Deep Learning-Based Classification of EEG Signals from Children with ADHD and Typically Developing Children: Postprint

Authors: Tian Bofan, Yan Hanying, Wang Suhong, Zou Ling

Date: 2018-05-20T00:00:00+00:00

Abstract

To address the classification problem between children with attention deficit hyperactivity disorder (ADHD) and typically developing children, this study employed the classic interference control task paradigm to investigate the event-related potentials (ERP) of both groups, aiming to achieve classification through ERP features. For the first time, this study utilized the long short-term memory (LSTM) method to analyze EEG signals from optimal electrodes ($p<0.05$) in the prefrontal and parieto-occipital brain regions during the latency period (200–450 ms) of both groups, and automatically learn and classify their ERP features. Compared with conventional classification methods, the classification accuracy of the LSTM method was slightly higher, reaching 95.78%. The results demonstrate that the LSTM method is beneficial for the classification of EEG signals in children with ADHD, providing a novel approach for individual diagnostic techniques for children with ADHD.

Full Text

Preamble

Title: Study of EEG Signal Classification Based on Deep Learning for ADHD Children and Normal Children

Authors: Tian Bofan[1,2], Yan Hanying[1,2], Wang Suhong[3], Zou Ling[1,2†]

Affiliations: 1. Faculty of Information Science & Engineering, Changzhou University, Changzhou, Jiangsu 213164, China 2. Changzhou Key Laboratory of Biomedical Information Technology, Changzhou, Jiangsu 213164, China 3. Department of Neuroscience, The Third Affiliated Hospital of Soochow University, Changzhou, Jiangsu 213003, China

Abstract: To address the classification problem between children with Attention Deficit Hyperactivity Disorder (ADHD) and normal children, this study investigated the event-related potentials (ERPs) of both groups using a classical interference control task paradigm, aiming to achieve classification through ERP characteristics. For the first time, the Long Short-Term Memory (LSTM) method was employed to analyze EEG signals from optimal electrodes ($p<0.05$) in the frontal and parietal-occipital brain regions of both groups during the latency period (200–450 ms), automatically learning and classifying ERP features. Compared with conventional classification methods, the LSTM method achieved a slightly higher classification rate of 95.78%. The results demonstrate that the LSTM method is beneficial for classifying EEG signals of ADHD children, providing a novel approach for individual diagnosis of ADHD.

Keywords: Interference control task experiment; ADHD; LSTM

0 Introduction

Attention Deficit Hyperactivity Disorder (ADHD), commonly known as childhood hyperactivity, is a neuropsychiatric disorder characterized primarily by inattention, hyperactivity, and impulsive behavior. Recent research has increasingly drawn social and familial attention to this condition. Salomone et al. utilized neurophysiological techniques such as electroencephalography (EEG) to identify executive function deficits in ADHD children, with the most core deficits manifested in three aspects: inhibitory processes, working memory, and shifting ability. Previous studies have employed interference control task paradigms to investigate inhibitory process deficits in ADHD, revealing that these children exhibit functional impairments in interference control, primarily attributed to structural differences in brain regions. Concurrently, research indicates that the frontal and parietal-occipital lobes are the main brain regions associated with interference control functional deficits.

Conventional EEG feature extraction methods, such as band power analysis, Common Spatial Pattern (CSP), multivariate adaptive autoregressive models, and independent component analysis, have been widely applied in EEG analysis. However, these conventional approaches involve cumbersome data processing and relatively simplistic feature selection. In contrast, deep learning methods possess automatic feature learning capabilities, transforming raw data into higher-level, more abstract representations through the combination of simple nonlinear modules. Deep learning can leverage its network architecture to learn from vast datasets, extracting more implicit information. The application of deep learning methods to conventional EEG data has become a research hotspot. For instance, Davidson et al. first applied the LSTM method to real-time analysis of EEG features in healthy subjects during a visuomotor tracking task, enabling timely error alerts when mental motor errors were detected and achieving a prediction accuracy of 84%. This study employs the LSTM method to process EEG signals from ADHD and normal children, comparing results with conventional methods such as AdaBoost and Bagging to provide new insights for computer-aided diagnosis and treatment of ADHD.

