



**HAL**  
open science

## EEG-BASED ART INTEREST DECODING

Marc Welter, J Casal Martínez, E Redmond, Jonathan Baum, Tomas Ward,  
Fabien Lotte

► **To cite this version:**

Marc Welter, J Casal Martínez, E Redmond, Jonathan Baum, Tomas Ward, et al.. EEG-BASED ART INTEREST DECODING. Neuroergonomics Conference 2024, Jul 2024, Bordeaux, France. hal-04638039

**HAL Id: hal-04638039**

**<https://inria.hal.science/hal-04638039v1>**

Submitted on 8 Jul 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

# EEG-BASED ART INTEREST DECODING

M. Welter<sup>1</sup>, J. Casal Martínez<sup>2</sup>, E. Redmond<sup>3</sup>, J. Baum<sup>1</sup>, T. Ward<sup>3</sup>, F. Lotte<sup>1</sup>

<sup>1</sup>Inria Centre at the University of Bordeaux / LaBRI, France

<sup>2</sup>Valencia Polytechnic University, Spain

<sup>3</sup>Dublin City University, Ireland

E-mail: marc.welter@inria.fr

## 1 Synopsis

Brain-Computer-Interfaces (BCIs) that decode aesthetic Interest could improve user experience in digital spaces by personalizing aesthetic stimuli selection without requiring explicit user feedback that might interrupt aesthetic experience. However, scientific understanding of aesthetic experience remains lacking, while validated BCI methods have not yet been applied to decode aesthetic Interest from EEG. We thus conducted a study in which participants gazed at visual art in a virtual museum and graded their Interest for each of them, while their EEG was being measured. Previous research suggested that brain oscillations could be informative of aesthetic preference. Therefore, we tested Filterbank Common Spatial Patterns feature extraction together with shrinkage Linear Discriminant Analysis, in a 2-class aesthetic Interest classification problem. We report promising aesthetic Interest decoding accuracies significantly and substantially above chance level.

## 2 Background

Passive Brain-Computer-Interfaces (BCIs) allow implicit and real-time monitoring of cognitive, affective and conative states in human users (Appriou & Lotte, 2021). Aesthetic experiences are complex constructs composed of such states, notably attentional, affective and reward-related states (Schaeffer, 2015). Today, we humans are exposed to an unprecedented amount of aesthetic stimuli, especially in digital spaces such as social media. In such spaces, presentation of artworks, e.g. visual art or music, relies on recommendation systems that require explicit user feedback. However, explicit feedback necessitates cognitive effort that might lessen aesthetic experience.

Passive aesthetic preference decoding BCIs, on the other hand, could allow personalization of art presentation in digital spaces without interruption, and thus, improve user experience (Welter, Bouneau, Lotte & Ward, 2023). Previous research on aesthetic preference decoding mostly focused on hedonic Liking (Welter & Lotte, 2024). However, automated art presentation based solely on Likes can easily result in filter bubbles of low aesthetic value (Yilma & Leiva, 2023). On the other hand, recommendations based on epistemic affects such as Interest and Curiosity could offer a wider range of aesthetic experiences to users (Kennett, Humphries & Chatterjee, 2023). In order to contribute towards the development of BCI-based art recommender systems that

result in interesting aesthetic experiences, we investigated aesthetic Interest decoding from Electroencephalography (EEG) data.

### 3 Methods

We collected EEG data from 13 healthy adults while they gazed at 120 high quality digital reproductions of diverse visual artworks in a virtual museum. The experiment consisted of 6 blocks of 20 artwork presentation and rating trials. At the start of each trial, a blank screen was displayed for a randomly chosen interval between 0.5 and 0.8s. After that, a fixation cross appeared for 5s, to washout potential emotions evoked by previous artworks and to measure a stable baseline. Then, an artwork stimulus was presented for 10s. Finally, the participants reported their Interest evoked by artworks on a scale from 0-100. These ratings served as ground truth for subsequent aesthetic Interest classification. After each run, the participants could rest for a minute. Balanced Interest/Disinterest classes were created by selecting the 45% highest and the 45% lowest rated artworks respectively. This partitioning resulted in 55-58 trials/class. Thus, we defined aesthetic Interest decoding as a 2-class supervised classification problem with an estimated chance level ( $\alpha=0.01$ ) of 60.9% (Combrisson & Jerbi, 2015).

EEG data were recorded at 256 Hz using an ActiChamp amplifier (Brain Products, Gilching, Germany) with 31 active electrodes on a standard 10-20 montage. Electrodes were placed on on a broad scalp covering. The signal was grounded at Fpz and during recording the reference was placed on Fz. During offline analysis, the data was re-referenced to common average reference.

