Scale-Invariant Locomotor Activity Patterns in Children with SAD

Original Research Article

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Abstract Seasonal Affective Disorder (SAD) is a recurring mood disorder with symptoms of fatigue and diminished energy. A prominent characteristic of patients with SAD is disturbance in circadian and semi-circadian rhythms. The purpose of this study is to investigate whether there are alterations in fluctuations within shorter time scales. Locomotor activity has scale invariant characteristics within a range of minutes and previous studies found alterations in these parameters for psychiatric disorders. In this study, we investigated the scale-invariant features of actigraphy recordings of children with SAD. Fourteen children with SAD (11.0±3.3 years) and 12 age matched healthy controls (11.6±3.7 years) were recruited for the study. Wavelet analysis was used to calculate the scaling exponent of daytime and night-time activities. Scaling exponents for periods with higher (maxima) and lower levels (minima) of activities were calculated separately. Children with SAD had larger scaling exponents compared to controls during daytime for periods with higher and lower activities (daytime maxima: p<0.01, minima p<0.05). This means that healthy controls have more abrupt activity bursts and dips while children with SAD have more sluggish transitions in their activity levels. These findings were consistent in night-time activities.

Keywords Seasonal Affective Disorder, Locomotor Activity, Wavelet Transform Modulus Maxima Method

1. Introduction

Seasonal affective disorder (SAD) is a recurring mood disorder that has an onset and remission at predictable times during the year. In the United States, 3.3% to 4.2% of youth have reported a seasonal onset of depressive symptoms [1, 2]. Aside from typical major depression symptoms, most patients with SAD have atypical symptoms characterized by fatigue, hypersomnia, carbohydrate cravings and weight gain [3]. A prominent characteristic of patients with SAD is an alteration in circadian rhythms. Previous studies show that the timing of melatonin secretion [4] and rhythms of temperature [5] are delayed in these patients. These disturbances in circadian rhythms could be observed in their daily activities. A study using activity monitors showed strong evidence for circadian dysregulation and weakened entrainment to 24 hours [6, 7].

Previous studies have investigated the circadian rhythms of patients with SAD using activity monitors. Some have
looked into the rhythms with shorter oscillations that have 2 cycle/day (hemi-circadian) [6, 7]. However, not many have studied the fluctuation beyond this frequency in SAD patients. In fact, fluctuations faster than the hemi-circadian rhythm appear aperiodic and do not show significant oscillations, but rather show a “scale-invariant” pattern [8 - 12].

The Suprachiasmatic nucleus (SCN), a brain region which plays a major role in controlling the circadian rhythm [13], has been implicated in being involved in the pathophysiology for psychiatric and mood disorders [14, 15]. SCN is also shown to be responsible for regulating scale-invariant behaviours in human activity [16].

“Scale-invariant” in activity means that the pattern of fluctuations in activity does not have any periodic oscillations but shows self-similarity over all scales. Fluctuations with self-similarity look similar to each other, whether one extracts slow fluctuations over long periods or rapid fluctuations during short periods. Because of this nature, one could use a single parameter called a “power-law scaling exponent” to characterize the pattern of fluctuations. This exponent relates to the rapidness of the activity transitions, such as abrupt onsets and offsets, or gradual changes in movements. The scale-invariant feature of activity data has been used to further understand activity patterns and clinical state for other psychiatric disorders, such as bipolar disorder [17] and depression [18, 19] and may provide greater insight into the nature of activity disturbances in other disorders as well.

Ohashi et al. [11] reported that locomotor activity data in healthy individuals have different power-law scaling exponents for periods with higher and lower activity levels. Healthy controls had smaller scaling exponents at higher levels of activity than at lower levels. This means that periods of high activity are associated with quicker bursts of activity, while lower periods of activity are associated with more gradual transitions. Patients with chronic fatigue syndrome lacked these abrupt peaks of activity and had equivalent scaling exponents during periods with higher and lower activity levels, possibly due to exaggerated fatigue [10, 11].

In this study, we used the same method, incorporating bidirectional analysis of scaling exponents [10, 11] and studied the alterations in the scale-invariant features of daytime and night-time locomotor activity data for children with SAD. We also reanalysed actigraph data previously reported by Glod et al [20].

