Loss Detection of Recurrence Rate in the EEG Signals of Children with ADHD

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Attention-deficit/hyperactivity disorder (ADHD) as an behavioral challenge, which affects the people's learning and experiences, is one of the disorders, which lead to reducing the complexity of brain processes and human behaviors. Nevertheless, most studies on the ADHD have currently focused on the frequency content of single and multichannel EEG segments and a few studies, which have tried to indicate this reduce, employed the approximate entropy, which is usually used for measuring the complexity of EEG signals in terms of their information. In this study, we tried to provided a different view of this reduce by focused on the tissue of patterns appeared on the auto-recurrence plots obtained from the trajectory of phase space reconstructed from the EEG signals recorded under the open-eyes and closed-eyes resting conditions. The outcomes of this analysis generally indicated a significant difference in the tissue of recurrence plots, which its reason was the increase of recurrence rate in the plots. Separating children with ADHD using the support vector machines with the radial basis function kernel developed by the features extracted from the recurrence plots also provided a remarkable accuracy (91.3% for the testing sets), which means the change in the tissue of recurrence plots relevant to the EEG signals of ADHD children. Comparing the classification results of this research and previous researches nonetheless represented that the statistical population usually affects this accuracy. Therefore, these findings generally proved that although the classifiers developed by an EEG segment are not applicable to clinical conditions, the ADHD averagely leads to reducing the complexity of EEG processes.

Keywords: ADHD, EEG, Recurrence plot, Complexity

Introduction

The ADHD is a neurobehavioral developmental disorder, which changes the interaction style of brain with the environment, so that person with this disorder often experience misbehaviors such as hyperactivity, impulsivity, and inattention.¹,² Hence, this disorder usually leads to increase the power of δ and θ bands and decreases the power of α and β bands.¹,³,⁴ Such change in the frequency content of standard EEG bands according to Lipsitz and Goldberger studies⁵,⁶ means decreasing the complexity of brain activities in these children. Accordingly, some researchers have currently applied techniques from the information and chaos theory such as entropy to quantify the ADHD effect on the EEG signals.⁷,⁸ Nevertheless, although these researches have obtained fairly good results, they often investigated the complexity of EEG signals in the time domain. In this work, we employed the recurrence plot for evaluating the complexity of high-dimension phase space of EEG signals in children with and without ADHD under the eyes-open and eyes-closed condition.

Materials and Methods

Subjects

Our analyses were made on two groups of children, which had an age range between 7 and 12 years. These groups, which generally consisted of 30 children diagnosed as ADHD and 30 healthy children, had almost similar condition in terms of gender distribution, so that the ADHD group included 11 females and 19 males and the healthy group included 13 females and 17 males. In distinguishing these children and grouping them, we had also help from a professional psychiatrist, which used the detailed history of past and current functioning, and the scales of integrated visual and auditory (IVA) test and child behavior checklist (CBCL) for diagnosing the ADHD. Figure 1a indicated the average value of T scores of DSM scales extracted from the child behavior checklist for the ADHD and healthy children. As shown in this figure, most DSM scales except the scale of somatic problems were along with

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an increase for the ADHD children. Evaluating the separability of these children in two groups: ADHD and healthy using the mentioned DSM scales and the t-test analysis (Figure 1b) also provided a significant separation, which means the existence of behavioral disorders, especially inattention coupled with hyperactivity and impulsivity, in the ADHD children. Measuring the scales of continuous performance of ADHD and healthy children