1 Methods

1.1 Subjects

All subjects were clinically diagnosed at the First People' s Hospital of Changzhou. A total of 69 ADHD children meeting experimental criteria were selected, with a mean age of 8.57 ± 2.41 years, including 54 combined type (ADHD-C), 4 inattentive type (ADHD-I), and 11 hyperactive-impulsive type (ADHD-HI). Additionally, 73 healthy children with a mean age of 8.37 ± 2.16 years were recruited. No statistically significant age difference existed between the ADHD and control groups ($p > 0.05$). The experimental protocol was approved by the Ethics Committee of the First People' s Hospital of Changzhou, and all participants or their guardians provided informed consent before voluntarily participating in the study.

1.2 Experimental Equipment

The study utilized a 128-channel 10-10 EEG acquisition system (EGI) with a sampling frequency of 500 Hz. Electrode impedance was maintained below 80 kΩ. Net Station software and the EEGLAB toolbox were employed for preliminary preprocessing operations, with average reference electrodes used for re-referencing.

1.4 Optimal Electrode Selection

Previous research using the Simon-spatial Stroop paradigm to study inhibitory function deficits in ADHD demonstrated significant differences in ERP amplitudes between ADHD and normal children in the frontal and parietal-occipital lobes ($p < 0.05$), indicating that optimal electrode EEG data could effectively distinguish between the two groups. This experiment selected optimal electrodes from the frontal and parietal-occipital brain regions under different stimulus modalities, as shown in Table 1 .

1.5 Algorithm Flow

The algorithmic process consisted of three main steps: First, EEG data were preprocessed and divided into training and test sample sets. Second, EEG signals from optimal electrodes in two brain regions—the frontal and parietal-occipital lobes—were selected for both ADHD and normal children. Finally, both conventional and deep learning methods were applied to process the EEG signals. Conventional methods employed Common Spatial Pattern (CSP) to extract ERP common features from the two brain regions, with AdaBoost and

Bagging classifiers used for feature classification. The deep learning approach utilized Long Short-Term Memory networks to automatically learn ERP features and perform classification.

1.5.1 EEG Signal Preprocessing Data preprocessing was initially performed using Net Station software, including low-pass filtering, high-pass filtering (0.1–30 Hz), segmentation (−200 to 1000 ms), manual artifact detection, bad channel replacement, averaging, reference conversion, and baseline correction (−200 to 0 ms). The focus was on the latency period of 200–450 ms, followed by manual data selection using the EEGLAB toolbox. Dataset details are provided in Table 2 .

1.5.2 LSTM Algorithm and Network Structure Long Short-Term Memory is a deep learning algorithm based on network architecture that extends recurrent neural networks with memory functionality. When processing EEG signals with LSTM, each subject' s raw EEG signals can be directly input into the network. The network can learn complex temporal relationships at arbitrary time scales and retain intrinsic information between signals from past moments, enabling prediction of possible outcomes at the next time point.

The experimental model was constructed based on the TensorFlow and Keras frameworks. The specific LSTM network structure is illustrated in Figure 3 [Figure 3: see original paper]. The deep learning network comprises three layers: an input layer, a hidden layer, and an output layer. The hidden layer includes an LSTM network structure layer, fully connected layers, and a softmax layer. To improve network learning efficiency and enable rapid feature learning, the fully connected layer was designed with three layers. However, as network depth increases, the learning rate between layers changes, potentially causing unstable gradient problems. To balance the learning rates across the three fully connected layers, the Adam algorithm from the Keras framework was employed—a gradient-based optimization algorithm with faster convergence speed. After multiple experiments, the learning rate parameter in the Adam algorithm was adjusted to 0.0001 to accelerate ROC loss curve decline. Since Kappa is a flexible real-time processing architecture capable of launching multiple instances for repeated calculations, which facilitates model optimization, the architecture parameter lambda in the Adam algorithm was changed to kappa while other parameters remained at default values.

The input layer received training dataset data consisting of 4,152 trials of two-channel EEG signals during the latency period. With a sampling frequency of 500 Hz and a selected latency period of 200–450 ms, the total number of sampling points was 126, forming a 126 × 2 × 4,152 matrix. To maintain consistency with the sampling point dimension, the input layer node count was set to 126. The training process included 20 iterations, with 20% of training samples used for cross-validation to improve iteration accuracy.