2. Method

2.1 Subjects and data collection

Fourteen children with SAD (11.0±3.3 years) and 12 age matched healthy controls (11.6±3.7 years) were recruited for the study. The data used in this study was previously reported by Glod et al. [20]. Activity levels were collected with a belt-worn ambulatory activity monitor (Motionlogger, Ambulatory Monitoring, Ardsley, NY) during usual weekdays. Acceleration counts above a threshold level were integrated for every 1 or 5 minutes over 72 consecutive hours. Children kept logs to note the times when the device was removed. Data was further checked by eye to ascertain the validity of the log. Details of the subjects, procedures and data collections are described elsewhere [20]. Data for the periods when the subjects removed the actigraph were marked invalid and were interpolated linearly. Data that was collected every minute was integrated to match the sampling rate of other data collected every 5 minutes. The ten most active hours during daytime and the eight most inactive hours during the night-time were used for analysis. For daytime, data missing more than 20 consecutive data points (100 minutes) were excluded from the analysis. For night-time, data were excluded when there were 12 consecutive data missing (60 minutes). There was an average of 2.76 days and 2.84 nights for 14 SAD subjects and 11 control subjects available for analysis.

2.1 Data analysis

We analysed the actigraph data using wavelet analysis. Muzy et al. [21] introduced wavelet transform modulus maxima (WTMM) to examine the scale-invariant dynamics of the data. In this study, we used a modified version of WTMM analysis [10, 11]. The general idea of this method could be understood intuitively as follows. We prepare a series of wavelets, in this case, “Mexican Hats” (see Figure 1a) with various scales. Scales refer to the width of the wavelet ranging from “skinny” to “fat”. Each of the wavelets are slid along the data as a template to examine how well the wavelets match the data, while also taking into account the amplitude of the data fluctuation. This mathematical procedure is called convolution and gives wavelet coefficients (Figure 1c). From its shape, a Mexican Hat wavelet could be considered as a template to match activity transitions for low-high-low activity patterns. Similarly, an upside down Mexican Hat wavelet detects activity patterns that have high-low-high transitions. If the wavelet coefficient is larger at larger scales, i.e., matched with “fatter” wavelets, then the activity is dominated by slower transitions. If the wavelet coefficients are larger at smaller scales, i.e., matched with “skinnier” wavelets, then the activity is dominated by quicker transitions. The scale-invariant features of the actigraph data can be visualized by drawing a log-log plot of wavelet coefficient vs. scale, which if invariant would form a straight line (see Figure 1f). Thus, the scale-invariant dynamics can be characterized by a single parameter, the slope of the line. When the slope is positive and steep, the overall activity transition is slower and when the slope is less steep the activity transition is faster. Muzy et al. [21] showed that it is sufficient to calculate the slope by only picking out the local maximum and minimum of the wavelet coefficients.
and combining them. In this study, we calculated the slope for local maximum (maxima) and minimum (minima) separately (Figure 1d, 1e). This was done to differentiate between the low-high-low activity burst patterns, which are detected by maxima and high-low-high patterns of dips in activity, detected by minima.

More precisely, the analysis is as follows. In this method, the activity data was integrated \( f(x) \) (where \( x; \) time), then convolved with a mother wavelet \( \psi(x) \) to calculate the wavelet coefficient:

\[
T\psi[\hat{f}](b,a) = \frac{1}{a} \int_{-\infty}^{\infty} \frac{x-b}{a} \hat{f}(x) \, dx,
\]

where \( a \) and \( b \) are the scale and the location of the mother wavelet, respectively. In this study, we used the Gaussian 3rd derivative

\[
\psi(t) = t(3-t^2)e^{-0.5t^2}
\]

as a mother wavelet with the values of \( 1 \leq a < 12 \) corresponding to approximately \( \leq 60 \) minutes. This is equivalent to using the Gaussian 2nd derivative (so-called “Mexican hat”) wavelet to examine the raw signals (Figure 1a, b). The advantage of integrating the data is that it automatically removes the local mean and the local linear trend of the original data. Next, the wavelet coefficient was calculated (Figure c) and local maxima and minima of the wavelet coefficients were picked out to evaluate the scale-invariant dynamics (Figure 1d, e). The variance of the maxima and the minima were added separately (\( Z_{\text{maxima}}(a) \) and \( Z_{\text{minima}}(a) \)). The \( Z_{\text{maxima}}(a) \) and \( Z_{\text{minima}}(a) \) were calculated from diurnal or nocturnal data for each day and were averaged for the available data for each subject.

From this, the scaling exponents, \( \tau_{\text{maxima}} \) and \( \tau_{\text{minima}} \), were calculated as (see Figure 1f):

\[
Z_{\text{maxima}}(a) \propto a^{\tau_{\text{maxima}}}, \quad Z_{\text{minima}}(a) \propto a^{\tau_{\text{minima}}},
\]

Thus for each subject, there are \( \tau_{\text{maxima}} \) and \( \tau_{\text{minima}} \) for daytime and night-time activities.