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Using the integrated visual and auditory test also recorded a reduction in the scales relevant to the ADHD children (Figure 1c), which means a change in the efficiency of children with the mentioned disorder. Interestingly, this reduction according to the results of t-test analysis developed by the scales of IVA test was significant (-log(p)>-log(0.05)) in most scales of IVA test. Figure 1d shows this separation as the logarithm of p values obtained from the t-test analysis. For each of the children studied in this research, the EEG signals were also recorded under eyes-open and eyes-closed conditions at 240 seconds. These signals were acquired from the FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz and Pz positions on the scalp according to
10–20 international system. Average of A1 and A2 electrodes was used as reference value. These electroencephalograms were also recorded in a psychiatric clinic sponsored by the Sampan University (Sampan in Iran) using a Mitsar-EEG-202 system. The sampling rate of Mitsar-EEG-202 system was set on 500 Hz with resolution 24 bit. The band pass filter of this system was set to DC-100 Hz. In the preprocessing phase, we first filtered signals by a Butterworth low pass filter$^{1,9,10}$ (order 6) with 40 Hz cutoff frequency for removing high frequencies and power line noises. Then, we partitioned the EEG signals into segments of 10 s without overlap. In the next subsection, we depicted the ADHD effect on the tissue of patterns appeared on the recurrence plots of EEG segments.

The auto recurrence plot in the ADHD children

The EEG signal has generally a sustainable and reversible behavior. Therefore, according to the Poincare recurrence theorem, we can estimate the amount of complexity of an EEG segment by using the amount and the style of reversibility of trajectories reconstructed from this EEG segment to a certain area. The recurrence plot (RP) as one of the techniques of nonlinear analysis introduced by Eckmann and colleagues in 1987, which can estimate the amount and the style of reversibility of phases to the old (other) phases in higher-dimensional phase spaces, is one of the methods of nonlinear dynamic domain, which usually provides useful information about the complexity of processes generated by a system. Hence, we used this technique to quantify the recurrence style of trajectories reconstructed from the EEG signals of ADHD and healthy children. The following equations is the mathematical formula that often used for computing the recurrence plots$^{11}$.

$$R_{ij} = \Theta(\epsilon - \|x_i - y_j\|) \quad i, j = 1,2,\ldots,N \quad \ldots \quad (1)$$

where x and y are trajectories generated from the change of states or phases of one system or two different systems. Therefore, R can be auto- or cross-recurrence values. In this equation, $\Theta$ is also a Heaviside function and $\epsilon$ is a threshold. The $\epsilon$ threshold is also an important parameter in this equation, because it determinants the recurrence basin of y trajectory to the x trajectory. Hence, the incorrect selection of this threshold (for example a constant threshold) can lead to the extraction of dissimilar information from the EEG segments relevant to a class. In this research, we used $\epsilon = D_{\text{min}} + \alpha(D_{\text{max}} - D_{\text{min}})$ for determining the $\epsilon$ threshold ($0 \leq \alpha \leq 1$). In this equation, the $\epsilon$ threshold depends on the largest ($D_{\text{max}}$) and smallest ($D_{\text{min}}$) Euclidean distance of two trajectories x and y. The $\alpha$ parameter also determines the rate of this dependence. Figure 2a averagely shows the effect of $\alpha$ parameter on the difference of recurrence rate (RR) of recurrence plots obtained from the EEG segments relevant to the healthy and ADHD children based on 19 EEG channels (from the FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz and Pz). As shown in these curves, the most difference between the RR parameter obtained from the recurrence plots of healthy and ADHD children averagely occurred around $\alpha = 0.25$. Therefore, we used this value for calculating the auto-recurrence plot of EEG segments. Figure 2c and 2d typically indicates the auto-recurrence plots calculated from two EEG segments of healthy and ADHD children recorded under eyes-open condition for the Cz channel. As seen in figure, there is a remarkable difference between the auto-recurrence plots of healthy and ADHD children, so that the recurrence rate (RR) in the auto-recurrence plot of EEG segment without ADHD (42.50%) was lower than that of EEG segment with ADHD (57.93%). Of course, in order to having such difference in most auto-recurrence plots, the lag and the embedding dimension needs to be determined. For determining the embedding dimension, we used the effect of embedding dimension on the difference of RR parameters obtained from the auto-recurrence plots of healthy and ADHD children. Figure 2b provides the effect of this parameter, i.e. the embedding dimension, on the difference of recurrence rate obtained from the 720 EEG segments of ADHD and healthy children recorded from 19 EEG channels under open-eyes and closed-eyes conditions. The curves of this figure indicate that the most difference averagely occurred around $m = 4$. For determining the lag, we also used the autocorrelation time, when the autocorrelation approaches $e^{-1}$. Actually, we first estimated the proper lag for each of the EEG segments using this method. Then, we calculated the probability of estimated lags. Figure 2e depicts the estimated lags and their probabilities. As shown in figure, the probability of lag 0.035s (sample/sampling frequency = 17/500) was more than that of other lags. Therefore, we used these values for computing the auto-recurrence plot of EEG segments. Figure 3a and 3b shows the logarithm of p-values obtained from the t-test analysis of recurrence rate computed from the recurrence plots of EEG segments relevant to the
ADHD and healthy children as a set of the brain maps. As seen in these maps, the logarithm of p-values for all of the EEG channels (19 channels) was more than two (p<0.01), which means significant separation in the distribution of recurrence rate extracted from the EEG segments of two groups: ADHD and healthy children. In the following subsections, we quantified the ADHD effect on the auto-recurrence plot using the recurrence quantification analysis (RQA) developed by the values of α, lag and embedding dimension (m) determined in this subsection.

