Original Article

Detecting ADHD Children using the Attention Continuity as Nonlinear Feature of EEG

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A B S T R A C T

Purpose- Attention Deficit Hyperactivity Disorder (ADHD) is the current description of the most prevalent psychiatric disorder of childhood. The essential feature is the developmentally inappropriate degree of inattention, impulsiveness and hyperactivity. Manifestations of ADHD usually appear in most situations, including home, school, work, sporting and social settings.

Method- Since the essential feature of ADHD is inattention manner, the nonlinear features of EEG may be equivalent to the attention that we investigate nonlinear features of the EEG. We evaluated 29 children with ADHD who were diagnosed by DSM-IV criteria and 20 age-sex matched controls. During recording EEG, we showed images of children and asked them to concentrate on those images and number them. Using this method we stimulated the visual attention of children.

Result- In this study, we used an MLP neural network as a classifier. By investigating these nonlinear features, we obtained a classification with 96.7% accuracy, using frontal lobe electrodes as the best result.

Conclusion- Results showed a significant difference between the accuracy of the frontal region and other regions. This result can confirm the defect in the anterior segment of the brain of ADHD children.

1. Introduction

The Attention Deficit Hyperactivity Disorder (ADHD) is one of ordinary behavioral disorders in childhood [1]. The ADHD children may be unable to sit still, plan ahead, finish tasks or be fully aware of what is happening around them. The prevalence of ADHD has been estimated approximately 12.1% among boys and 3.9% among girls [2]. Presistent adult ADHD may cuase serious long-term consequences such as poor academic achievement and job performance, increased risk of antisocial behavior, drug and alcohol abuse [3]. Early recognition of ADHD children causes the early and efective interventions [4]. The current diagnostic criteria of ADHD is based on manifested behavior and reported symptoms [5]. As these criteria are based on behavior, in most cases preschool recognition of ADHD children may be difficult and in these cases using electroencephalogram can be recommended to be used.

EEG is a useful method which provides information about the background activity of the brain and indexes the substrate of cognition and

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behavior [6]. According to the literature, EEG has a main role in the evaluation of neural function of ADHD children [7]. Therefore, it can be a useful gadget for investigating and diagnosing the abnormal behavior of ADHD children. There are many studies which employed EEG analysis for diagnosing ADHD. In 2013, Nazhvani *et al*, used N2 and P2 peaks of ERP to diagnose ADHD and achieved 92.9% accuracy [8]. Mueller investigated 75 ADHD and 75 control children using ERP features and achieved 91% accuracy [9]. In 2011, Sadatnezhad used fractal dimension, AR model and band power of EEG for detecting ADHD children and achieved 86.4% accuracy. In 2010, Ahmadlou used wavelet-synchronization methodology for detecting ADHD children and showed that this algorithm can discriminant ADHD and control children with 87.5% accuracy [10]. In our recent study, we used nonlinear features of EEG contained fractal dimension and combined these features with symbolic dynamic and showed that the decrement of these nonlinear features can be interpreted as the increment of attention and vice versa and we achieved 86% accuracy in detecting ADHD children [11].

In this paper, the continuity of attention will be investigated for ADHD and control children and using this continuity a new approach will be introduced. In the following, firstly EEG recording will be described, then the methodology of analysis will be introduced and finally the results will be demonstrated.

2. Materials and Methods

2.1. Subjects and EEG Recording

Twenty-nine children with ADHD symptoms (18 boys and 11 girls, ages 7-12) voluntarily participated in this study. The patients were evaluated by a psychiatrist and received a primary DSM-IV [12] diagnosis of attention deficit hyperactivity disorder. Twenty children without any psychological disorder, epileptic history, drug abuse, head injury (11 boys and 9 girls, age 7-12 years) voluntarily participated as control children. All subjects were schoolchildren and right handed.

