Psychological dynamics are complex: a comparison of scaling, variance and dynamic complexity in simulated and observed data

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The behavior of complex systems is often unpredictable, not because it is random, but because its current behavior depends on a unique history of interactions with its internal and external environment. Therefore, studying snapshots of the behavior of a complex system in a static manner, or, relying on the laws of probability to generate expectations of future behavior will be generally uninformative. In order to predict where a complex system might be going, one needs a record of where it has been. This requires analytic techniques that are able to describe the characteristics of the data generating process underlying an unique observed history of an observable of the system, known as idiographic time series methods. Delignières et al. (2004) explain: 'time series analyses are generally based on the assumption that the dynamics of the series is explained in terms of the current value's dependence on past values' (Delignières, Fortes, & Ninot, 2004). Some well-known time series analysis, such as lag-1 autoregressive models, model how values at time *t* are dependent on values at *t-1*. Research shows, however, that the dependencies in time series are generally not restricted to lag-1 correlations (Wijnants, 2014). In fact, measurements of a wide variety of human behaviors including for example heart rate, limb movement, reaction time, and even self-esteem, yield time series that have very complex temporal structures with long-range temporal correlations that exceed way beyond lag-1 (for reviews see Diniz et al., 2011; Wijnants, 2014).

In this chapter, we first briefly introduce the different global temporal structures that can be observed in time series. Next, we will test how dynamic complexity (Schiepek & Strunk, 2010), a complexity measure for short time series, and variance are related to these different temporal structures on the basis of both simulated and observed data. The overall aim of the present study is to examine whether dynamic complexity and variance can be informative about the nature of the dynamical patterns that are present in short time series, such as those collected in Ecological Momentary Assessment (EMA) research. It is important to know whether EMA series exhibit long range temporal dependencies, because most contemporary analysis strategies used to draw inferences from such data are valid only when no such dependencies are present (e.g., see Bastiaansen et al., 2019).

Different colors of noise

One way to quantify the temporal structure of time series is by spectral analysis. This involves translating the time series to the frequency domain using Fourier transformation and inspecting the scaling relation between power and frequency. This is done by plotting the power of each contributing wave at the frequency in a log-log power spectrum. In figure 1, an example is shown for three temporal structures that are known as white noise (or Gaussian noise; upper panel), pink noise (or 1/f noise; middle panel) and red noise (or Brownian noise or Brownian motion; lower panel). White noise is uncorrelated with completely independent data points. The scaling relation between power and frequency is zero as indicated by the value of the slope in the log-log power spectrum of ±0 (also called the scaling exponent). Brownian noise is strongly positively correlated and can be generated by adding successive observations of white noise (a random walk). Here, slow waves have very large amplitudes and dominate the dynamics, the scaling exponent is -2. Pink noise turns out to be the most interesting temporal pattern. It is characterized by an inversely proportional scaling relation (scaling exponent of -1) between log power and log frequency, meaning that slower waves have proportionally higher amplitudes compared to faster waves. This makes pink noise a so-called 'fractal in time' (Wijnants, 2014), the dynamical patterns observable at a global scale (i.e. the scale of observation), are also observable at the shorter time scales as a self-affine version of the global pattern (i.e., it indicates there is no characteristic scale at which the dynamics can be described, it is essentially a scale-free process). Pink noise is suggested to be a hallmark of self-organization in complex systems (Bak, Tang,

& Wiesenfeld, 1987; Van Orden et al., 2003; Van Orden, Kloos, & Wallot, 2011). Because it is scale-free, pink noise can be viewed as a sign of flexibility, a balance between rigidity and randomness. Pink noise has been found in a wide variety of time series in humans including, for example, heart rate, breathing and reaction times (for a review see Wijnants, 2014). Interestingly, deviations from pink noise in both the direction of white noise and red noise have shown to be related to ageing, sub-optimal performance and even (psycho)pathology (Goldberger et al., 2002; Wijnants, 2014).

