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ADHD Diagnosis and Recognition Based on Functional Classification

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Abstract. This research starts from the lack of reliable and effective disease identification biomarkers for attention deficit hyperactivity disorder (ADHD). Based on the functional classification methods, including functional generalized linear model (FGLM), functional linear discriminant analysis (FLDA) method and functional principal component analysis (FPCA), we establish models of corpus callosum (CC) shape and give some analyses. The purpose is to verify whether the corpus callosum shape data can be used as an effective classification basis for disease discrimination and classification, and to provide a new auxiliary discriminant diagnosis idea for ADHD disease discrimination.

Keywords: ADHD, functional classification, FGLM, FLDA, FPCA.

1. Introduction

Attention deficit hyperactivity disorder (ADHD), commonly known as hyperactivity, is a common mental disorder in childhood, and its pathological causes are based on neurology [1]. It has been reported that the incidence of ADHD in school-age children in China is about 1.5%~12%, and that in foreign countries is 3%~10% [2]. Although the level of hyperactivity in children with ADHD will decrease with age, follow-up studies have found that 30% ~ 80% of children's symptoms will continue into adolescence, and still meet the diagnosis of ADHD. While 50% ~ 65% of symptoms will continue into adulthood [3]. Due to the high incidence of ADHD and its adverse effects, ADHD has become a research hotspot in many fields.

In recent years, technologies such as electroencephalography, magnetic resonance imaging, and functional magnetic resonance imaging have been used in the auxiliary diagnosis of ADHD. At the same time, the rapid development of machine learning has also made it used effectively in ADHD classification and diagnosis. Riaz et al. [4] proposed a machine learning framework based on support vector machines (SVM) for imaging data and non-imaging data to study the functional connection changes between ADHD patients and control groups. Du et al. [5] proposed a discriminative sub-network selection method, based on the kernel principal component analysis method to extract the main features from the discriminant network to classify and recognize ADHD. Sen et al. [6] studied structural MRI image features and fMRI features, and used them to train linear SVM classifiers for ADHD classification. Shao et al. [7] proposed a dual-objective ADHD classification scheme based on the L1-norm SVM model to achieve ADHD classification.

In addition, research on ADHD based on a functional data analysis framework is a new perspective. With the widespread application of big data, data tends to become more complex, quantified, diversified, heterogeneous, etc., and functional data analysis methods emerged and are widely used in many fields. The functional data classification methods can be divided into the following three categories: (1) Functional classification based on regression. The classification labels and functional predictors are connected through a regression model, then use training set to estimate parameters for classification [8, 9]. (2) Functional classification based on probability density. Functional data is firstly projected to a finite feature space, then estimate the probability density of each category with parametric or non-parametric methods. At last, predict and classify new samples based on this probability density [10, 11]. (3) Functional classification based on algorithms. Firstly, perform dimensionality reduction similar to Method 2, and then choose a non-parametric classification tool to do the classification.

Based on the above research status, we can find that attention deficit hyperactivity disorder is a medical problem that is very worth studying. Functional data analysis is a new branch of statistical data

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analysis, and it is also one of the popular research objects of statistics, which can find out the internal contact of the observation. Domestic research on this aspect is still relatively lacking. It is of great significance to use the FDA method to study the classification of ADHD and provide scientific auxiliary diagnosis guidance based on theoretical research.

This article is organized as follows: Section 2 mainly introduces the data source and data preprocessing. In Section 3, we briefly introduce three typical functional data classification methods, and use them to classify the corpus callosum thickness curve. Finally, in Section 4, we analyze the research results and give a summary

2. Data acquisition and processing

2.1 Data source

The MRI data set used in this article comes from the ADHD-200 global competition training data set. Due to the lack of objective biological tools in the clinic, it is impossible to provide individuals with ADHD diagnostic information to guide clinicians to make treatment decisions. In 2011, the 1000 Functional Connectomes Project team shared its database and organized a global ADHD Disease classification and discrimination contest based on MRI images. The purpose is to hold an ADHD medical image diagnosis competition to discover ways to help diagnose ADHD patients based on computer picture recognition, and accelerate the scientific community's understanding of the neural basis of ADHD.

Here we choose a data set with a sample size of 245 in the Peking University sub-data set (Peking U imaging point) (see: http://fcon_1000.projects.nitrc.org/indi/adhd200/). There are a total of 245 subjects in the data set, all of whom are children and adolescents (8-18 years old), including 143 healthy controls, with an average age of 11.42 years; 102 ADHD patients, with an average age of 12.08 years. All patients were evaluated by the scale and met the ADHD diagnostic criteria of DSM-IV. All subjects were right-handed, excluding past or existing psychiatric diseases or a history of mental disorders, learning disabilities or other psychiatric diseases as determined in DSM-IV, also all of them have no history of loss of consciousness due to head trauma. See Table 1 for specific data.

Table 1. Sample information

Diagnosis	Total number	Female	Male	Age range
Typically Developing	143	59	84	8~15（mean:11.42） year-old
ADHD-Combined	38	0	38	8~15（mean:11.56） year-old
ADHD-Inattentive	64	12	52	8~17（mean:12.39） year-old

2.2 Data processing

We perform the following processing on the CC morphological data of each research individual in the ADHD-200 data set. First, use FreeSurfer[12] (http://surfer.nmr.mgh.harvard.edu/) to process each T1-weighted MRI data, including translation correction, non-parametric non-uniform intensity normalization, and affine transformation to MNI305 Atlas, intensity standardization, skull removal, automatic cortical segmentation, etc. Keep quality control on each output image data, and intracranial volume (ICV) information can also be obtained from the output results of the FreeSurfer software package. The comparison chart before and after data preprocessing is shown in Figure 1. Then use the processed image as the input of Yuki package [13] (http://www.nitrc.org/projects/art) for corpus callosum segmentation and thickness extraction (Figure 2 left), and obtain the thickness curves of the two types of samples See Figure 2 (right).

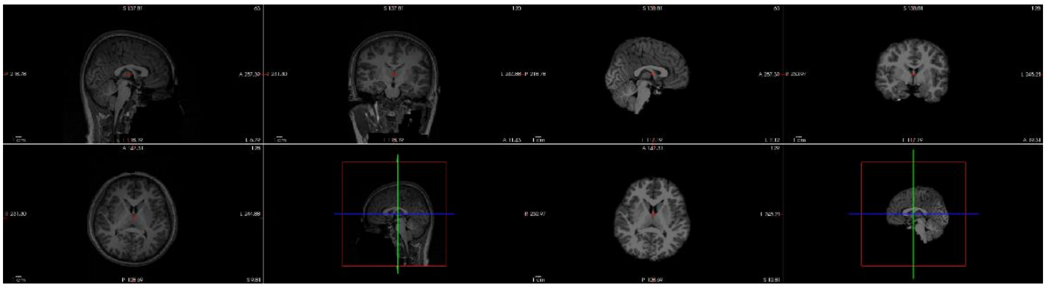

Fig 1. Data pre-processing before (left), after (right) comparison