Metacognitive Skills are Preserved in Drowsiness

Additional Material

Contact

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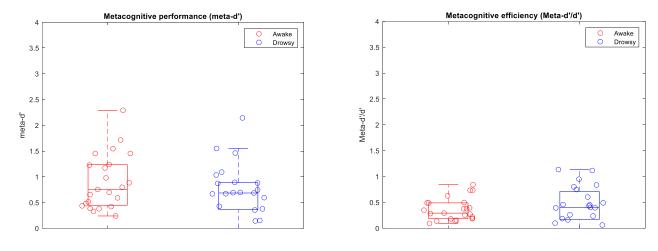
What is in this document?

In this document you will find additional results we obtained from our analysis of the behavioural and EEG data. First, you will find an analysis of participants' metacognitive performance when confidence is not binarized but semi-continuous (20 sub-categories) — these results might better reflect participants' metacognitive skills by better taking into account the responses participants gave using the joystick. We then introduce classifiers "neural scores" — i.e., multivariate neural information associated with the processing of Type I or Type II decisions — and how we used them to attempt to learn more about the relationship between both decision types (and other variables such as alertness or difficulty). Then you will find the results from some modelling analysis we conducted using these same neural scores and modulatory factors such as alertness or difficulty. With a second model, we tried to see if we could predict participants' confidence decision (joystick data) using the multivariate neural information from the Type I response processing (i.e., neural scores). We also show the results we obtained from a cross-decoding analysis across decision types. Finally, we discuss future analyses we have been planned: cross-decoding, modelling, new experiment — let us know if you have any comments or ideas!

1. Results

1.1. Behavioural results: confidence as a continuum

Figure 1Participants metacognitive performance and efficiency, both in awake and drowsy states, with confidence as a continuous variable

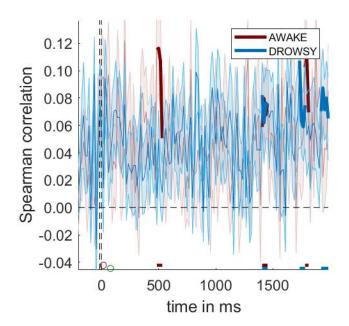


Note. Joystick values were grouped into 20 categories (quantiles). There is no significant difference between awake and drowsy states.

1.2. Correlation of classifiers' neural scores

Classifiers confidence scores (or "neural scores" to avoid any confusion) are a measure of how "confident" classifiers are of their classification¹, e.g., if the neural information should be rather associated with "tone" or "cone" — see also neural distance-to-bound approach^{2,3}, for which confidence can be seen as the distance to a decision boundary¹. Contrary to decoding weights which are calculated across trials, confidence scores are a feature of the AUC measure which can be retrieved for every participants, trials and time points¹. They constitute multivariate neural information (in our case, across all channels) that can be used for further analyses.

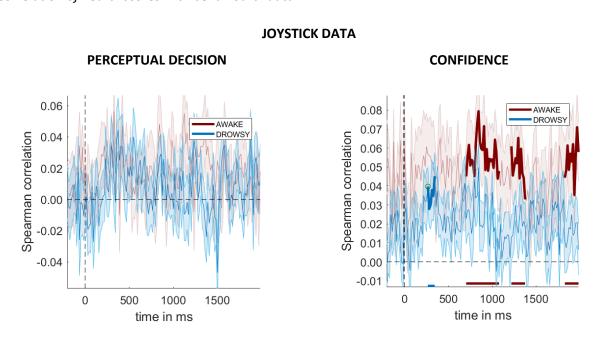
Figure 2Correlation of the neural scores from the perceptual and confidence decisions decoding

