

Animate Your Thoughts: Reconstruction of Dynamic Natural Vision from Human Brain Activity

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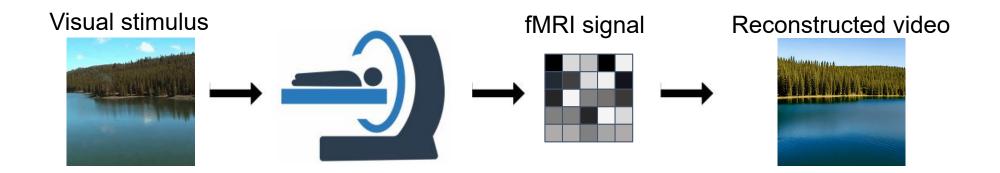
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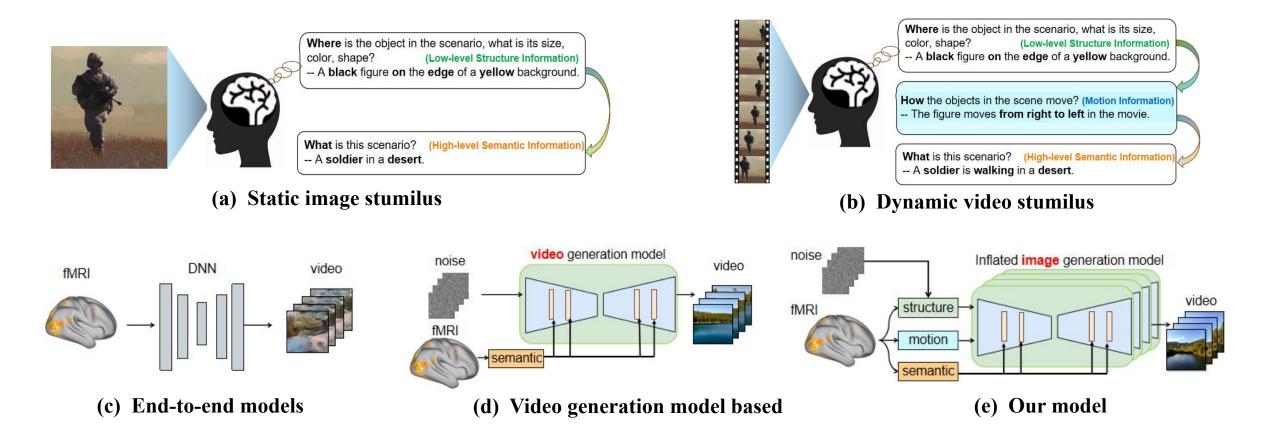


Introduction



- (1) **Method:** We propose Mind-Animator, which enables video reconstruction by decoupling semantic, structural, and motion information from fMRI data for the first time.
- (2) Interpretability: We use voxel-wise and ROI-wise visualization techniques to elucidate the interpretability of our proposed model from a neurobiological perspective.
- (3) Comprehensive evaluation: We introduce eight evaluation metrics that comprehensively assess the reconstruction results of our model and all previous models across three dimensions—semantic, structure, and spatiotemporal consistency—on three publicly available video-fMRI datasets. This establishes our work as the first unified benchmark for subsequent researchers. We will release all data and code to facilitate future research.