Figure 1. Wavelet transform modulus maxima method. A series of wavelets, “Mexican Hats” with various scales, i.e. “skinny” to “fat” (a), are slid through and convolved with the data (b). This gives wavelet coefficients (c). We pick out the local maximum (d) and the local minimum (e) of the wavelet coefficients and plot them in double-logarithmic scales to calculate the slope for maxima (\( \tau_{\text{maxima}} \)) and minima (\( \tau_{\text{minima}} \)) (f).
Figure 2. Daytime and night-time maxima and minima. The power of maxima and minima are plotted in double-logarithmic scales for children with SAD (SAD) and healthy controls (CONTROL) during daytime and night-time periods. The plots represent group average and S.E.M. The regression line for shaded area (<30 minutes for daytime, <20 minutes for night-time) is shown in dashed lines.

<table>
<thead>
<tr>
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<th>SAD</th>
<th>Control</th>
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<tbody>
<tr>
<td><strong>Daytime</strong></td>
<td></td>
<td></td>
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<tr>
<td>$\tau_{\text{maxima}}$</td>
<td>1.14 ± 0.209**</td>
<td>0.917 ± 0.168</td>
</tr>
<tr>
<td>$\tau_{\text{minima}}$</td>
<td>1.07 ± 0.152*</td>
<td>0.935 ± 0.106</td>
</tr>
<tr>
<td><strong>Night-time</strong></td>
<td></td>
<td></td>
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<tr>
<td>$\tau_{\text{maxima}}$</td>
<td>0.788 ± 0.406*</td>
<td>0.408 ± 0.239</td>
</tr>
<tr>
<td>$\tau_{\text{minima}}$</td>
<td>0.620 ± 0.364*</td>
<td>0.350 ± 0.239</td>
</tr>
</tbody>
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**p <0.01 and p <0.05 between control group by the standard t-test.

Table 1. Scaling exponents $\tau$ at maxima and minima (mean ± S.D.)

Statistical analysis was performed using Student’s t test for unpaired data to compare $\tau$ values for local maxima ($\tau_{\text{maxima}}$) and minima ($\tau_{\text{minima}}$) between the SAD subjects and the control group. P values of 0.05 were considered statistically significant.

3. Results

Figure 2 shows the results of the wavelet analysis applied to the activity data. The power of the maxima and minima exhibited straight lines in log-log plots for both the SAD and the control groups for daytime activity for up to scale 6, corresponding to approximately 30 minutes (=1.5 for x-axis in Figure 2). For night-time activity, the data showed scale-invariant dynamics for scales up to approximately 4, corresponding to 20 minutes (1.3 for x-axis in Figure 2). This suggests that locomotor activity for both SAD subjects and control subjects have scale-invariant dynamics for up to scales of approximately 30 minutes during daytime and 20 minutes during night-time. The slope of the regression, i.e., the scaling exponent $\tau$, was larger in SAD subjects than in controls, especially for maxima during daytime periods (p<0.01) (Table 1). The scaling exponent $\tau$ for minima during daytime periods and maxima and minima for night-time periods were also significantly larger in SAD subjects than in controls (p<0.05). Beyond 20-30 minutes the scale invariance was attenuated, as expected, as the 8–10 hour windows examined were too short for full assessment of wavelet coefficients at larger scales (longer periods).
This indicates that the locomotor activity of children with SAD was characterized by having slower or “sluggish” transitions of locomotor activities. Both low-high-low and high-low-high activity patterns were matched to wavelets with larger scales, i.e., “fatter” wavelets. This means that children with SAD had slower activity bursts and Dips, while healthy children had faster transitions between bursts and interruptions of activity.

4. Discussion

We demonstrated that the locomotor activity of children has scale-invariant dynamics for up to 30 minutes during daytime periods and 20 minutes during night-time periods, and that the scale-invariant dynamics were preserved in children with SAD. The scaling exponents were larger in locomotor activities of children with SAD compared to healthy controls. This shows that the patterns of locomotor activities were altered in children with SAD. Children with SAD are likely to have, in a statistical sense, sluggish transition of locomotor activities and appear more indolent. Although further study is needed to investigate the relationship between scale-invariant dynamics and the symptoms of SAD, the altered patterns of locomotor activities in children with SAD may be due to symptoms of SAD such as fatigue or lack of energy. Investigating the patterns of locomotor activities, which provide more insight into the complex dynamics and structure of activity patterns, may lead to better understanding of activity disturbances in children with SAD, in which traditional measures such as mean activity levels could not capture.

5. References