The hidden layer was primarily responsible for feature learning and model establishment. The number of memory unit nodes in the LSTM network structure layer matched the input layer at 126 nodes. Each unit contained three gates: an input gate, a forget gate, and an output gate. Each gate performed state activation through an activation function, enabling effective read, write, and forget operations on input information. Through collaborative gate interactions, unit node state updates were accomplished. The tanh function was selected as the activation function for the input gate and unit state transformation to reduce iteration 次数, as it is more suitable for solving nonlinear problems. The three gating state calculations are represented by equations (1)-(3), while state transformation and update calculations are represented by equations (4)-(6).

The output layer converted the output values ht from each LSTM memory unit in the hidden layer into predicted classification results yt after fully connected layer and softmax layer processing. The softmax layer primarily performed normalization on extracted feature vectors to calculate probability values for each class, from which classification rates were ultimately computed.

---

2 Results and Discussion

2.1 Stimulus Pattern Analysis and Selection

N2 can serve as a reference indicator for diagnosing conflict monitoring function in ADHD children, while N1 and P2 are associated with visual attention and the ability to ignore irrelevant information. Research has found that across four stimulus modalities—Simon Congruent (SmC), Simon Incongruent (SmI), Stroop Congruent (StC), and Stroop Incongruent (StI)—the ERP waveforms from optimally superimposed and averaged electrodes in the frontal and parietal-occipital brain regions of ADHD and normal children are as shown in Figure 4 [Figure 4: see original paper].

Figure 4(a) and (b) display ERP waveforms from the 9th channel in the frontal region and the 67th channel in the parietal-occipital region under SmC stimulus mode. Figures 4(c) and (d) show results from the 11th frontal channel and 71st parietal-occipital channel under SmI mode. Figures 4(e) and (f) present results from the 9th frontal channel and 71st parietal-occipital channel under StC mode. Figures 4(g) and (h) illustrate results from the 10th frontal channel and 89th parietal-occipital channel under StI mode. The frontal region ERPs reveal that ADHD children exhibit higher N2 amplitude peaks than normal children, while the parietal-occipital region shows lower P2 amplitude peaks in ADHD children. Although N2 amplitudes were slightly higher under incongruent stimulus modes (SmI and StI) compared to congruent modes (SmC and StC), the amplitude differences in N2 and P2 between the two groups were most pronounced under SmC stimulation. Consequently, the SmC stimulus mode was selected for subsequent analysis.

2.2 Feature Selection Under SmC Stimulus Mode

Based on the experimental task paradigm, ERP waveforms during the latency period for optimal electrodes in the frontal and parietal-occipital brain regions under SmC stimulation were plotted, as shown in Figures 5 [Figure 5: see original paper] and 6 [Figure 6: see original paper]. Figure 5 displays the latency ERP waveform for the 9th frontal channel optimal electrode, while Figure 6 shows the waveform for the 67th parietal-occipital channel optimal electrode. These figures clearly demonstrate significant amplitude differences between ADHD and normal children under SmC stimulation, indicating that these features can be effectively utilized for classification.

2.3 Common Feature Extraction from Optimal Electrodes in Frontal and Parietal-Occipital Regions

Given the distinct EEG manifestations in the frontal and parietal-occipital brain regions under the same stimulus mode, the Common Spatial Pattern (CSP) algorithm was applied to electrode data from both regions to extract common features and visualize them, as shown in Figure 7 [Figure 7: see original paper]. Analysis of common features across the four stimulus modalities revealed that only features under SmC stimulation were readily distinguishable. Therefore, utilizing the common features from both brain regions under SmC stimulation could effectively differentiate ADHD children from normal children.

2.4 Conventional Method Classification Results

Conventional AdaBoost and Bagging classifiers were applied to classify the common EEG features extracted by CSP from the two brain regions' optimal electrodes. Using the most discriminative common features under SmC stimulation, the iterative training error rate curves for both classifiers are presented in Figure 8 [Figure 8: see original paper].

2.5 Deep Learning Classification Results

The ROC curve for LSTM network training on the EEG sample dataset is shown in Figure 9 [Figure 9: see original paper]. The curve clearly demonstrates that classification accuracy increased incrementally with each training iteration, while the loss rate calculated by the loss function decreased correspondingly. After 20 iterations, classification accuracy stabilized at over 90%, with loss rates dropping to approximately 0%.

