Using Generative Adversarial Network for modeling joint task/response distribution in functional Magnetic Resonance Imaging

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Introduction

- Functional Magnetic Resonance Imaging (fMRI) provides information about brain activity.

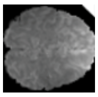
- We tried to model the joint distribution of brain response (fMRI) and task (experimental condition) using Generative Adversarial Network (GAN).

Materials & Methods

Material

- Task-evoked fMRI were acquired from Human Connectome Project WU-Minn HCP 1200 Subjects Data (HCP S1200) [2]

Response:
fMRI matrix
(64 x 64)



Task:
hand movement
(1)

$$\begin{cases} \text{if left hand} = 0 \\ \text{if right hand} = 1 \end{cases}$$

Methods

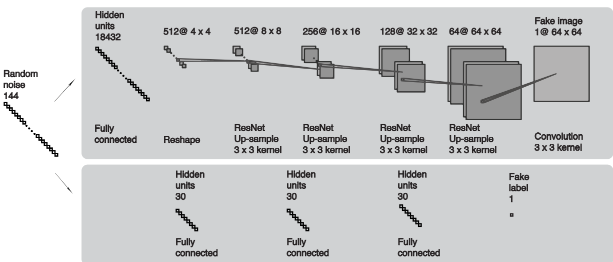
- Wasserstein distance GAN with gradient penalty (WGAN-GP) [2]

$$L = \mathop{\mathbb{E}}_{\tilde{\boldsymbol{x}}\sim\mathbb{P}_g}[D(\tilde{\boldsymbol{x}})] - \mathop{\mathbb{E}}_{\boldsymbol{x}\sim\mathbb{P}_r}[D(\boldsymbol{x})] + \lambda \mathop{\mathbb{E}}_{\hat{\boldsymbol{x}}\sim\mathbb{P}_{\hat{\boldsymbol{x}}}}\left[(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1)^2\right]$$

D(x): Discriminator output
$\mathbb{P}_g$: pdf of generated data
$\mathbb{P}_r$: pdf of real data

λ : Lipschitz constraint
$\mathbb{P}_{\hat{\boldsymbol{x}}}$: sampled from the line $\mathbb{P}_g$ and $\mathbb{P}_r$

- Generator network structure



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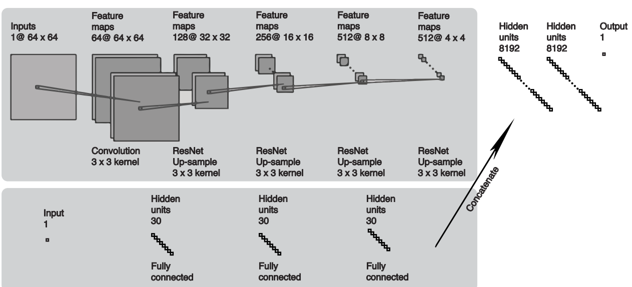
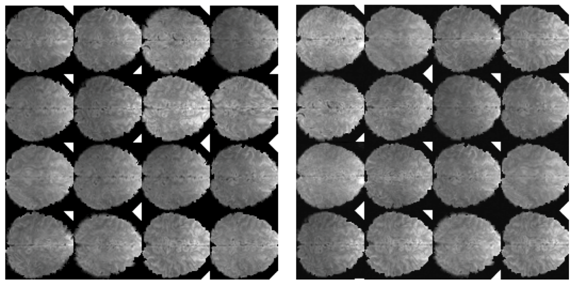


Results

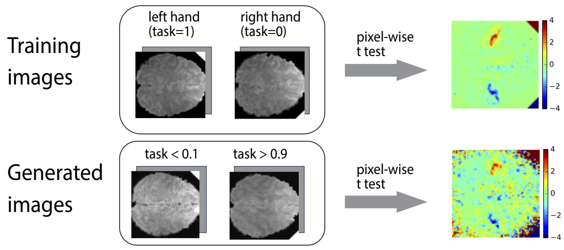
- Visual comparison



Training data Generated data

- Evaluation of the generated images

For the **training dataset**, t-tests were conducted between images paired with task variable 0 (n=400) and images paired with task variable 1 (n=400).
For the **generated dataset**, t-tests were conducted between images with task variables smaller than 0.1 (n=374) and images with task variables bigger than 0.9 (n = 433).



Conclusion

- We demonstrated that WGAN-GP is capable of estimating the data distribution of 2-dimensional fMRI signals and generating realistic fMRI data.

- The generated images by the trained WGAN-GP replicated the task relevant fMRI signals in motor cortex.

- The result suggests that the WGAN-GP learned the joint task/response distribution of motor task fMRI.

References

[1] Gulrajani, I., Ahmed, F., Arjovsky, M., Dumoulin, V., & Courville, A. C. (2017). Improved training of wasserstein gans. In Advances in Neural Information Processing Systems (pp. 5767-5777).

[2] Van Essen, D. C., Smith, S. M., Barch, D. M., Behrens, T. E., Yacoub, E., Ugurbil, K., & Wu-Minn HCP Consortium. (2013). The WU-Minn human connectome project: an overview. Neuroimage, 80, 62-79.