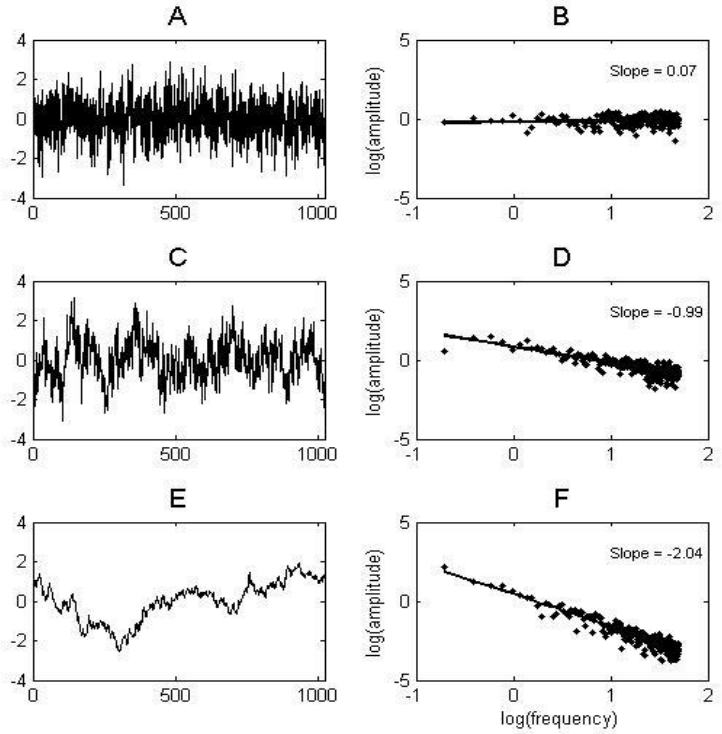

Figure 1. Three different classes of temporal variability, white noise (a), pink noise (c), and red noise (e), and their respective power spectra are shown in the respective panels at the right.

Dynamics of ecological momentary assessment

In contrast to physiological or reaction time series that are often used to study the scaling exponents described above, EMA data usually do not have enough time points to get a reliable estimate of the scaling exponent (Delignières, Ramdani, & Torre, 2006). As a consequence, the possibility of long-range temporal correlations in EMA data has mostly been ignored in the literature (but see: Delignières et al., 2004). We test whether it is possible to get information about the temporal structure (in terms of scaling relations) of short EMA data using a complexity measure that was developed for short time series: *dynamic complexity* (Haken & Schiepek, 2010; Schiepek, 2003; Schiepek & Strunk, 2010). Dynamic complexity is a combination of two algorithms: *F*, which measures the intensity of fluctuations in terms of frequency and amplitude and *D*, which measure the randomness of the distribution of a time series. Dynamic complexity is computed by multiplication of *F* and *D*, making that dynamic complexity is high when fluctuations are frequent, large and irregular, and low when fluctuations are absent or regular (e.g. a sine wave). In the next sections we explore the relation between dynamic complexity and scaling exponents. We also look at variance, as this is a well-known measure that is often used in EMA research. If dynamic complexity and variance are related to scaling exponents, they can be informative of the temporal structure of short EMA time series.

Dynamic complexity and variance computed for different simulated scaling exponents

Time series simulation

We simulated time series data with different scaling exponents in order to test the relation between spectral slopes, dynamic complexity and variance. All analyses were performed in R (R Core Team, 2017) using the package casnet (Hasselman, 2018). One hundred time series of 512 data points containing random uniform noise, varying between 0 and 6, were created. Each time series was used as input to simulate 9 variants of the original random uniform noise, but with different spectral slopes ranging from -2 (persistent, positively correlated noise) to 2 (anti-persistent, negatively correlated noise). Anti-persistent noise was included for comparison, but note that this type of noise is very rare in observed data. simulated data was rounded to 4 decimals. See Figure 2 for an example of these time series. The time series with a spectral slope of 0 are similar to the original random uniform noises. Because EMA data usually is much shorter than 512 data points, we trimmed the time series in order to create three shorter time series of 64, 128 and 256 data points. The idea behind this is that observed EMA time series also capture only part of the complete temporal pattern.