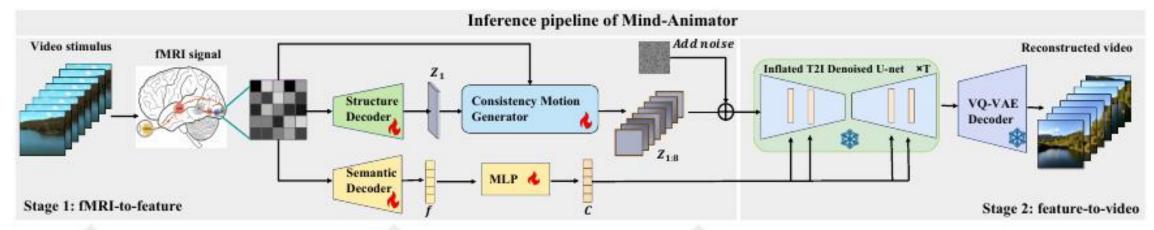
Motivation and Related works

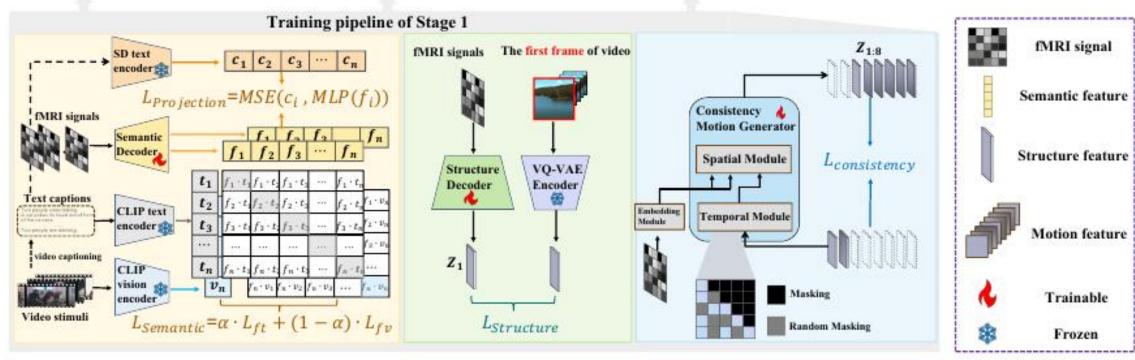


Existing Issues:

- (1) Unable to accurately model semantic, structural, and motion features.
- (2) External video data (e.g., motion priors learned by video generation models) interfere with the motion features in the reconstructed video.

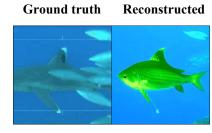
Methodology





Results (reconstruction task)

Ground truth Reconstructed





























Results (retrieval task)

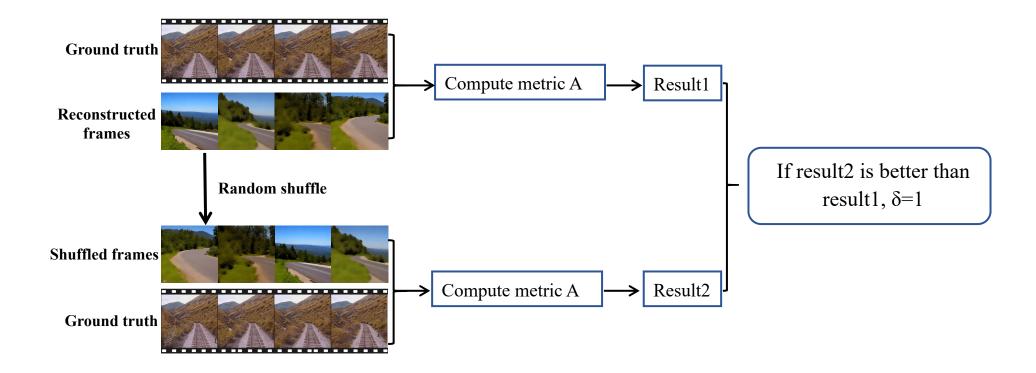
Retrieved video



Detecat		CC2017							
Dataset		Subjet1		Subjet2		Subjet3		Average	
Model	Test set	top-10	top-100	top-10	top-100	top-10	top-100	top-10	top-100
Wen (Wen et al. (2018))	Small	2.17_{*}	19.50_{*}	3.33_{*}	19.17_{*}		-	2.75*	19.33_{*}
Kupershmidt (Kupershmidt et al. (2022))	Small	1.09_{*}	8.57_{*}	0.92_{*}	8.24_{*}	0.84_{*}	8.24_{*}	0.95_{*}	8.35_{*}
Mind-video (Chen et al. (2024))	Small	3.22*	19.08_{*}	2.75*	16.83_{*}	3.58_{*}	22.08*	3.18_{*}	19.33_{*}
Ours	Small	3.08	22.58	4.75	26.90	4.50	24.67	4.11	24.72
Wen (Wen et al. (2018))	Large	1.41*	11.58_{*}	2.08*	9.58_{*}			1.75_{*}	10.58_{*}
Kupershmidt (Kupershmidt et al. (2022))	Large	0.17_{*}	2.94*	0.17_{*}	2.77_{*}	0.25_{*}	2.18_{*}	0.19_{*}	2.63*
Mind-video (Chen et al. (2024))	Large	1.75_{*}	7.17_{*}	0.83_{*}	5.17_{*}	1.25_{*}	9.00_{*}	1.28_{*}	7.11_{*}
Ours	Large	2.17	12.50	2.25	17.00	2.75	16.42	2.39	15.31

