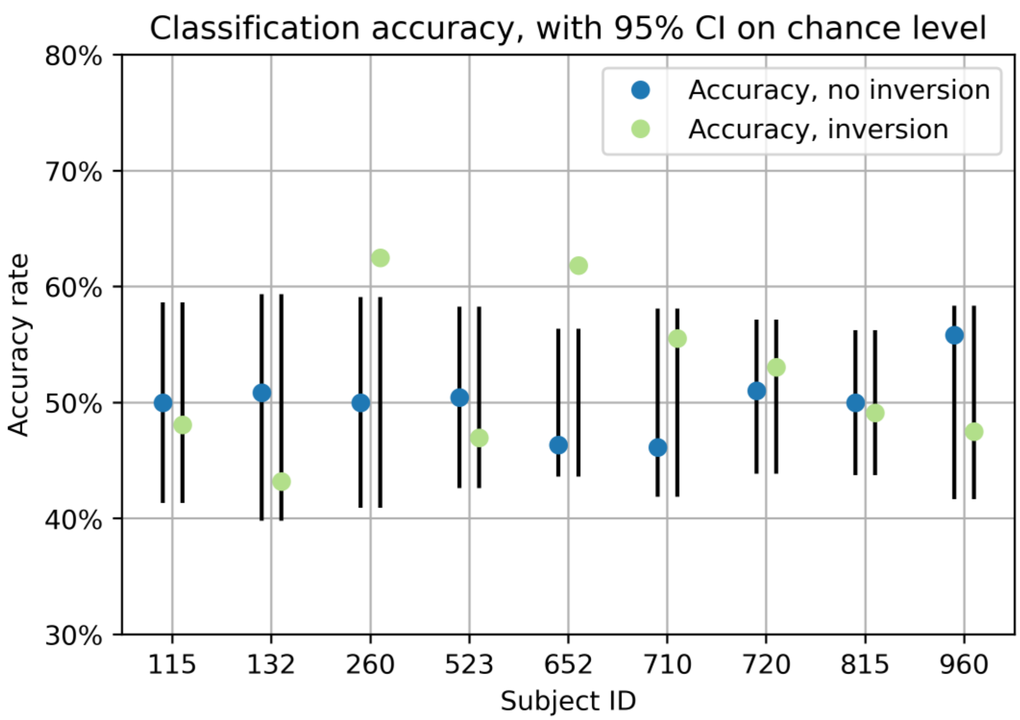

Figure 1. Classification accuracy using SVM using stimulus labels ("no inversion") and labels where some are inverted based on assumptions on the response times ("inversion"). The 95% confidence intervals were obtained by randomly permuting labels and running the gridsearch and cross-validation again for each sampling, and testing the obtained model on the same test set.

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