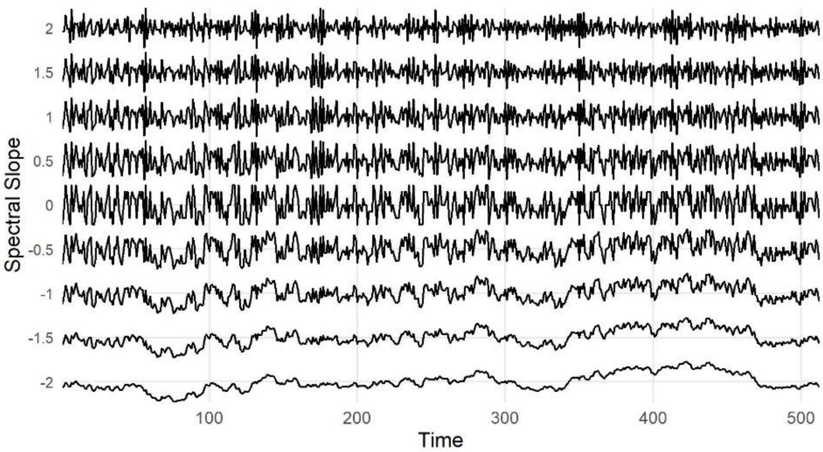

Figure 2. Example of random uniform noise series (spectral slope of 0) and variants with different spectral slopes ranging from -2 to 2.

Dynamic complexity and variance results

Dynamic complexity and variance were computed over all time series (of different length) with a sliding window of 7 data points. The window width was chosen because it is often used for dynamic complexity analyses in time series of daily self-ratings (Schiepek et al., 2016; other window widths did show similar results). The results for the different time series lengths were very similar, therefore we only report the results of the shortest time series with length 64, which is a common time series length for EMA data in psychotherapy (e.g. Olthof et al., 2019).

The results show that both dynamic complexity and variance are sensitive to the scaling exponents of the simulated time series, even when computed over short windows of 7 data points, in time series of only 64 data points (see figure 3 & 4). Dynamic complexity and variance are lowest for the most persistent noise and highest for white noise. For anti-persistent noises, dynamic complexity and variance are again lower, but with very wide distributions. The results suggest that dynamic complexity (which ranges theoretically from 0 to 1) can be expected to be very low for the types of dynamics that can reasonably be expected in EMA data (i.e., with some level of positive long-range correlations, spectral slopes between -2 and 0).

It is very surprising that dynamic complexity and variances in windows of 7 data points are so strongly related to spectral slopes that are usually estimated over more than 1024 data points. An explanation can be found in the fact that our data was simulated within a fixed range from 0 to 6. Scaling exponents are indicative for the proportion of local variance (of parts of the time series) to global variance (of the whole time series). When the global variance is restricted (i.e., by applying a fixed range), the local variance by itself (as measured by dynamic complexity and variance in small moving windows) can be informative about the long-range correlation structure of the data, as appears from our results. This is interesting for EMA research specifically because EMA data have a restricted range as well (i.e., the answering scale).

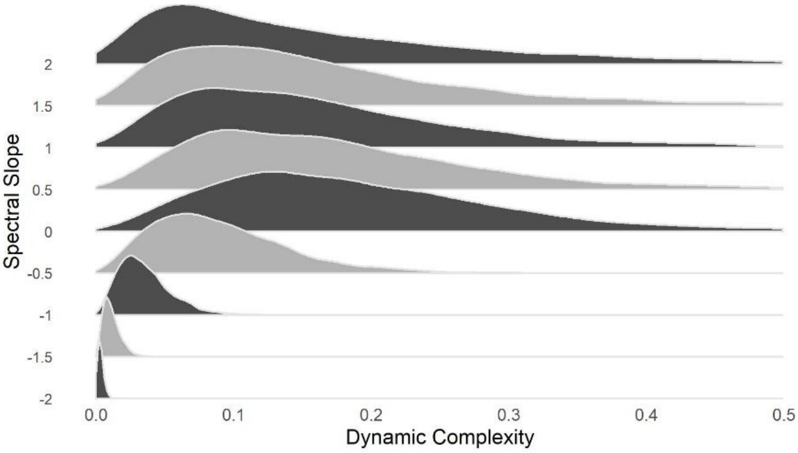

Figure 3. Dynamic complexity computed in 7-day sliding windows over 100 simulated time series of length 64, containing noise with different spectral slopes ranging from -2 to 2.

