Classifier Visualisation Reveals Salience, Valence, and Serial Dependency in a Modified Implicit Cursor Control Paradigm

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Introduction

Brain-computer interfaces (BCIs) use classifiers to detect specific patterns in brain activity, allowing them to interpret ongoing activity, both post hoc and in real time [1]. Some classifier types can be interpreted neurophysiologically, meaning an inspection of their weight vectors can reveal aspects of the underlying brain processes [2]. This makes these classifiers, originally designed for BCI experiments, particularly useful for post hoc analyses in traditional neuroscientific studies, effectively providing a data-driven method to study effects between conditions—provided that these effects can indeed be revealed using the chosen inspection method. Commonly, interpreting classifier weights is done by looking at their *pattern*, i.e. the forward model revealing the projection pattern of the brain process isolated by the classifier [2]. It remains a challenge, however, to interpret these scalp-level patterns in terms of cortical *sources*, i.e. the actual regions of the brain where the relevant brain activity originated. To that end, we have previously developed a classifier visualisation technique that combines these forward models with a blind source separation decomposition [3]. In its current iteration, this method returns a visual representation of the relevance of sources to the classifier. Here, this method was applied to a modified implicit cursor control paradigm. It allowed the separation of two different cognitive processes, and revealed a serial dependency in the experimental design hidden to any other analysis.

Implicit cursor control

Implicit cursor control here refers to an experimental paradigm, first shown in 2014 [4,5]. In it, the participants observe a cursor move on a computer screen, and, unbeknownst to them, a passive BCI interprets their implicit brain activity in response to individual cursor movements in order to guide the cursor towards a target. The target was originally given, but can be self-chosen as well [6]. Cursor movements were interpreted by the participant as either "good" or "bad" with respect to reaching this target. The classifier could detect this interpretation with roughly 70% accuracy, and use it to guide the cursor in the "good" direction, i.e., towards the target. A potential confound in the original design of this experiment was that the target was visually salient on the screen, and "good" movements were thus always "towards" a salient point, whereas "bad" movements were "away" from the salient point. It is thus possible that cognitive processes related to visual salience (towards/away) overlapped with the main processes of interest related to valence (good/bad).

Methods

This current experiment uses a modified experimental paradigm in which the two processes of salience and valence are separated. This is done by placing the visually salient target in the middle of a semi-circular grid and having two conditions in which participants are told to either interpret 1) "towards" the target as "good" and "away" as "bad", or 2) vice versa. We could thus isolate valence from salience by looking at cursor movements that went in the same direction but had different interpretations, and isolate salience from valence by looking at cursor movements in different directions that had the same interpretation. We used the same windowed-means paradigm as in [5] to implement the classifier, and applied the classifier visualisation method of [3] to interpret it.

Results and conclusion

Results are shown in Figure 1. A classifier calibrated to isolate valence (top) shows different source contributions than a classifier isolating salience (middle). The salience classifier sees more contributions from occipitoparietal sources whereas the valence classifier is focused more on medial-prefrontal sources. This is in line with expectations. Importantly, however, significant differences were also found in the contributed sources between participants who performed one, or the other condition first. The lower row in Figure 1 shows the sources, similar for both valence and salience classifiers, for participants who first interpreted "towards" as "bad". This surprising finding of serial dependency in the study design was revealed only by the classifier visualisation method; other measures, e.g. reaction times and event-related potentials, did not produce significant differences.

To conclude, a visual inspection of different classifiers reveals that both valence and visual salience can play a role in implicit cursor control. The fact that it is possible to create a valence-focused classifier has potentially wide-ranging implications for human-computer interaction, but has an important ethical component as well, as the subjective interpretation of what is "good" and "bad" can potentially reveal highly sensitive information. Finally, in this experiment, the classifier visualisation method uniquely identified a serial dependency in the data not seen by other analyses.

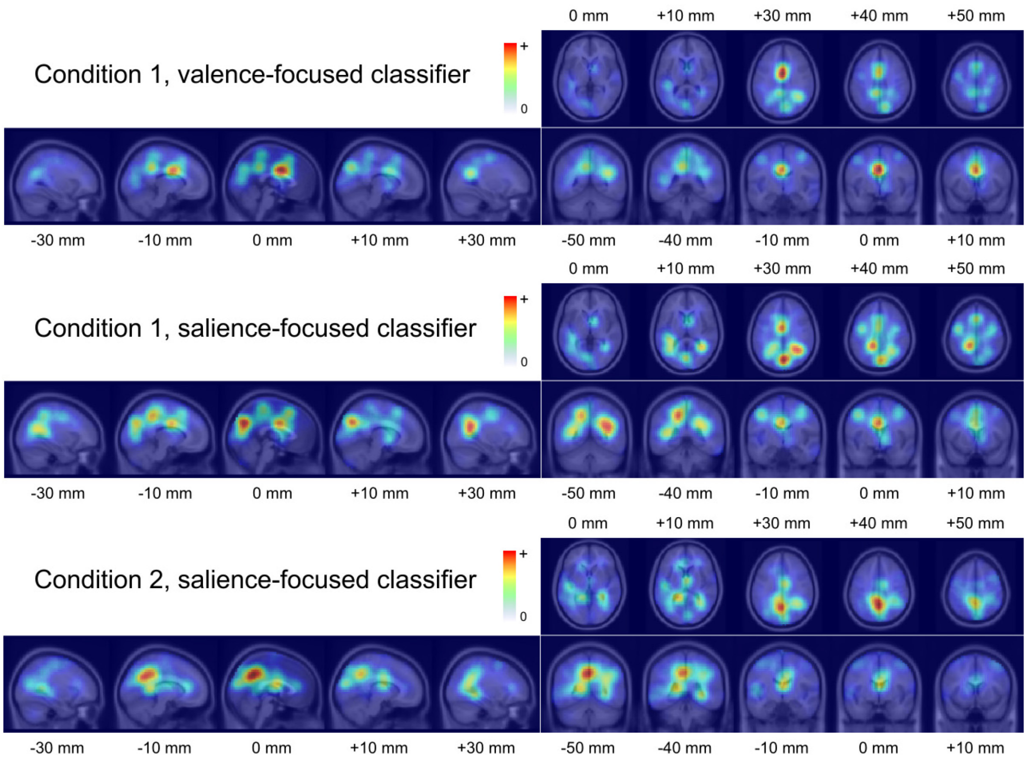

Figure 1. Classifier visualisation results.

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