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Using GAN for learning joint task/response distribution in fMRI

Ju Young Lee[1] JU.YOUNG.LEE@TUEBINGEN.MPG.DE
Alexander Loktyushin[1,2] ALEXANDER.LOKTYUSHIN@TUEBINGEN.MPG.DE
Johannes Stelzer[1,3] JOHANNES.STELZER@TUEBINGEN.MPG.DE
Gabriele Lohmann[1,3] GABRIELE.LOHMANN@TUEBINGEN.MPG.DE

[1] *Max-Planck-Institute for Biological Cybernetics, Tbingen, Germany*
[2] *Max-Planck-Institute for Intelligence System, Tbingen, Germany*
[3] *University Hospital Tbingen, Tbingen, Germany*

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Abstract

This is a proof-of-principle study on using generative adversarial network (GAN) to synthesize functional Magnetic Resonance Imaging (fMRI) data. We trained GAN to model the joint distribution of motor task functional magnetic resonance imaging (fMRI) data and the corresponding task labels. Synthesized images by the trained GAN successfully replicated the task relevant fMRI signal in the motor cortex. This result shows a potential for using GAN to augment fMRI data.

1. Introduction

Functional magnetic resonance imaging (fMRI) provides temporal and spatial information about neuronal activity in the brain. This study proposes generative adversarial network (GAN)(Goodfellow et al., 2014) as a method to simulate fMRI data. Simulated fMRI data can be used for augmenting dataset or developing new analysis method. Here, we trained a Wasserstein generative adversarial networks with gradient penalty (WGAN-GP) to model the joint distribution of fMRI signal and task label.

2. Method

2.1. Wasserstein GAN with gradient penalty

Wasserstein distance is a distance function defined between probability distributions. The loss function for Wasserstein GAN (WGAN) (Arjovsky et al., 2017) uses Wasserstein distance between two probability distributions; the output of the discriminator network given generated data and the output of the discriminator network given training data. Lipschitz constraint was enforced by adding a gradient penalty(Gulrajani et al., 2017). The code for this study was developed based on implementation provided in the link below [1] . We

1. https://github.com/igul222/improved_wgan_training/blob/master/gan_64x64.py

added an extra parallel network to the original architecture to include task labels. The generator network was modified so that the latent variables are projected to two separate neural networks; a convolutional neural network to generate an image and a network with fully connected layers to generate a scalar. The discriminator network received an image and a scalar through separate networks without sharing weights. The hidden layers of the two networks were concatenated. After concatenation, we added another fully connected hidden layer before the output.

2.2. Training data preparation

In this experiment, each data sample consisted of a pair: an fMRI image and a binary variable that denotes the task label. Images with task variable 0 are fMRI signals acquired when the subjects were moving left hand. Images with task variable 1 are fMRI signals acquired when the subjects were moving right hand. We used minimally pre-processed motor task fMRI of 20 subjects from Human Connectome Project (HCP) 1200 Subjects Dataset (Van Essen et al., 2013). Each fMRI is a time series of a 3-dimensional volume shaped as (x axis, y axis, z axis, time points) = (91, 109, 91, 284). We chose 61th z-plane, which included motor cortex of both hemispheres.

During fMRI scanning, subjects repeated both left and right hand movement task two times. We selected 20 time points for left hand task and 20 time points for right hand task. We added a mark to each image that indicates the relevant task. Images for left hand task was marked with a saturated triangle on top right corner and images for right hand task with a saturated triangle on the bottom right corner (see Figure 1 first row on the left). The total size of the training dataset was 800 (20 subjects x 20 time points x 2 tasks). The images were normalized and the patch size was 64 x 64 pixels.

3. Results

The loss converged after about 120k iterations of training. Examples of training images and the generated images are shown in Figure 1 on the left. We used pixel-wise t-test between two tasks for validating the generated data. First, we used the trained model to generate 840 data points to match the size of the training dataset. Second, we divided the generated data into two groups by thresholding the generated task variables. Among the dataset, 44.64 % (375 data) had a task variable that is smaller than 0.1 and 51.19% (430 data) had a task variable that is bigger than 0.9. Only 4.16% (35 data) had a task variable ranging between 0.1 and 0.9. Third, we computed T statistics for each pixel to test for the statistical significance between different tasks (see Figure 1 on the right). For the training dataset, we conducted t-tests between pixel densities of images paired with task variable 0 and task variable 1. The pixels with statistical significance between the two groups appeared in motor cortex and the corners. For the generated dataset, we conducted t-tests between pixel densities of images with task variables smaller than 0.1 and pixel densities of images with task variables bigger than 0.9. Again, the pixels in motor cortex and the corners showed a significant difference between the two groups. Thus, we can infer that the WGAN-GP learned the joint distribution of task variables and fMRI response in motor cortex.

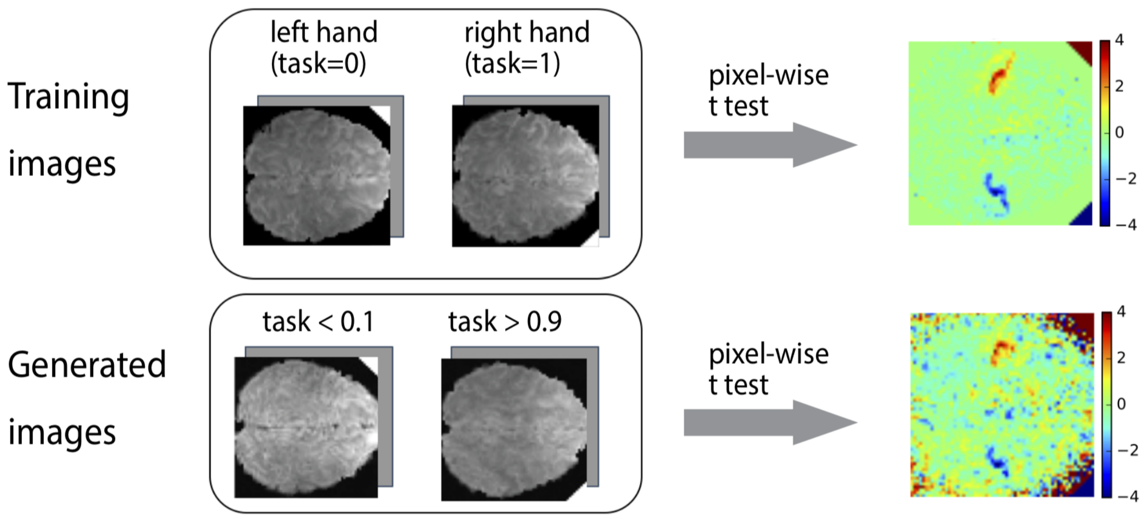

Figure 1: **Computing t-statistics map** The first row shows examples of training images on the left and the t-statistics map on the right. The second row shows examples of generated images on the left and the t-statistics map on the right.

4. Conclusion

We demonstrated that WGAN-GP is capable of estimating the data distribution of 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. In future work, simulated fMRI data using GAN can be used for augmenting dataset or developing new analysis method.

References

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