Since one of the deficits in ADHD children is visual attention [13] and ADHD children cannot be fully aware about events, we decided to design an EEG recording protocol based on the visual attention and mental tasks. During EEG recording children were asked to do two "attention tasks". In the task, a set of pictures which had a number of animation characters were shown to the children and they were asked to enumerate the characters. Figure 1 shows an example of a set of pictures. Using this procedure for EEG recording, the visual attention and mental ability of children was stimulated.
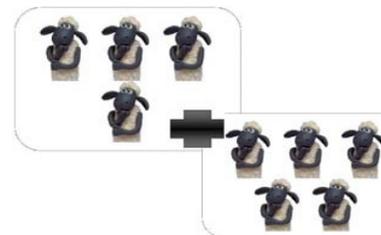
Figure 1. An Example picture which was shown to children.

During this task, 20 channels EEG (Fp1-A1, Fp2-A2, F7-A1, F3-A1, Fz, F4-A2, F8-A2, T3-A1, C3-A1, CZ, C4-A2, T4-A2, T5-A1, P3-A1, Pz, P4-A2, T6-A2, O1-A1, Oz, O2-A2) was recorded with 128 Hz sampling frequency and 16 bits EEG resolution. The EEG was filtered by software lowpass Bessel filter with 35 Hz cutoff frequency.

2.2. Nonlinear Features

As nonlinear features of time series can be interpreted as the complexity of its system and also attention makes one sense strong while making others weak and reduce the complexity of the brain, therefore nonlinear features of the EEG can be suitable tools for investigating the attention. In this paper, nonlinear features of EEG consist of Lyapunov exponent, Higuchi fractal dimension, Katz fractal dimension and Sevcik fractal dimension. In what follows, we will explain these features.

2.3. Lyapunov exponent

Lyapunov exponent is a quantitative measure for chaotic systems. It is a measure of the rate of attraction and repulsion from a fixed point in state space. In another word, Lyapunov exponent is a measure of the divergence of nearby trajectories. The system's behavior is chaotic if its average Lyapunov exponent is a positive number. Lyapunov exponent is used to determine the stability of any

steady-state behavior [14]. The wolf method will be used in this paper. In this approach at first step, a state space should be reconstructed and by selecting one point in this space, the nearest neighbor must be acquired. When the distance of initial condition and its nearest neighbor (L_0) has been determined, the system will be evolved forward some fixed time (evolution time) and the new distance (L_i) will be calculated. This evolution and calculating the successive distance will be repeated until the separation become greater than a certain threshold. Finally, Lyapunov exponent can be estimated using the following equation:

$$\lambda = \frac{1}{t_k - t_0} \sum_{i=1}^{k} \log \frac{L_i}{L_{i-1}} \tag{1}$$

Where k is the number of time evolution.

2.3.1. Katz fractal dimension

In 1988 an approach for calculating the fractal dimension of the signal had been introduced by Katz [15]. In this method, fractal dimension is defined as:

$$FD = \frac{\ln(N-1)}{\ln(N-1) + \ln(\frac{d}{L})} \tag{2}$$

Where N is the number of points of data, L is length of data and d is diameter of data.

2.3.2. Sevcik fractal dimension

For calculating Sevcik method in the first step, data should be normalized to be within a unit square by rescaling the abscissa (time axis) [16] and the ordinate (EEG signal) of the data space:

$$i'=i/N, s'(i') =(s (i)-s_{min})/ (s_{max}-s_{min}) \tag{3}$$

Where s(i) ans s'(i') are the original and normalized EEG signals of the ith data point, s_{max} and s_{min} are the maximal and minimal values of the signal and i=1, 2..., N is the serial number of the data points and i' is the normalized one. Now fractal dimension can be calculated by the following equation:

$$FD=1 + \frac{\ln(L)}{\ln(2(N-1))} \tag{4}$$

Where L is the total length of the data section in the normalized coordinate system.