**Feature extraction**

As shown in the previous section, the auto-recurrence plots of EEG segments obtained from the ADHD children had remarkable difference with that of healthy children, so that the recurrence rate of EEG signals in these children averagely had significant difference with that of healthy children. Therefore, we...
quantified the auto-recurrence plots of EEG segments in the ADHD and healthy children by using some of the features introduced in the recurrence quantification analysis:\(^1\):

1) The recurrence rate (RR): This parameter measures the density of recurrence points in a recurrence plot.
2) The probability of diagonal lines (PDL) with minimal length \(l_{\text{min}}\) in the recurrence plot: This parameter measures the parallel convergence behaviors of the x and y trajectories.
3) The probability of horizontal lines (PHL) with minimal length \(l_{\text{min}}\) in the recurrence plot: This parameter measures the convergence behaviors of the x trajectories to the y trajectories in a special time.
4) The maximal diagonal line length \((\text{L}_{\text{d, max}})\): The \(\text{L}_{\text{d, max}}\) is related on the time, in which the long segments of the phase space trajectories run parallel. We quantified this parameter as \(\text{DIV} = 1/\text{L}_{\text{d, max}}\).
5) The maximal horizontal line length \((\text{L}_{\text{h, max}})\): The \(\text{L}_{\text{h, max}}\) is related on the time, in which the long segments of the x trajectory converge to a point of y trajectory. We quantified this parameter as \(\text{HIV} = 1/\text{L}_{\text{h, max}}\).

Fig. 3, a-b) The logarithm of p-values obtained from the t-test analysis of recurrence rate computed from the recurrence plots of EEG segments relevant to the ADHD and healthy children in 19 EEG channels, c-d) The logarithm of p-values obtained from the t-test analysis for the features of two classes: ADHD and healthy in 19 EEG channels recorded under the eyes-open and eyes-closed conditions.
1) The Shannon entropy of the probability that a diagonal or horizontal line (EDL or EHL) has exactly length l. This parameter measures the structural complexity of recurrence plots.

2) The linear regression coefficient between the density of recurrence points in a line parallel to the LOI (line of identity) and its distance to the LOI. This parameter provides information about the stationarity of recurrence plots. We formulated it as following:

\[ R_{ij} = -100 \sum_{i=1}^{N}(i-N/2)(P_i - P^>)^2 \]
\[ P_k = \sum_{i,j=k-N/4}^{i,j=k+N/4} R(i,j) \]

Figure 2f averages the density of recurrence points in the lines parallel to the LOI for the ADHD and healthy children in the Cz channel. As shown in this figure, the linear regression coefficient (slope) in the ADHD children under the eyes-open and eyes-closed conditions was more than that of healthy children. Therefore, we considered this parameter as a feature.

**Poincaré recurrence time (PRT):**

This parameter is the length of time elapsed until the recurrence. Therefore, it is an index for measuring the complexity of signal. In this research, we used the average of length of diagonal lines (\( \langle l_d \rangle \)) resulted from the non-recurrence points for estimating this parameter. Meantime, we added the Shannon entropy (En) and the power (P) of EEG signals to our feature vector, because these features extract other part of the EEG information, which consists of the information stored in the EEG amplitude. In next section, we provided the results obtained from separating the ADHD by using the introduced features.