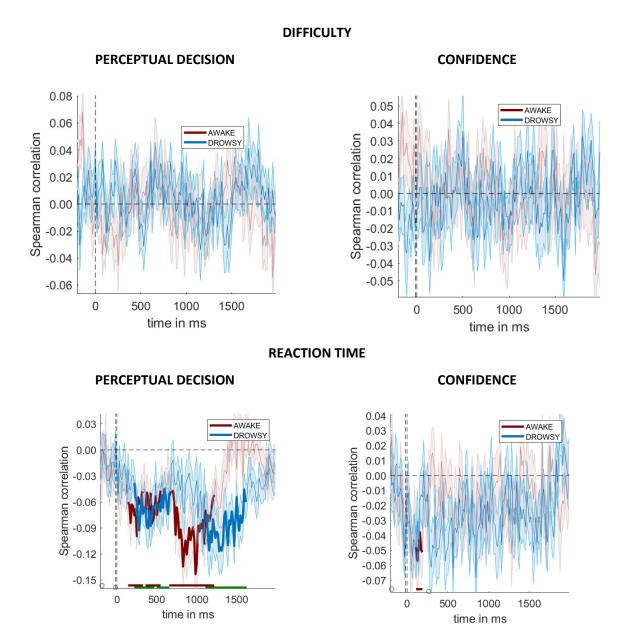


Note. Spearman correlation of the neural scores retrieved from the decoding of the perceptual and confidence decisions.

Figure 3

Correlation of neural scores with behavioural data





Note. On the left, correlation of the perceptual decision neural scores. On the right, correlation of the confidence decision neural scores.

1.3. Modelling results

1.3.1. Model 1: impact of drowsiness on perceptual decision processing neural information

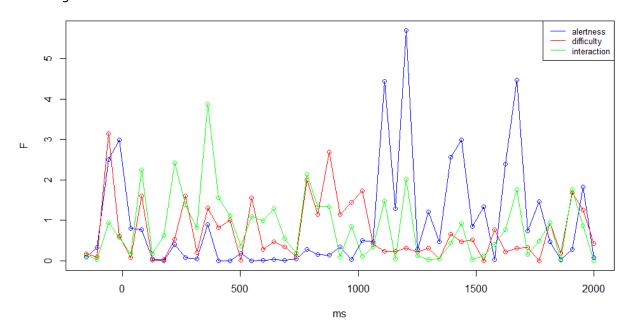
Formula 1

Linea mixed effect model: effect of alertness and difficulty on neural scores

$$model1 = lmer(neural \sim alertness * difficulty + (1 | subjects))$$

Note. Imer: fit linear mixed effect model, neural: neural scores from the perceptual decision decoding. The formula was entered in R and the model was run with the data from the experiment.

Figure 4Results from model 1: impact of alertness and difficulty on the neural scores from the perceptual decision decoding over time



Note. The model was run for 47 time windows of approximately 45ms.

1.3.2. Model 2: only drowsiness and difficulty impact the final Type II outcome

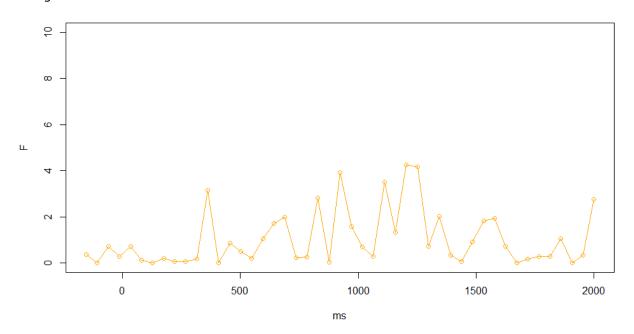
Formula 2

Linea mixed effect model

$$model2 = lmer(confidence \sim neural * alertness * difficulty + (1 | subjects))$$

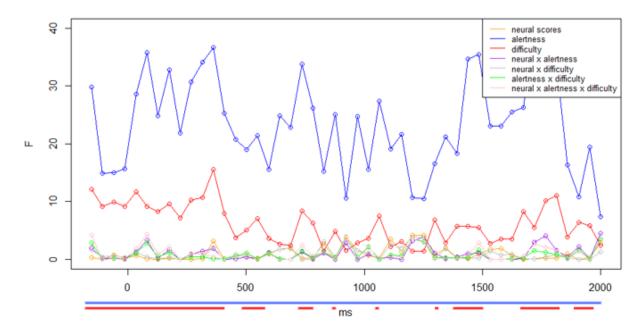
Note. Imer: fit linear mixed effect model, confidence: confidence rating with the joystick, neural: neural scores from the perceptual decision decoding. The formula was entered in R and the model was run with the data from the experiment.