2.6 Comparison of Classification Results

The comparative results for both methods are presented in Table 3 . All classification rates exceeded 90%, with the LSTM method outperforming conventional methods by 2.03 percentage points. Compared to conventional classifiers, the LSTM deep learning method achieved stable classification rates with only a small number of iterations, maintaining consistently high classification performance throughout training and testing processes for both ADHD and normal children, with test sample classification reaching 95.78%.

Table 3: Comparison of Classification Results

SmC Stimulus Mode	Training Sample Classification Rate	Test Sample Classification Rate
AdaBoost	99.98%	93.75%
Bagging	98.12%	91.44%
LSTM	97.21%	95.78%

---

3 Conclusion

Although conventional feature extraction and classification methods offer advantages in data processing speed, they require manual feature selection with relatively limited feature choices—a limitation that becomes particularly prominent when processing large datasets. In contrast, deep learning methods require no manual intervention and can automatically learn features containing more implicit information, thereby improving classification rates and diagnostic accuracy. Furthermore, conventional methods must re-establish training models for each classification due to input data variations, making them less robust to data changes. Deep learning LSTM methods can establish unified training models based on large sample datasets. With advancements in computer hardware, the speed difference between deep learning and conventional methods for processing multi-channel EEG data will gradually diminish, while the advantages of deep learning will become more pronounced.

This study employed an interference control task with spatial integration paradigm, using deep learning LSTM methods to automatically complete EEG signal feature learning and classification. Compared with conventional classifiers AdaBoost and Bagging, the LSTM method achieved a classification accuracy of 95.78%. Preliminary findings suggest that under SmC stimulation, the ERP amplitude differences between the ADHD and control groups are most significant when averaged within brain regions, and these ERP features can effectively distinguish ADHD children from normal children, providing important scientific evidence for clinical individualized diagnosis of ADHD.

References

[1] Salari R, Bohlin G, Rydell A M, et al. Neuropsychological functioning and attachment representations in early school age as predictors of ADHD symptoms

in late adolescence [J]. Child Psychiatry & Human Development, 2017, 48(3): 370-384.

[2] Salomone S, Fleming G R, Bramham J, et al. Neuropsychological deficits in adult ADHD: evidence for differential attentional impairments, deficient executive functions, and high self-reported functional impairments [J]. Journal of Attention Disorders, 2016, 1-12.

[3] Ma I, van Holstein M, Mies G W, et al. Ventral striatal hyperconnectivity during rewarded interference control in adolescents with ADHD [J]. Cortex; a journal devoted to the study of the nervous system and behavior, 2016, 82-93.

[4] Zou L, Yang J J, Wang S H, et al. Classification study of ADHD and normal children based on EEG principal component analysis and k-nearest neighbors [J]. Journal of Biomedical Engineering, 2016, 33(2): 232-238.

[5] Billinger M, Brunner C, Müller-Putz G R, et al. Single-trial connectivity estimation for classification of motor imagery data [J]. Journal of neural engineering, 2013, 10(4): 1-8.

[6] Wang Y, Wang Y T, Jung T P, et al. Translation of EEG spatial filters from resting to motor imagery using independent component analysis [J]. Plos One, 2012, 7(5): 1-12.

[7] LeCun Y, Bengio Y, Hinton G, et al. Deep learning [J]. Nature, 2015, 521(7553): 436-444.

[8] Soleymani M, Asghari-Esfeden S, Fu Y, et al. Analysis of EEG signals and facial expressions for continuous emotion detection [J]. IEEE Transactions on Affective Computing, 2016, 7(1): 17-28.

[9] Davidson P R, Jones R D, Peiris M T R, et al. EEG-based lapse detection with high temporal resolution [J]. IEEE Transactions on Biomedical Engineering, 2007, 54(5): 832-839.

[10] Dong H, Supratak A, Pan W, et al. Mixed Neural Network Approach for Temporal Sleep Stage Classification [J]. IEEE Trans on Neural Systems and Rehabilitation Engineering, 2017, 99: 1-11.

[11] Michelini G, Kitsune G L, Hosang G M, et al. Disorder-specific and shared neurophysiological impairments of attention and inhibition in women with attention-deficit/hyperactivity disorder and women with bipolar disorder [J]. Psychological medicine, 2016, 46(3): 493-504.

[12] Xie L, Ren M, Cao B, et al. Distinct brain responses to different inhibitions: Evidence from a modified Flanker Task [J]. Scientific Reports, 2017, 7(1): 1-12.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.