**Experimental results & Discussion**

The patterns of Figure 3c and 3d, which show the logarithm of p-values obtained from the t-test analysis of features extracted from 19 EEG channels relevant to the ADHD and healthy children under the eyes-open and eyes-closed conditions, depicted a significant difference (p-value < 0.01) in the distribution of features (except the DIV feature) extracted from the EEG segments of ADHD and healthy children with a logarithmic value over 2, which means changing the tissue of recurrence plots obtained from the EEG signals of ADHD children compared to that of healthy children. According to this analysis, the HIV feature also revealed a significant difference in most of the EEG channels recorded under the eyes-open and eyes-closed conditions, which had more difference compared to other features. It was remarkable that the logarithm of p-values relevant to the features extracted from the recurrence plots also was larger than the features extracted from the EEG amplitude, i.e. the Shannon entropy (En) and the power (P) of EEG signals. Therefore, this condition in the mentioned features proves that the recurrence plots extracted from the EEG signals are informative for diagnosing the ADHD. The 10-fold cross-validation of sequential forward selection (SFS) algorithm for classifying the children with and without ADHD in Figure 4a is other confirmation for the stated issues. This figure actually indicated that an optimal combination of features extracted from 19 EEG channel recorded under the eyes-open and eyes-closed conditions (2x19x11 feature) could averagely provide an accuracy about 97.86%, 96.34% and 91.3% for the training, validating and testing sets, respectively. The rank of features provided in this figure also indicated that the features extracted from the EEG signals recorded under the eyes-closed condition had a special role in separating the EEG segments of ADHD and healthy children and most features selected by this algorithm, i.e. the SFS algorithm, relevant to the EEG signals recorded under eyes-closed condition. Besides, this 10-fold cross-validation showed that the change of statistical population in the testing set could create a change about ± 2% in the accuracy of support vector machines (SVM) with the radial basis function (RBF) kernel. The following algorithm provides the used SFS algorithm. Comparing the classification results obtained in this research with the results reported in the previous researches, which provided in Figure 4b as the effect of statistical population on the results of ADHD diagnosis, generally shows that the accuracy obtained from diagnosing the ADHD using the RBF-SVM developed by the features extracted from the recurrence plots of EEG signals was similar to the result of reports, which the number of subjects (N = 60) was equal to present research. Therefore, this condition indicated that the recurrence plots of EEG signals were a useful informational resource in the ADHD diagnosis. Nevertheless, changing in the statistical population due to the incomplete sampling can lead to changing the classification accuracy. It was also noteworthy that the line fitted on the data of Figure 4b with displaying an indirect relationship between the number of subjects (N) in the statistical
population and the classification accuracy, generally showed that increasing the number of subjects can significantly decrease the accuracy of ADHD diagnosis. Therefore, it seems that diagnosing the ADHD using a classifier developed by an EEG segment cannot currently be a suitable method for the clinical application. Figure 4c, which typically provides the average and standard deviation of recurrence rate obtained from the recurrence plot for 24 EEG segments get from the 30 ADHD children and 30 healthy children under the eyes-closed condition (each of the points of these curves obtained from the sorted recurrence rate of 24 EEG segments)

Fig. 4 a) The 10-fold cross validation of SFS algorithm for classifying the children with and without ADHD, b) The effect of statistical population on the results of ADHD diagnosis based on the results of this research and previous reports [2, 4], c) the average and standard deviation of recurrence rate obtained from the recurrence plot for 24 EEG segments get from the 30 ADHD children and 30 healthy children under the eyes-closed condition (each of the points of these curves obtained from the sorted recurrence rate of 24 EEG segments)
in various peoples is different. In the next section, we presented a brief discussion and conclusion about the results obtained in this study.

