ArtEEGAttention: an advanced deep learning approach for art brain decoding

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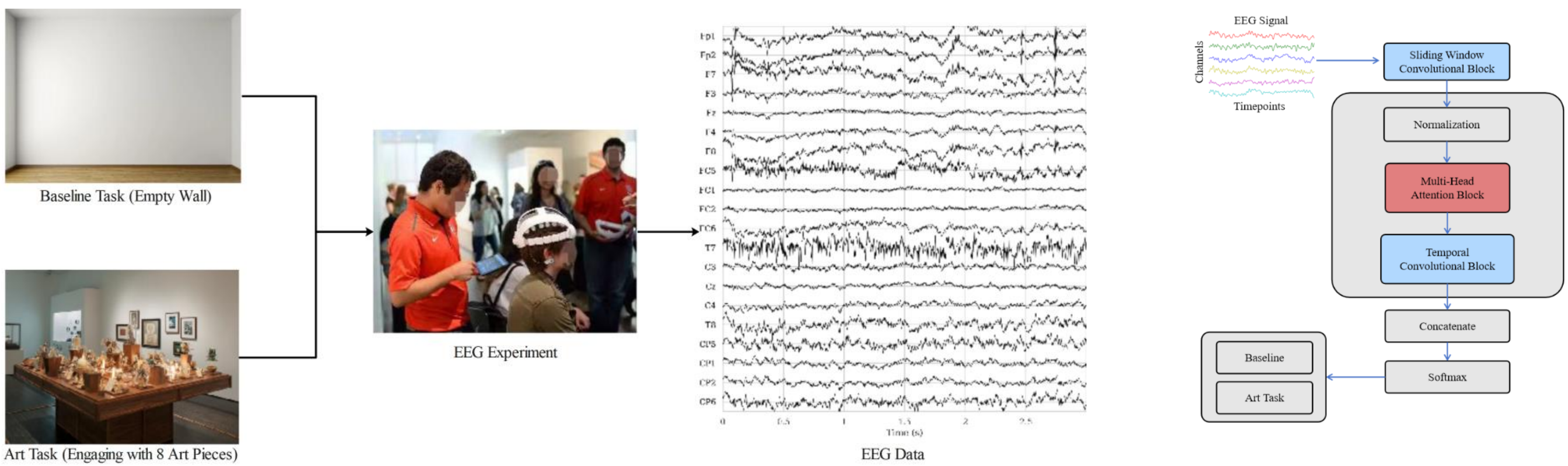
Problems & Ideas

- Problems of art brain decoding by EEG:
  – Lack of EEG datasets for art scenarios.
  – Lack of high-performance deep learning models for EEG decoding.
- Ideas: We collect EEG data from participants viewing artworks, filter and segment the signals to create a dataset, and propose the ArtEEGAttention deep learning model for neural decoding.



Left:The art EEG experiment overview. Participants wear EEG devices for two tasks, namely the baseline task and the art task, while their EEG signals are recorded as they watch. Right: The ArtEEGAttention model.

Main Contributions

- Contributions:
  - We contribute a binary classification EEG dataset. The refined EEG records for 16 subjects are segmented into 3-second epochs, labeled as either observing a blank wall or viewing artwork, thereby creating a binary classification dataset.
  - We propose ArtEEGAttention, a novel model that combines sliding window convolution with self-attention mechanisms for enhanced EEG classification performance. When compared with the state-of-the-art baseline methods, our model achieves an optimal cross-subject average accuracy of 77.96%, demonstrating its superior generalization capabilities.
  - we observe notable variations in inter-session and cross-session classification accuracies among individuals, reflecting the subjective nature of art perception, where individuals respond differently to the same artworks.

Table 2 Classification accuracy of different methods for the Art EEG dataset (the mean ± standard deviation (%))

Method	Inter-Session Accuracy	Cross-Session Accuracy	Cross-Subject Accuracy
EEGNet [32]	64.56±12.86	59.19±22.94	52.43±15.70
Conformer [35]	62.78±14.12	58.01±23.05	73.61±4.87
ShallowFBCSPNet [31]	64.52±16.32	60.42±31.92	63.40±9.43
ATCNet [36]	66.70±16.15	59.04±30.19	77.61±3.05
Deep4Net [31]	55.54±14.69	50.96±22.83	67.77±7.15
EEGInception [39]	68.05±15.34	61.41±28.71	73.88±3.23
TIDNet [33]	64.19±15.88	60.03±30.14	61.58±17.40
EEGITNet [40]	61.53±16.14	56.67±24.02	48.48±13.08
HybridNet [31]	66.02±16.96	61.91±32.50	62.84±7.87
Our ArtEEGAttention	**70.05±15.53**	**65.03±28.78**	**77.96±3.68**