EEGS: A Brain-Driven Framework for Affective Image Dataset Construction via EEG-Guided Visual Stimuli Generation

BMEB215

机器学习与医学工程应用

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› Introduction

Affective image datasets are widely used in emotion recognition, yet they often fail to align with individual brain responses. We propose **EEGS**, a novel framework that leverages EEG signals to guide visual stimulus generation and construct a personalized, brain-driven affective image dataset.

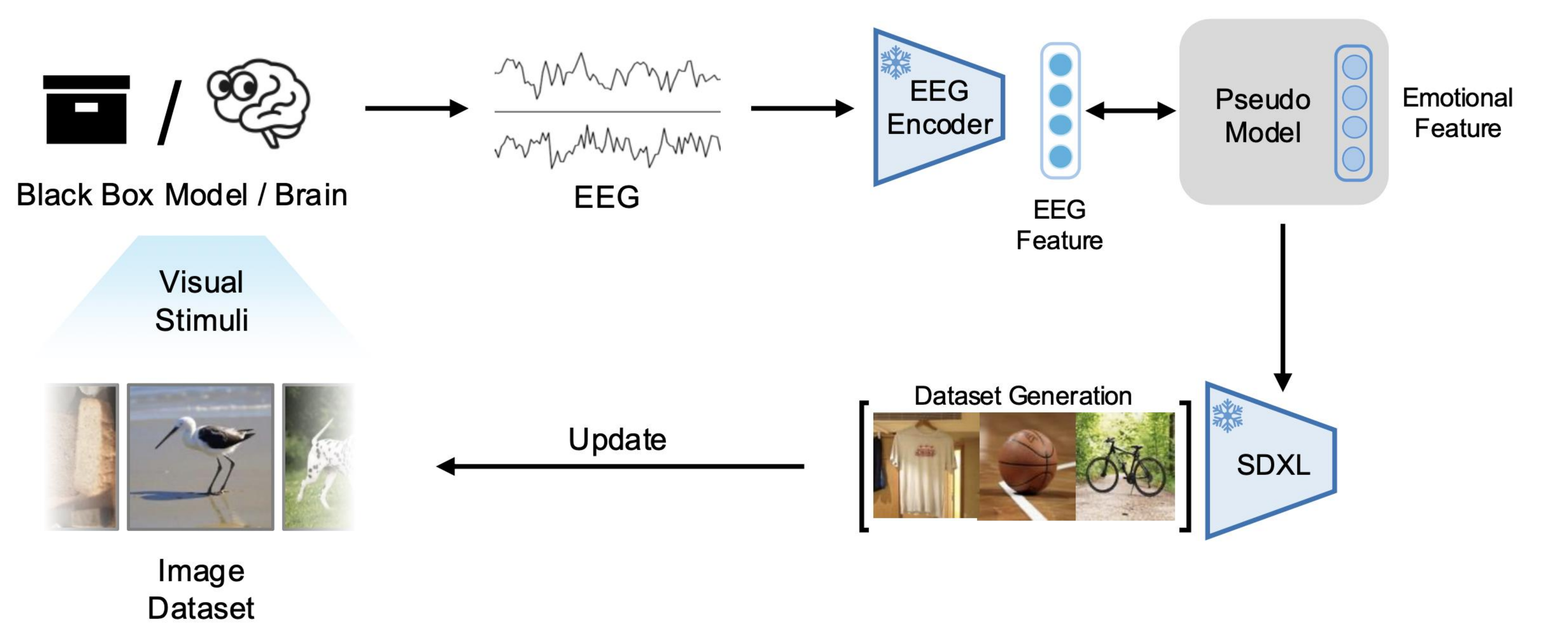

Fig1. **Conceptualization of the EEGS Framework.** EEGS generates affective images guided by EEG responses. Visual stimuli evoke EEG signals, which are encoded into features and mapped to emotional space via a pseudo model. A diffusion model (SDXL) then generates new images, updating the dataset iteratively.

Compared to traditional datasets, EEGS-generated images significantly enhance classification performance under EEG-based emotion decoders.