In order to decode aesthetic interest for visual art from the EEG signal, the following pipeline was used and validated with a 10-fold shuffled an stratified cross-validation: First, we manually inspected the data to reject bad channels. Then, we applied a 1-100Hz bandpass filter and a notch filter at 50 Hz to remove line noise. Afterwards, we created fixed epochs of 1s length and cleaned these epochs using a local Autoreject (Jas et al., 2016). These pre-processed epochs were then given to an Extended Infomax Independent Component Analysis (Lee, Girolami & Sejnowski, 1999). The resulting ICs were classified with ICLabel (Pion-Tonachini, Kreutz-Delgado & Makeig, 2019). Then, non-artefactual components were used to reconstruct a clean signal from the raw EEG. Then, trial epochs were extracted from 0.1-10s ( $t=0$ s being the start of the artwork display) during stimulus presentation and baseline corrected from -4s to -0.01s before stimulus appearance. We extracted discriminant features of the EEG epochs for classification with Filterbank Common Spatial Patterns (FBCSP) (Ang et al., 2012) A bank of 8 bandpass filters was used ( 1-4Hz, 4-8Hz, 8-13Hz, 13-16Hz, 16-20Hz, 20-30Hz, 30-50Hz, 50-70Hz). Note that we included frequencies above 30Hz - often rejected due to artefacts - as previous studies have suggested their link with aesthetic experience (Strijbosch et al., 2022). For each of these band-pass filter, 6 CSP spatial filters were learned from the train set and applied on the test set during each global cross-validation fold. During the computation of the spatial filters, covariance matrices were estimated using Oracle Approximating Shrinkage Estimator (Chen, Wiesel, Eldar & Hero 2010). After spatial filtering, log-transformed bandpower features were extracted. For each cross-validation fold, optimal features were selected using Recursive Feature Elimination (Guyon, Weston, Barnhill & Vapnik, 2002) with a local 5-fold shuffled and stratified cross-validation (inner cross-validation) on the training set data of that fold (from the outer cross-validation). The selected features were then fed into a shrinkage Linear Discriminant Analysis (sLDA) (Blankertz et al., 2011)

classifier and aesthetic Interest decoding performance was evaluated by computing the mean test accuracy over global cross-validation folds for each subject.

## 4 Results

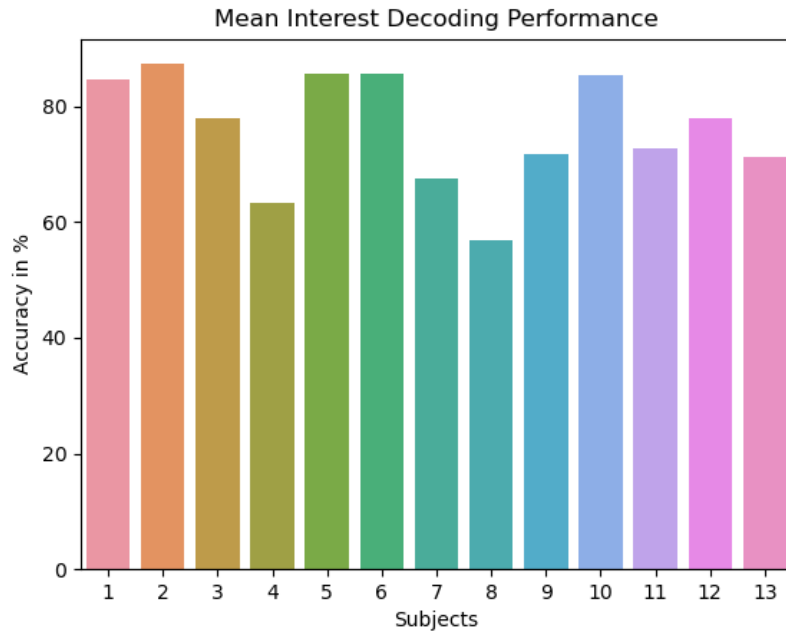


Figure 1: Mean aesthetic Interest FBCSP-sLDA decoding accuracy for all subjects

The overall mean decoding performance was  $75.9\% \pm 9.4$  (see Figure 1).

## 5 Discussion

EEG Aesthetic Interest decoding with FBCSP-sLDA worked quite well on average. Performance was below chance for one subject only. It should be noted, however, that ‘Interest’ is used with a range of different meanings (Pekrun, 2019) and thus, participants might have understood the Interest rating task differently.

Despite the relatively high FBCSP-sLDA Interest classification performance, bridging the gap towards online aesthetic preference decoding, and thus automated art presentation BCIs, remains challenging. Many BCIs require training on balanced data samples. Unfortunately, it is often uncertain whether an individual will find an artwork interesting or not. Statistical artwork properties, such as symmetry or complexity, have been correlated with subjective aesthetic ratings (Geller, Bartho, Thoemmes & Redies, 2022) and could be used to estimate aesthetic preference a priori. In conclusion, aesthetic Interest decoding BCIs seem feasible, but future work should investigate optimal training data selection during online calibration.

## 6 Disclosures

This research was funded by CHISTERA project BITSCOPE (grant ANR-21-CHRA-0003-01).

