Modeling Relationship between the Brain Structure and the Personality Traits using a Three Dimensional Convolutional Neural Network

1217004 LIU Jingxin 【 Human-Engaged Computing Laboratory 】

1 Introduction

Many studies indicate that individual differences in personality traits have a great influence on individual, especially regarding individual behavior, personal capabilities, and personal value. Further, personality traits are associated with life satisfaction, happiness, subjective well-being, self-esteem, and individual innovativeness. After decades of research, the field of personality psychology is finally approaching the consensus on a general taxonomy of personality traits, the Big Five personality traits dimensions: openness to experience, extraversion, conscientiousness, agreeableness, and neuroticism.

Personality traits have been associated with specific brain regions. Most of researchers adopt voxel-based morphometry (VBM) analysis to explore the personality-brain mechanism from two levels: vertex and regional based. However, their findings are mixed with great inconsistencies, and they do not have a full understanding of the brain-personality relationship. Several unknown features could explain the brain-personality traits relationship. Thus, we contributes to the exploration of the relationship between the brain structure and the personality traits with a predictive model based on deep learning.

Deep learning techniques have been very actively investigated in recent years, such as convolutional neural network (CNN)[1] can allow us to capture features relevant to the personality traits that previous researchers would not have think of. We hence proposed a three dimensional convolutional neural network (3D CNN), using Big Five personality traits (Big Fives) as training labels. We applied our model to raw preprocessed T1-weighted structural magnetic resonance imaging (MRI) data. Big Fives were measured by the Ten-item Personality Inventory (TIPI-J) in Japanese version.

2 Methods

2.1 Preprocessing

We selected two personalities as labels: 300 of openness subjects and 300 of accommodativeness subjects.

Neuroimaging preprocessing steps are required. Indeed, for instance, magnetic resonance images are not comparable across different scanners, subjects, and visits, even when the same protocol is used. We designed a standard analysis pipeline with neuroimaging preprocessing steps of structural brain MRI: bias field correction, skull stripping, and intensity normalization.

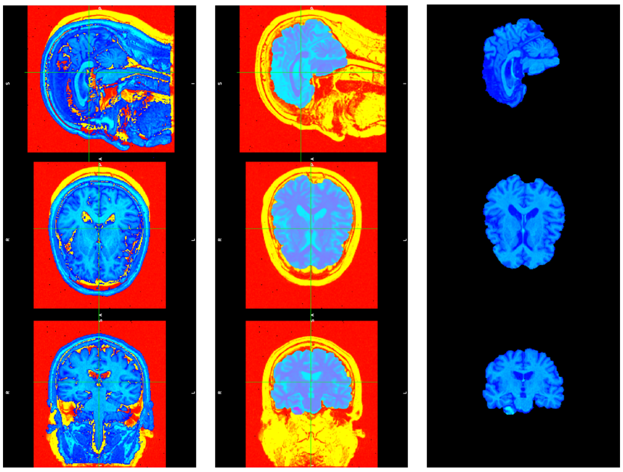

図 1 Left: the overlapping image of MRI before and after bias field correction operation; Middle: the overlapping image before and after BET operation; Right: extracted brain region

We adopted n4 bias field correction (N4ITK) for the correction of the MRI data contrast due to magnetic field inhomogeneity, Brain extract tool (BET) for skull stripping to remove the skull and other non-brain tissue from magnetic resonance images, and white stripe normalization for normalizing intensity across all individuals. Figure 1 illustrates the bias field correction and skull stripping.

After neuroimaging preprocessing, we adopted the min max normalization to rescale all intensity values between 0 and 1.

2.2 3D CNN

Residual networks won the ImageNet contest in 2015 and demonstrated the great improvement of the depth of the neural network while having fast convergene. We developed a 3D convolutional neural network adopting residual network 50 (ResNet-50) architecture figure (2). The architecture has 50 layers containing four types of residual blocks each with three batch normalization layers. The first residual blocks includes three convolutional layers with 64 filters of 1 x 1 x 1, 64 filters of 3 x 3 x3, and 256 filters of 1 x 1 x 1. The second residual blocks includes three layers with 128 filters of 1 x 1 x 1, 128 filters of 3 x 3 x 3, and 512 filters of 1 x 1 x 1 for convolution. The third residual blocks includes three convolutional layers with 256 filters of 1 x 1 x 1, 256 filters of 3 x 3 x 3, and 1024 filters of 1 x 1 x 1. Th fourth residual blocks includes three convolutional layers with 512 filters of 1 x 1 x 1, 512 filters of 3 x 3 x 3, and 2048 filters of 1 x 1 x 1. The output of the last residual block is sent to a 3D average pooling layer to further reduce it, followed by a fully connected layer and an output for binary classification with softmax nonlinearity.