› Method

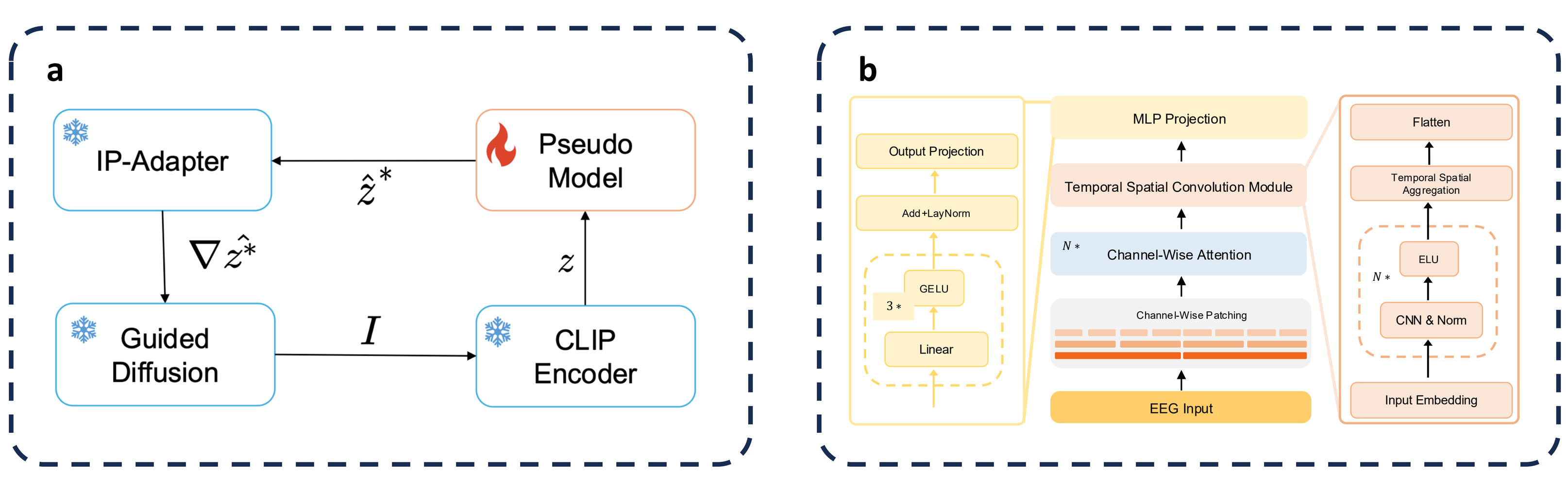

Fig2. (a) A pseudo reward estimator is introduced to approximate the mapping between EEG-derived emotional targets and visual features. (b) Architecture of our EEG-based emotion classifier (ATM-S-FC). It combines a frozen ATM-S encoder for feature extraction with a 3-layer fully connected classification head for binary emotion decoding (Sadness vs. Amusement).

EEG Generation: We generate EEG signals by presenting affective visual stimuli to human subjects or a black-box brain model. These signals reflect neural responses to emotional content and are used to guide the downstream generation process.

EEG Feature Extraction: A pre-trained ATM-S encoder transforms raw EEG signals into 1024-dimensional semantic features. This step captures meaningful brain representations without additional training.

Heuristic Generator: We map EEG features into an emotional latent space using a pseudo-emotion model, then condition an SDXL diffusion model to generate brain-aligned images. This process is iterated to refine a personalized affective image dataset.

EEG Emotion Classifier: We construct an EEG-based binary emotion classifier (ATM-S-FC) using the frozen ATM-S encoder and a trainable 3-layer MLP: 1024→512→256→2, with ReLU and Dropout. The model outputs logits for *Sadness* and *Amusement*.

