Working Memory Related Brain Network Connectivity in Individuals with Schizophrenia and Their Siblings

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Abstract

A recent study shows that schizophrenia reflects a "dysconnection" syndrome, which means schizophrenia can result in damaging functional brain connectivity in neural networks. We are interested in schizophrenia, so we decide to look into their studies to see if their conclusion makes sense. Therefore, we download the data they got during their tests and redo their analysis by following their steps in the paper. Even though we aren't able to go through all the analysis they did, we expect to get the same result for the analysis we do.

1 Introduction

Schizophrenia is a chronic, severe, and disabling brain disorder that has affected people throughout history. Or you can just think it as an illness that causes abnormal social behavior and failure to recognize what is real. Previous studies showed that changes in the function of a single brain region, or even a brain system, cannot explain the functional impairments seen in this illness. This means that the causes of schizophrenia is much more complicated than we think. A recent study shows that individuals with schizophrenia have reduced connectivity between neural networks, which could be a forward step to solve the cause of this illness.

The paper suggests this conclusion is "Working memory related brain network connectivity in individuals with schizophrenia and their siblings" [1], and the data they used is available on OpenFMRI.org under "Working memory in healthy and schizophrenic individuals". The paper thinks that neural networks which are critical for cognitive function might be affected by schizophrenia, because individuals with schizophrenia have severe cognitive issues. In particular, these neural networks are (1) Dorsal fronto-parietal network (FP), (2) Cingulo-opercular network (CO), (3) Cerebellar network (CER) and (4) "Default mode" network (DMN).