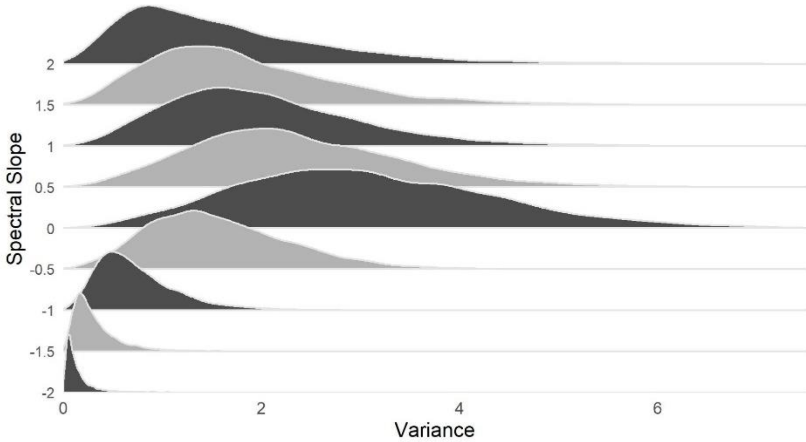

Figure 4. The distribution of Variance values computed in 7-day sliding window for 100 simulated time series of length 64 containing noise with different spectral slopes ranging from -2 to 2.

Dynamic complexity and variance computed over observed data

As a next step, we wanted to compare the dynamic complexity and variance values for our simulated data to dynamic complexity and variance of observed EMA data. We therefore analyzed dynamic complexity and variance scores on a large dataset (22554 data points) containing daily self-ratings from 328 patients with mood disorders (described in Olthof et al., 2019) as collected with the

Synergetic Navigation System (SNS; Schiepek et al., 2016)[1]. We computed dynamic complexity and variance in 7-day overlapping windows per item for each patient separately. The results are shown in Figure 5 and Figure 6. One can immediately see that both dynamic complexity and variance are extremely low compared to our simulations. Related to the simulation results, it appears that all segments of the empirical item series show some form of persistent noise with spectral slopes that should be negative in value suggesting the presence of pink or brownian noise (this can clearly be seen for the results of variance, which never exceeds 1).

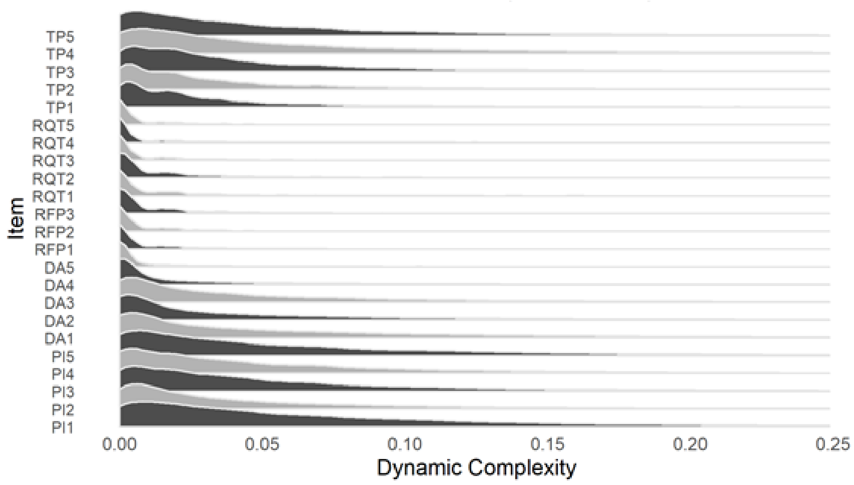

Figure 5. Dynamic complexity computed over 7-day windows over daily self-ratings of 21 items for 328 patients.