## References

- Ang, K. K., Chin, Z. Y., Wang, C., Guan, C., and Zhang, H. (2012). Filter Bank Common Spatial Pattern Algorithm on BCI Competition IV Datasets 2a and 2b. *Frontiers in Neuroscience* 6. DOI: 10.3389/fnins.2012.00039. URL: <https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2012.00039>.
- Appriou, A. and Lotte, F. (2021). Tools for affective, cognitive and conative states estimation from both EEG and physiological signals. *Neuroergonomics Conference (NEC)*.
- Blankertz, B., Lemm, S., Treder, M., Haufe, S., and Müller, K.-R. (2011). Single-trial analysis and classification of ERP components — A tutorial. *NeuroImage* 56.2. Multivariate Decoding and Brain Reading, pp. 814–825. ISSN: 1053-8119. DOI: <https://doi.org/10.1016/j.neuroimage.2010.06.048>. URL: <https://www.sciencedirect.com/science/article/pii/S1053811910009067>.
- Chen, Y., Wiesel, A., Eldar, Y. C., and Hero, A. O. (2010). Shrinkage Algorithms for MMSE Covariance Estimation. *IEEE Transactions on Signal Processing* 58.10. ISSN: 1941-0476. DOI: 10.1109/tsp.2010.2053029. URL: <http://dx.doi.org/10.1109/TSP.2010.2053029>.
- Combrisson, E. and Jerbi, K. (2015). Exceeding chance level by chance: The caveat of theoretical chance levels in brain signal classification and statistical assessment of decoding accuracy. *Journal of Neuroscience Methods* 250. Cutting-edge EEG Methods, pp. 126–136. ISSN: 0165-0270. DOI: <https://doi.org/10.1016/j.jneumeth.2015.01.010>. URL: <https://www.sciencedirect.com/science/article/pii/S0165027015000114>.
- Geller, H. A., Bartho, R., Thömmes, K., and Redies, C. (2022). Statistical image properties predict aesthetic ratings in abstract paintings created by neural style transfer. *Frontiers in Neuroscience* 16. ISSN: 1662-453X. DOI: 10.3389/fnins.2022.999720. URL: <https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2022.999720>.
- Guyon, I., Weston, J., Barnhill, S., and Vapnik, V. (2002). Gene Selection for Cancer Classification Using Support Vector Machines. *Machine Learning* 46, pp. 389–422. DOI: 10.1023/A:1012487302797.
- Jas, M., Engemann, D., Bekhti, Y., Raimondo, F., and Gramfort, A. (2016). Autoreject: Automated artifact rejection for MEG and EEG data. *NeuroImage* 159. DOI: 10.1016/j.neuroimage.2017.06.030.
- Kenett, Y., Humphries, S., and Chatterjee, A. (2023). A Thirst for Knowledge: Grounding Curiosity, Creativity, and Aesthetics in Memory and Reward Neural Systems. *Creativity Research Journal* 35, pp. 1–15. DOI: 10.1080/10400419.2023.2165748.
- Lee, T.-W., Girolami, M., and Sejnowski, T. (1999). Independent Component Analysis Using an Extended Infomax Algorithm for Mixed Sub-Gaussian and Super-Gaussian Sources. *Neural Computation* 11, pp. 417–441. DOI: 10.1162/089976699300016719.

- Pekrun, R. (2019). The Murky Distinction Between Curiosity and Interest: State of the Art and Future Prospects. *Educational Psychology Review* 31. DOI: 10.1007/s10648-019-09512-1.
- Pion-Tonachini, L., Kreutz-Delgado, K., and Makeig, S. (2019). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage* 198. DOI: 10.1016/j.neuroimage.2019.05.026.
- Schaeffer, J. (2015). *L'Expérience esthétique*. Paris: Gallimard.
- Strijbosch, W, Vessel, E. A., Welke, D, Mita, O, Gelissen, J, and Bastiaansen, M (2022). On the neuronal dynamics of aesthetic experience: Evidence from electroencephalographic oscillatory dynamics. *Journal of Cognitive Neuroscience* 34.3.
- Welter, M, Bouneau, A, Lotte, F, and Ward, T (2023). *Abstracts from the 8th Visual Science of Art Conference (VSAC) Amsterdam, The Netherlands, August 24th–27th, 2022*. Vol. 11. Art & Perception 2. Leiden, The Netherlands: Brill.
- Welter, M and Lotte, F (2024). Ecological decoding of visual aesthetic preference with oscillatory electroencephalogram features—A mini-review. *Frontiers in Neuroergonomics* 5. DOI: 10.3389/fnrgo.2024.1341790. URL: <https://www.frontiersin.org/articles/10.3389/fnrgo.2024.1341790>.
- Yilma, B. A. and Leiva, L. A. (2023). The Elements of Visual Art Recommendation: Learning Latent Semantic Representations of Paintings. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. Hamburg, Germany: Association for Computing Machinery. ISBN: 9781450394215. DOI: 10.1145/3544548.3581477. URL: <https://doi.org/10.1145/3544548.3581477>.