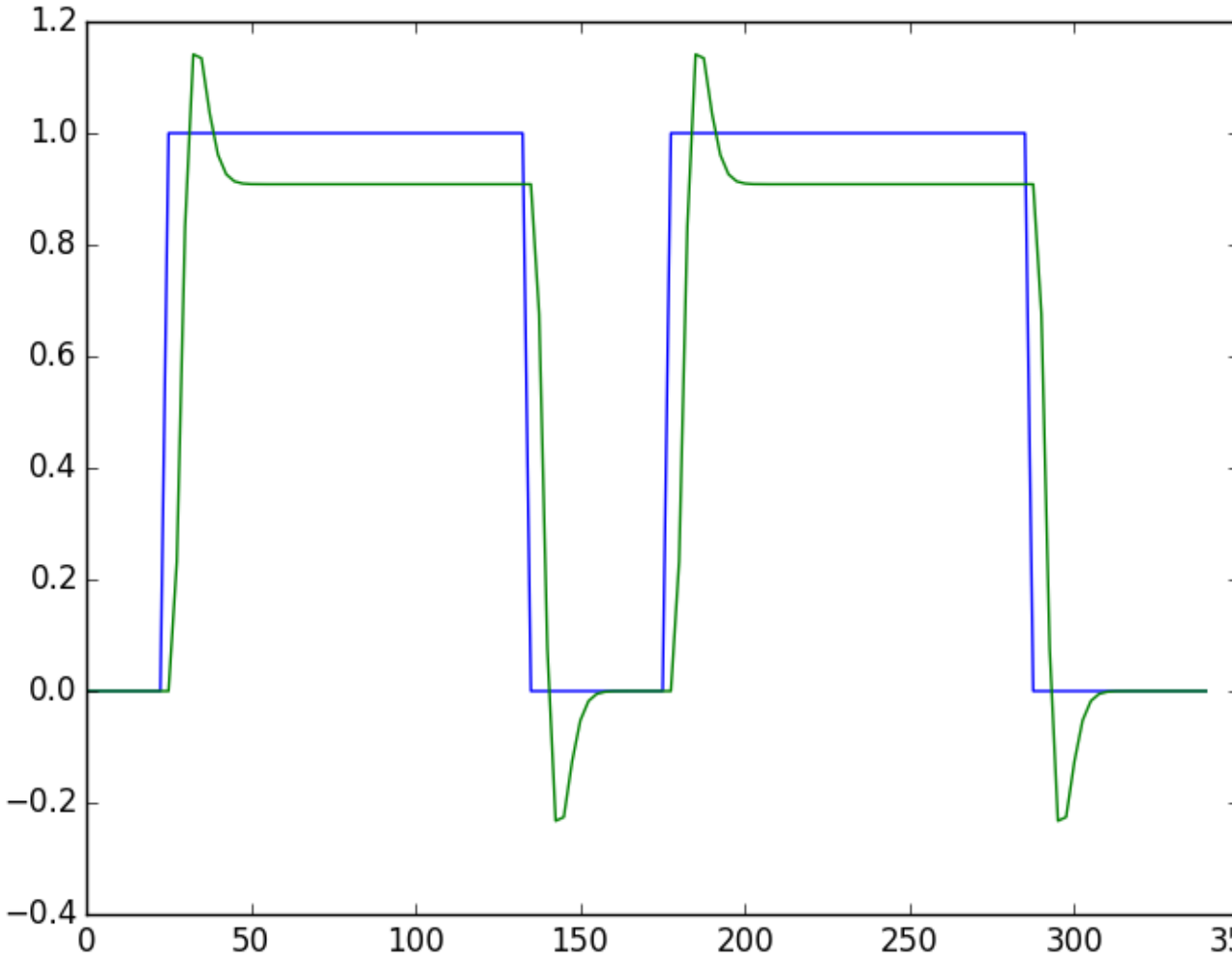
2 Data

We went to OpenFMRI.org and looked through all the files it has for this paper. The are many data files grouped by subjects and we only downloaded "ds115-sub001-005.tg", which contains the brain image of the first five subjects, and the "ds115-metadata.tg", which contains metadata for the paper. Since we only chose one subject, which is sub001, we only need his part in the data file.

First, we checked all the files for sub001 and found there are three tasks for our subject. We realized that these were "N - back" working memory task in the paper. This task was to respond for each letter shown whether it was the same as a pre-specified letter (0-back), the same as the immediately preceding letter (1-back), or the same as the letter shown two trials previously (2-back). For our subject, there were three BOLD runs, each consisting of two blocks of 0-back, 1-back, or 2-back working memory task.

Second, we found that under each task there are four brain images. We thought one of them should be the raw image and the others were some-how processed by the authors. Therefore, we plotted these four brain images and chose the most blurred one (This is probably because it is after smoothing), which is "BOLD-mcf-brain.nii".

Then, similar to what we did in class, we used HRF function to convolve our neural prediction, This will give us a hemodynamic prediction, under the linear-time-invariant assumptions of the convolution. This is a very important step because we will use convolution data in our linear modeling process in the future. Here is the comparison between the original neural prediction and convolved.



3 Methods

3.1 Linear Modeling

First of all, we did a muti-variables linear regression on convolving response (design matrix X) and blood pressure(response Y). We constructed the design matrix X, which dimension is (133, 2) and reshaped our blood pressure data from 4 dimension to 2 dimension. Second, under the assumption of constant variance and normality of our data, we use OLS method to calculate $\hat{\beta}$, the formula is $\hat{\beta_{ls}} = (X^T X)^{-1} X^T Y$. We plug in X and Y to get our $\hat{\beta_{ls}}$, which is a 2 by 147456 matrix. Then we reshaped it into 4 dimension. Based on the $\hat{\beta_{ls}}$ we got from muti-variables linear regression, we compute the fitted value $\hat{Y}$, which equals $X\hat{\beta_{ls}}$. The residual $\hat{e}$, which equals $Y - \hat{Y}$. The residual sum of squares RSS, which is $\hat{e}^T\hat{e}$. The covariance matrix of $\hat{\beta_{ls}}$ is $cov(\beta_{ls}) = \sigma^2(X^T X)^{-1}$. Here σ^2 is unknown, we use $\hat{\sigma}^2 = \frac{RSS}{n-r}$, which is an unbiased estimate of σ^2. Thus the covariance matrix $cov(\beta_{ls}) = \frac{RSS}{n-r}(X^T X)^{-1}$.

Then, we generated our null hypothesis test:

$\hat{\beta} = 0$.

By using t-test and set our significance level as 10%, we found there are 1507 out of 147456 voxels that have the significant effect between our task and blood pressure, so we defined the sub-area of brain contains the most significant voxels by plotting a p-value map.

4 Results

5 Discussion

References

[1] G. Repovs and D. M.Barch, *Working memory related brain network connectivity in individuals with schizophrenia and their siblings*, Frontiers in Human Neuroscience, 6 (May 2012).