Figure 3Results from model 2: impact of neural scores from the perceptual decision classification on confidence rating over time



Note. The model was run for 47 time windows of approximately 45ms.

Figure 4Results from model 2: impact of neural scores, alertness and difficulty on confidence rating over time



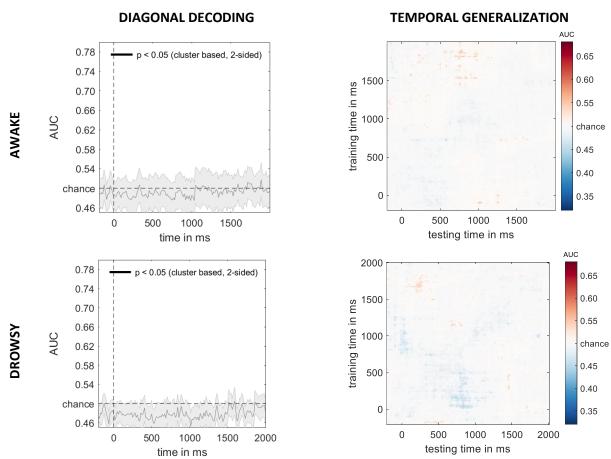
Note. The F values (output from the model) are on the y-axis. Time on the x-axis (ms). The blue and red lines indicate significance for alertness and difficulty, respectively. The model was run for 47 time windows of ~45ms.

1.4. Cross-decoding results

Results from the cross-decoding analyses (trained on perceptual decisions and tested on confidence decisions) did not result in significant results (see Figure 5). There was no generalization across time, or repeating themselves later. This might suggest that the neural information/signature is different for the two processes, giving some evidence that they rely on different brain mechanisms — however, these results are tricky to interpret and one must be careful with conclusions. Performing a temporal generalization is also informative, as confidence decisions might rely on the same mechanism/information but delayed.

Figure 5

Cross-decoding perceptual/confidence decisions



Note. The classifier was trained on perceptual decisions (tone/cone) and tested on confidence decisions (high/low).

2. Next steps

2.1. Cross-decoding across states

The results from our temporal generalization analysis suggest that similar information processing — but delayed — occurs in drowsiness for the processing of perceptual decisions. However, the processing of confidence appears to rely on a different mechanism when participants are drowsy. This difference between Type I and Type II decisions processing might explain the dissociation we observe behaviourally: an adaptive mechanism might support the maintenance of metacognitive skills as alertness decreases. With this new analysis, we directly compare the information processing in both states — for both decisions — using cross-decoding. Training classifiers across time (temporal generalization analysis) should help us detect similarities, even if the information processing is delayed in drowsiness.

2.2. Improvements of the models

The models we ran are linear and fairly simple — that might limit our ability to detect an effect. The neural scores might also be too noisy and we are considering other measures, e.g., using tools from the information theory.

2.3. Type II correctness?

We wanted to run a decoding of Type II correctness (to better target metacognitive abilities) but we were missing Type I incorrect trials. A future step could be new data collection with a more difficult task (for the current task participants' d' was still quite high, even when drowsy).

Comments regarding the interpretation of the results? Other ideas of future analyses? Give us your input!

3. References

- 1. Ort, E., Fahrenfort, J. J., Ten Cate, T., Eimer, M. & Olivers, C. N. Humans can efficiently look for but not select multiple visual objects. *ELife* **8**, e49130 (2019).
- 2. Grootswagers, T., Cichy, R. M. & Carlson, T. A. Finding decodable information that can be read out in behaviour. *NeuroImage* **179**, 252–262 (2018).
- 3. Ritchie, J. B. & Carlson, T. A. Neural decoding and "inner" psychophysics: A distance-to-bound approach for linking mind, brain, and behavior. *Front. Neurosci.* **10**, 190 (2016).