2.3.3. Higuchi fractal dimension

Higuchi's method for calculating fractal dimension of trajectory is based on a different length of signal [17]. For a given time series of the data to be analyzed, *k* new time series were constructed as below:

$$\left\{s(m), s(m+k), s(m+2k), \dots, s\left(m+int\left(\frac{N-m}{k}\right)k\right)\right\}, m \tag{5}$$

Where *m* is the initial data point; *k* is the interval to select the subsequent data points; and function int(*x*) is to take the integer part of *x*. For each new time series, its average length L_m(k) was defined as:

$$L_m(k) = \frac{\left\{\sum_{i=1}^{int(\frac{N-m}{k})} |s(m+ik) - s(m+(i-1)k)| \cdot \frac{(N-1)}{int\left(\frac{N-m}{k}\right) \cdot k}\right\}}{k} \tag{6}$$

Where *(N − 1)/ (*int*((N − m)/k) · k)* is a normalization factor. The mean length of the original time series was calculated as the average of L_m *(k)*:

$$L(k)= \frac{1}{k} \sum_{m=1}^{k} L_m (k) \tag{7}$$

Since *L(k)* is proportional to k^{-FD} for a fractal time series, FD of the signal was obtained in this study as the slope of the curve ln*(L(k))* versus ln*(1/k)* using the least-squares linear best-fitting method.

2.4. Feature Extraction

For analyzing EEG signal, we segmented EEG by one second windows and extracted nonlinear features for each window. Using this segmentation and feature extraction, we obtained four time series for each electrode which were time series of Lyapunov exponent, Katz fractal dimension, Higuchi fractal dimension and Sevcik fractal dimension. Figure 2 illustrates an example of this time series.
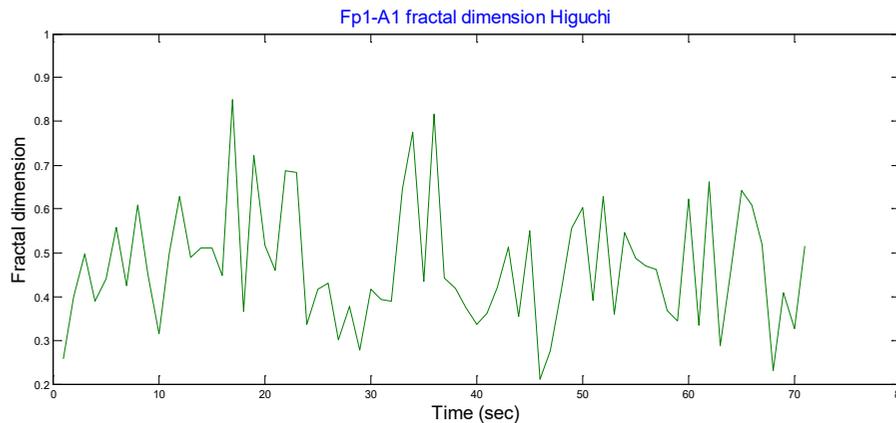
Figure 2. Time series of Higuchi fractal dimension.

As mentioned above, our aim in this study is to investigate the attention continuity in ADHD children and compare it to normal children. Whereas attention is increasing strength of one or more senses and decreasing the strength of other senses, we can phrase attention to decreasing the complexity of the brain. For investigating attention continuity, we divided the scale of each time series to three sub-scales low, middle and high as illustrated in Figure 3.
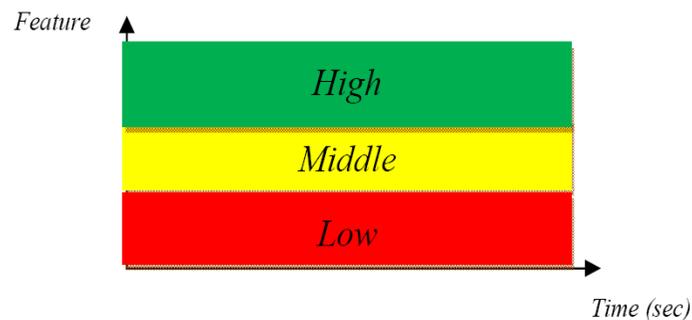
Figure 3. Dividing feature scale to three subscales.

Referring to the definition of attention, we can claim that attention may reduce the complexity of brain functions, therefore it may reduce the complexity of the EEG and this reduction may reduce the measure of non-linear features. Hence, "Low" sub-scale may be interpreted as maximum attention. Thus, for the investigation of attention and its continuity, we should investigate the probability of being time series in "Low" sub-scale and shifting from this sub-scale to itself. For the investigation of attention continuity, we investigated attention for one sample to five consecutive samples and calculated the probability of continuity of attention for each subject and each electrode.

