Denoising task fMRI data for image reconstructions

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Research Question 1

How does denoising of task fMRI data impact the performance of visual stimulus reconstruction models?

Introduction 2

Numerous denoising algorithms have been proposed in the literature, **including independent component analysis [1], confound regression and filtering [2], and GLM denoise [3].**

Given limited availability of task fMRI data in some datasets, state of the art techniques, such as GLM denoise, are not always applicable due to requiring extensive time series data.

There remains a significant knowledge gap in understanding the impact of denoising algorithms for fMRI data on the performance of reconstruction models.

Selected denoising algorithms 3

- Noise ceiling
- Nuisance regression with constant and linear terms
- Component-based methods using kurtosis to identify noise components,
  such as independent component analysis(ICA) and principal component analysis(PCA)
- A combination of the above

Method 4

0. (only for subquestion 2) Add noise sampled from a gaussian or a uniform distribution to the whole dataset

1. Apply a denoising pipeline (one or more denoising algorithms chained together) to the full dataset)

2. Split the dataset into train and test sets for cross-validation

3. Train the encoder and the decoder models

4. Evaluate the model through a 5-way and a 10-way ranking process involving using the original image, the reconstructed image and n-2 (given n-way process) distractor images.

5. Calulate accuracy of the ranking process through establishing how often the original image is ranked first and score of the reconstructions - the average rank across the test dataset

6. Evaluate the performance of denoising pipelines given the score, as well as reconstructed images through manual inspection

Ranking the candidates 5

The ranking process is based on Learned Perceptual Image Patch Similarity (LPIPS) metric[1]

The difference between the original image and the candidate image is ranked by the distance between image patches calculated with LPIPS. The lower the distance the higher the rank.

LPIPS works by utilizing deep network activations of a VGG model and supervisory signals. More information can be found in the PerceptualSimilarity github repository[1]

1. https://github.com/richzhang/PerceptualSimilarity

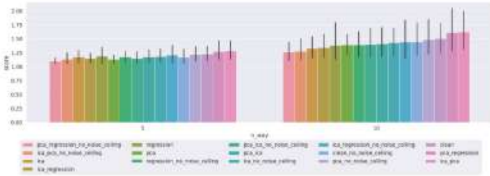

Figure 1: score (the lower the better)

exp_name n_way	clean	ica	ica_pca	ica_regression	pca_ica	pca	pca_regression	regression
5	1.174	1.184	1.136	1.210	1.148	1.222	**1.102**	1.176
10	1.446	1.426	1.274	1.442	1.400	1.486	**1.260**	1.390

Table 1: score without noise ceiling (the lower the better)

exp_name n_way	clean	ica	ica_pca	ica_regression	pca_ica	pca	pca_regression	regression
5	1.228	1.176	1.288	1.146	1.178	**1.128**	1.272	1.186
10	1.302	**1.332**	1.624	1.340	1.412	1.388	1.612	1.386

Table 2: score with noise ceiling (the lower the better)

exp_name n_way	clean	ica	ica_regression	pca	pca_regression	regression
5	**1.746**	1.812	1.778	2.206	2.154	2.164
10	**2.634**	2.844	2.842	3.752	3.500	3.682

Table 3: score (the lower the better) for experiments with artificially induced noise sampled from a gaussian distribution

exp_name n_way	clean	ica	ica_regression	pca	pca_regression	regression
5	1.568	**1.404**	1.460	1.770	1.750	1.372
10	2.230	**1.852**	2.038	2.646	2.700	2.266

Table 4: score (the lower the better) for experiments with artificially induced noise sampled from a uniform distribution

Results 6

The encoder model was trained for 50 epochs. The decoder model was trained for 150 epochs for denoising pipelines without added artificial noise and 30 epochs for pipelines with added artificial noise.

The ranking process has been repeated 10 times per experiment to improve replicability.

Conclusion 7

Overall, denoising algorithms improve the performance of visual stimulus reconstruction models (fig. 1, tables 1 and 2).

Kurtosis-based PCA with nuisance regression was the best-performing algorithm, improving score by 6.2%, suggesting the presence of non-gaussian noise

Artificial noise significantly negatively impacted reconstruction quality. Denoising algorithms designed for task fMRI signal processing fail to negate the effects of artificial noise (tables 3 and 4). However, ICA manages to improve reconstruction quality with added noise sampled from a uniform distribution applied.

The choice of a noise component identification algorithms for PCA and ICA is heavily limited due to the small dataset size, suggesting the necessity for custom-tailored denoising strategies

Future Work 8

Future work should focus on efficiency of denoising algorithms under varying dataset sizes and noise types, as well as model types, and improving reproducibility and robustness of these methods in the research community.

References

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2. T. D. Satterthwaite, M. A. Elliott, R. T. Gerraty, K. Ruparel, J. Loughead, M. E. Calkins, S. B. Eickhoff,H. Hakonarson, R. C. Gur, R. E. Gur, and D. H. Wolf. An improved framework for confound regression and filtering for control of motion artifact in the preprocessing of resting-state functional connectivity data. NeuroImage, 64:240-256, 2013.

3. Kendrick Kay, Ariel Rokem, Jonathan Winawer, Robert Dougherty, and Brian Wandell. Glmdenoise: a fast, automated technique for denoising task-based fmri data. Frontiers in Neuroscience, 7, 2013