As stated in the introduction, some of researchers such as Vaillancourt and Newell\textsuperscript{19} believe that the observed increase or decrease in complexity with aging and disease is dependent on the intrinsic dynamics of the system and the short-term change required to realize a local task demand. In other words, these researchers and also Lipsitz and Goldberger\textsuperscript{5,6} with displaying the negative effects of aging and diseases on the complexity of physiological and behavioral systems have generally indicated the loss of complexity in the physiological processes is resulted from relative frequency reduction in the high-frequency components and corresponding increase in the relative contribution of lower-frequency components. Actually, these changes in the frequency components generally proved that the more complex processes have a broader active frequency pattern, while the loss of complexity in a process is usually along with a narrowing of the frequency spectrum. It is interesting that the ADHD as a neurobehavioral developmental disorder, which often appears as inattention and distractibility with or without accompanying hyperactivity, is a change in the brain activities, which its effect on the EEG signals is usually more activity in low frequency components (the δ and θ bands) and less activity in high frequency components (the α and β bands). Therefore, such conditions in the behavioral indicators and the indicators obtained from the EEG signals of ADHD children generally represents that the ADHD can reduces the complexity of processes generated by the brain. The results reported by previous researches such as Khoshnoud’s report\textsuperscript{7} on the entropy of EEG signals are a confirmation for this reduction in the complexity of brain activities relevant to the ADHD children. Reducing the recurrence rate in the recurrence plots reconstructed from the EEG signals of ADHD children compared to that of healthy children in 19 EEG channels studied in this research, especially the EEG channels located on the frontal lobe under eyes-open and the frontal and occipital lobes under eyes-closed are also another confirmation for the mentioned reduction in the brain activities of children with ADHD. This reducing in the recurrence rate actually according to the Poincaré recurrence theorem, which considers the complexity of a process generated by a system, depends on the recurrence rate of system states or phases to each other, proves that the ADHD usually leads to decreasing the complexity of behaviors and brain activities in the human. It was also remarkable that computing the probability of diagonal and horizontal lines (PDL and PHL) in the recurrence plots obtained from the trajectory of phase space reconstructed from the EEG signals relevant to the ADHD children depicted a significant increase (difference), which its reason was the parallel and similar behaviors in the above-mentioned trajectory. The existence of a significant accuracy (about 91.3% for the testing set) in the output of RBF-SVM classifier developed by the features extracted from the recurrence plots of EEG segments was other reason for these parallel and similar behaviors, because increasing these behaviors in the trajectories of phase space reconstructed from the EEG signals is a factor for increasing the probability of occurrence of diagonal and horizontal lines in the recurrence plots. Therefore, these changes in the tissue of patterns appeared on the auto-recurrence plots obtained from the trajectory of phase space reconstructed from the EEG signals recorded under the open-eyes and closed-eyes resting conditions not only indicates the ADHD lead to a decrease in the complexity of brain processes, but also these change is other conformation for Vaillancourt’s and Lipsitz’s reports\textsuperscript{5,19}.

**Conclusion**

Although, the discussed results provides a significant difference for the ADHD children, the influence of statistical population on the accuracy of classifiers indicated that there are intrinsic limitations for diagnosing the ADHD using a EEG segment due to the ability of self-organizing and creativity of brain. Actually, the influence of statistical population on the accuracy of classifiers in the present research and previous researches represented a decrease in the accuracy of ADHD diagnosis compared to increasing the number of subjects in the statistical population, which means the inefficient of classifiers developed based on an EEG segment for the clinical application. Therefore, it seems that the ADHD diagnosis using several EEG segment can be more suitable for the clinical application. Evaluating the recurrence rate obtained from the recurrence plots of 24 EEG segment relevant to the ADHD and healthy children in this study with displaying two different bands for the recurrence rate of EEG segments of ADHD and healthy children, in addition to conforming this issue, represented that the information of an EEG segment
cannot always guarantees the ADHD diagnosis. This evaluating also proves that the ADHD have different grades in various peoples. Therefore, it seem that the development of diagnostic methods based on several EEG segments, the study of reliability in the accurate diagnosis of ADHD using several EEG segments, the comparison of mentioned reliability with the reliability of self-reports and continuous performance tests can be interesting start points for the future works.

References