› Results

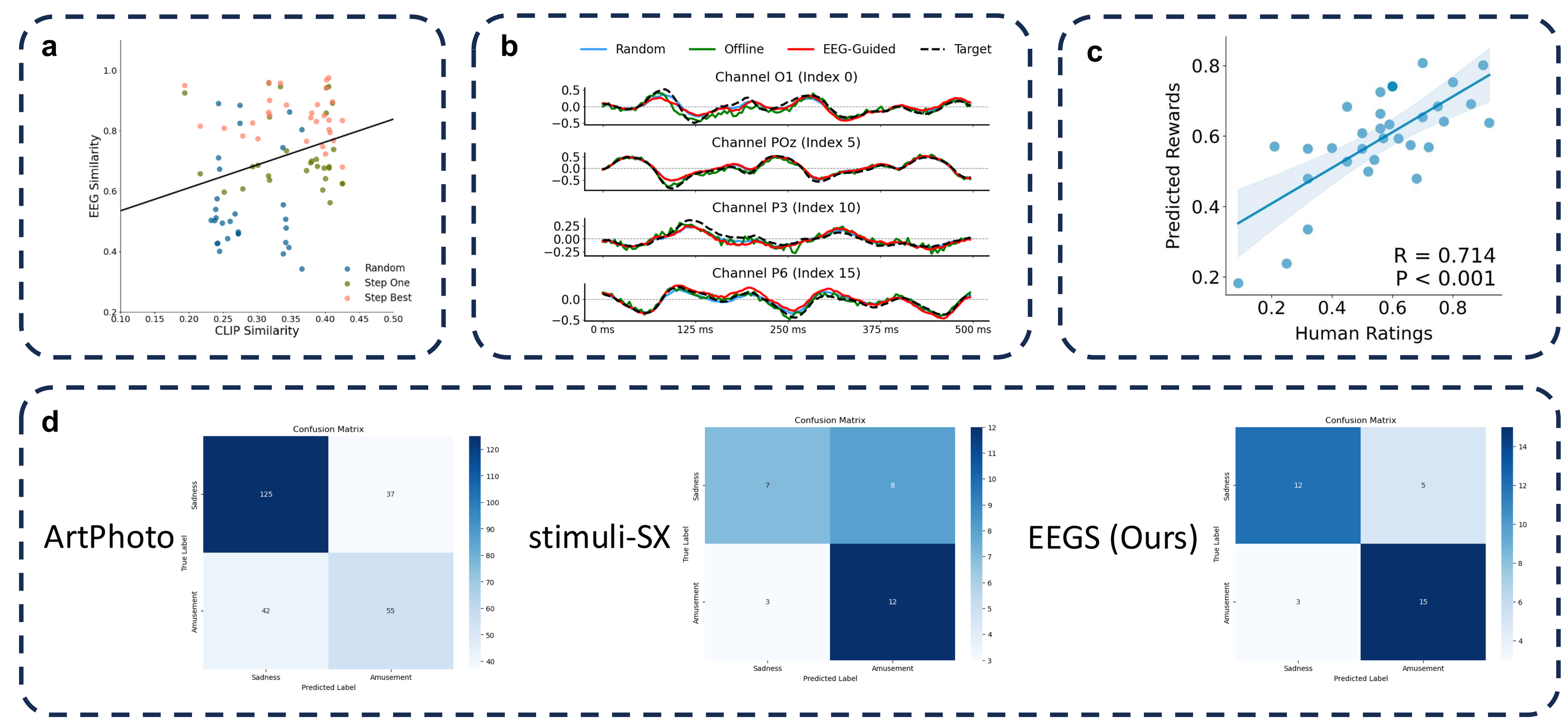

Fig3. (a) Correlation of the semantic similarity score. (b) Correlation between the predicted emotion from the estimator and human ratings. (c) Representative examples of heuristic image generation guided by CLIP-based brain activation across EEG channels. (d) Confusion matrices of emotion classification on different datasets.

Table 1. Performance comparison of emotion classification using different EEG stimulus datasets and classifiers. Our EEGS-generated dataset achieves the highest F1-score, demonstrating better alignment between stimuli and EEG representations.

Dataset	Classifier	F1-Amuse ↑	F1-Sad ↑	F1-avg ↑
ArtPhoto	ATM-S-FC	0.58	0.76	0.69
	EEGNetv4	0.44	0.79	0.66
stimuli-SX	ATM-S-FC	0.69	0.56	0.62
	EEGNetv4	0.79	**0.81**	0.80
EEGS (Ours)	ATM-S-FC	**0.79**	**0.75**	**0.77**
	EEGNetv4	**0.82**	0.77	**0.80**

Fig 4. **Overview of the EEGS-generated image dataset.**

› Summary

By leveraging neural responses and a diffusion model, EEGS produces personalized emotional stimuli that align better with brain activity. Experimental results show that classifiers trained on EEGS-generated images outperform those using traditional datasets, especially in decoding emotional states from EEG. Our work bridges brain signals and visual semantics, opening new directions in affective computing and brain-aligned dataset design.

› Reference

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