3. Results

For classification, we used a multilayer perceptron neural network as a classifier with one hidden layer by five neurons. In this layer, the output function of the neural network was sigmoidal function. For training, we selected 24 subjects from ADHD group and 15 subjects from control group randomly. In order to test this classifier, we used 5 remained subjects of ADHD group and 5 remained subjects of the control group. For classification, we used five regions of electrodes on the scalp. First, we made this classification for all electrodes on the scalp. Since from recent researches we know that ADHD children have brain defects in frontal and prefrontal lobe, we made this classification for the

prefrontal and frontal lobe of the scalp. In the third condition, we made this classification for central electrodes. Next, we made this classification of parietal and occipital regions of scalp.

In following tables, we present the results of the classification using attention and its continuity from one sample to five consecutive samples.

Table 1. The accuracy of classifications using the sequence of Low subscale.

	All Electrodes	Frontal Region	Central Region	Parietal Region	Occipital Region
L	92.2%±0.4	96.7%±0.2	88.9%±1.6	83.3%±1.5	61.1%±2.1
LL	78.6%±1.6	96%±1.3	72%1.7	71%±2.1	65.6%±1.8
LLL	93.3%±0.5	92.2%±2.7	80%±0.7	81.1±0.8	61.1%±2.6
LLLL	86.7%±2.7	88.9%±1.9	72.2%±0.9	74.4%±2.8	64.4%±1.3
LLLLL	81.1%±2.1	78.9%±1.9	74.4%±1.5	64.4%±2.3	62.2%±4.7

Table 2. The sensitivity of classifications using the sequence of Low subscale.

	All Electrodes	Frontal Region	Central Region	Parietal Region	Occipital Region
L	98.9%±0.3	98.9%±0.3	90.5%±1.5	86.1%±1.7	61.3%±2.3
LL	83.2%±1.4	98.9%±1.3	76.7%±1.6	75.3±2.1	69.8%±1.7
LLL	98.9%±0.4	98.9%±1.9	85.3%±0.8	87.1%±0.9	61.3%±2.8
LLLL	92.4%±2.9	94.6%±1.7	77.6%±0.8	78.1%±2.6	67.8%±1.4
LLLLL	87.4%±2	86.3%±1.9	82.1%±1.6	71.1%±2.5	65.5%±4.3

Table 3. The specificity of classifications using the sequence of Low subscale.

	All Electrodes	Frontal Region	Central Region	Parietal Region	Occipital Region
L	87.6%±0.5	95.2%±0.6	87.8%±1.8	81.4%±1.5	61%±2.4
LL	75.4%±1.3	94%±1.5	68.8%±1.7	68%±2.2	62.7%±1.9
LLL	89.4%±2.6	87.6%±1.5	76.3%±0.5	77%±2.4	61%±1.7
LLLL	82.8%±2.8	85%±1.6	68.5%±0.6	71.8%±2.8	62.1%±1.6
LLLLL	76.7%±2.3	73.8%±1.4	69.1%±1.9	59.8%±2.1	59.9%±5.1

The best obtained accuracy is 96.7% for classification with features which extracted from the frontal region of scalp EEG.

4. Discussion

In this study, 20 normal children and 29 ADHD children were evaluated by EEG recording. For the first step, the nonlinear features of EEG signal were extracted. Using these features, the attention continuity was investigated and using this continuity the children were classified to normal and ADHD children and the best classification accuracy was 96.7%. In our recent study [11], we used symbolic dynamics of nonlinear features of EEG for detecting ADHD children. In that study,

the accuracy of classification was 86% which obtained from classifying by features of frontal lobe EEG. However, in this study, we achieved the 96.7% accuracy with frontal lobe EEG. Both studies showed that the most discriminant of features of ADHD and control children are frontal lobe.

The best accuracy appeared when the classification was done by features of the frontal region of EEG. Table 1 shows a significant difference between the accuracy of the frontal region and other regions. This may be caused by the frontal and prefrontal deficiency of ADHD children.

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