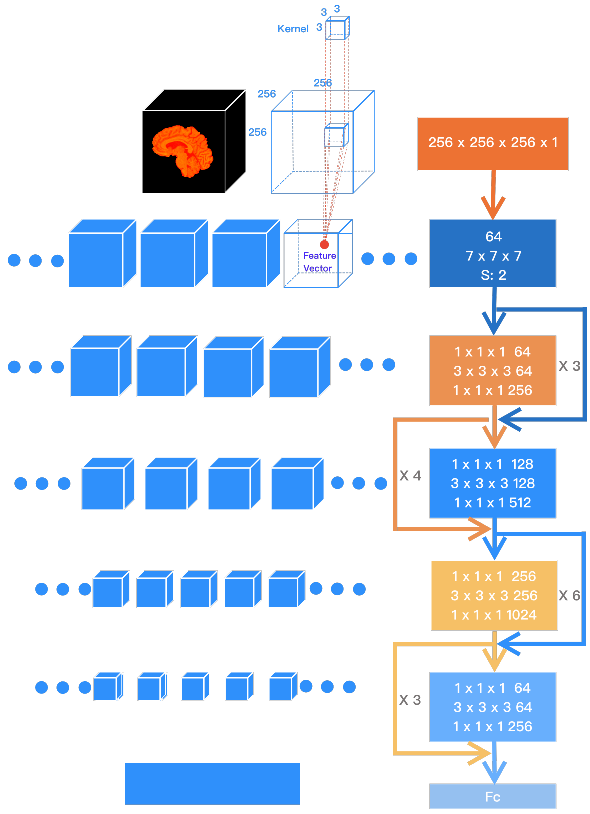

図 2 3D CNN architecture

The whole brain grayscale MRI (Height: 256, Width: 256, Slices: 256) serves as the input to predict the Big Fives labels as the output.

3 Analysis

During the training phase with 300 epochs (figure 3), the accuracy increased stably and gradually. During the training phase with 300 epochs (figure 4), the loss decreased gradually.

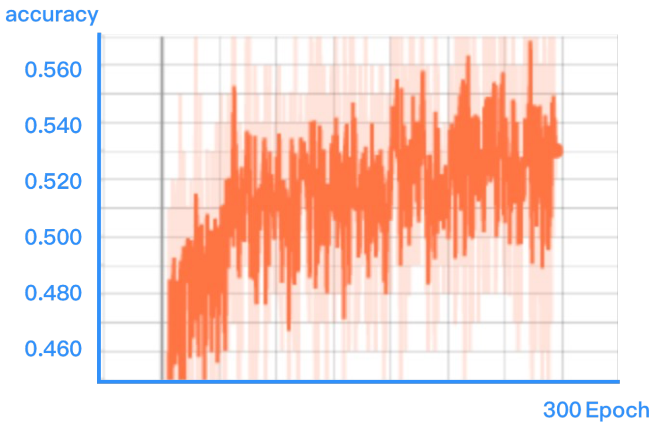

図 3 The accuracy in the training phrase.

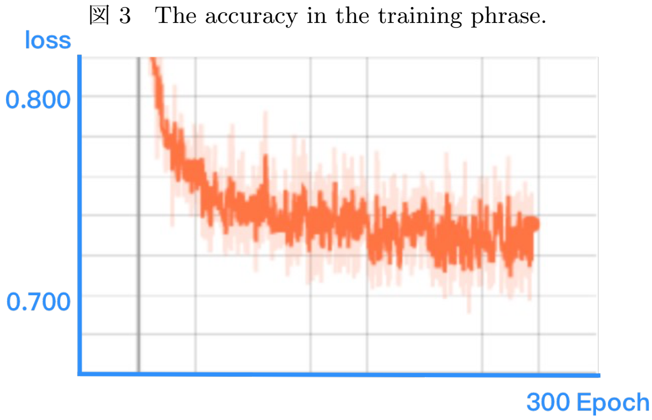

図 4 The loss in the training phrase.

4 Conclusion

Knowing more about ourself is important, especially personality traits are relevant to several human life aspects. In our study, we investigated the relationship between human brain structure and personality traits, using a 3D convolutional neural network with ResNet-50 architecture we developed. Our model was used to classify openness and accommodativeness on human brain MRI. The results shows that the classification accuracy was higher than chance level (50%). Our preliminary result indicates that there is the relationship between brain structure and personality traits.

For the next step, we can still explore the finetuning of other parameters, such as batch size, learning rate and optimization function. We also envision different approaches to analyze our model accuracy.

参考文献

[1] LeCun, Yann, and Yoshua Bengio. "Convolutional networks for images, speech, and time series." The handbook of brain theory and neural networks 3361.10 (1995): 1995.