Interpretability

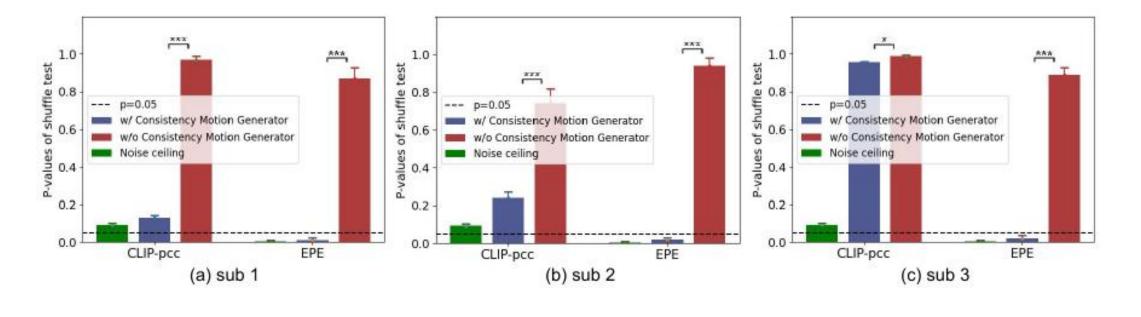
· Have we truly decoded motion information from fMRI?

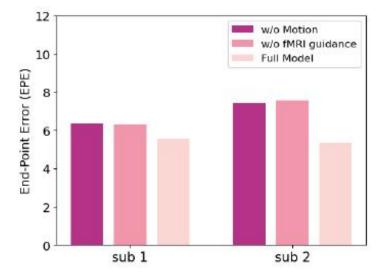


Repeating the aforementioned procedure 100 times, the P-value of the shuffle test can be estimated as $P = \sum_{i=1}^{100} \delta_i/100$

A lower P-value indicates a higher consistency between the reconstructed video frames and the ground truth before shuffling.

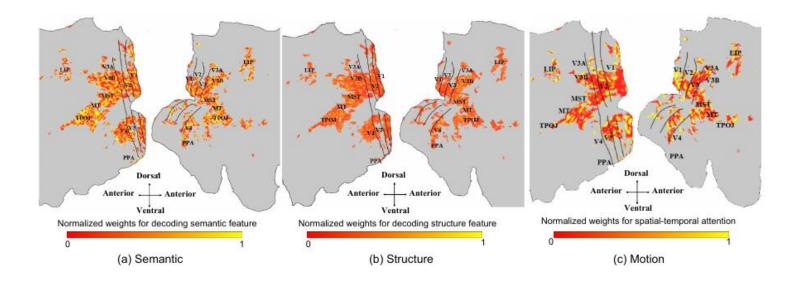
Interpretability

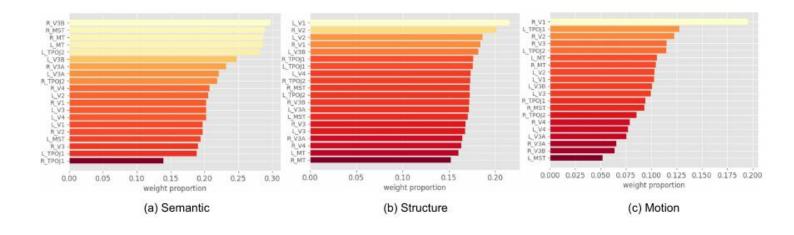




Interpretability

· Which brain regions are responsible for decoding different features, respectively?





Ablation Study

Ground truth Reconstructed



Without Semantic



Without Structual



Without Motion











Case 1: Decoding errors in semantic, structural, or motion features due to low decoding accuracy.



Case 2: The data acquisition paradigm causes abrupt content transitions at the boundaries of video clips, which are uniformly segmented from the complete videos viewed by the subjects during data collection.



Thanks!