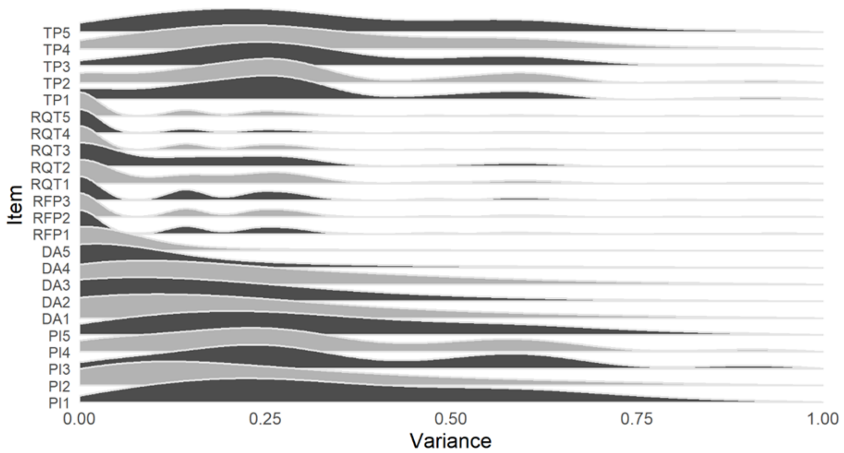

Figure 6. Variance computed in 7-day windows over daily self-ratings of 21 items for 328 patients.

While this is an interesting result, there is one major limitation in the interpretation of dynamic complexity and variance in real data in relation to simulated data: people do not use the measurement scale in the same way as the simulation. Translating the simulation results to the results of the observed data implies assuming that the whole measurement scale ranging from 0-6 was used by all patients in the sample in a consistent way. It is unlikely that this assumption was met. Therefore, these results should be interpreted with caution. Still, the fact that there appears to be almost no overlap between the dynamic complexity and variance of real data and of white noise is remarkable and suggests that even when patients used the whole measurement scale was used (which should probably

[1]We thank Günter Schiepek, Guido Strunk & Benjamin Aas for the possibility to use this dataset in this study.

occur sometimes in this dataset with more 22.000 measurement points) the dynamics indeed appear non-random.

A direct comparison of dynamic complexity, variance and spectral slopes in EMA data

The optimal way to test whether indeed dynamic complexity and variance in observed data are lower than in simulated data with the same spectral slopes would be a direct comparison between the three measures. The self-ratings analyzed above are unfortunately too short for computation of reliable spectral slopes (Delignières et al. 2006) and therefore a direct comparison is impossible. Luckily there is data available from an EMA study by Delignières et al. (2004) in which 4 participants answered 6 questions about their self-esteem and physical self for two times a day during a period of 512 days, resulting in time series of 1024 measurement points. Answers were given on a visual analog scale ranging from 0 to 10. The authors found pink noise in all time series with spectral slopes ranging from -0.95 to -1.39, showing the presence of long-range correlations.

We re-analyzed this data for a direct comparison of dynamic complexity, variance and spectral slopes. We recoded the answers to a range of 0 to 6, in order to compare the analysis with the results obtained from the simulated data and the psychotherapy data. We compared our findings for dynamic complexity and variance to the spectral slopes found by Delignières et al. (2004). In line with the presence of pink noise in the time series, the values for the dynamic complexity and variance of all windows (size=7) per item also suggests the presence of long-range correlations, when we compare to the simulation results (see figure 7). The extremely low values of median dynamic complexity (<.006) and variance (<.10) occur in the simulation only frequent for spectral slopes that are below -1.5 (in between pink and red noise; see Figures 3 & 4). The 'expected' spectral slopes based on visual inspection of dynamic complexity and variance values for the simulated data are thus lower than the observed spectral slopes. As explained before, this might be due to the fact that participants, in contrast to the simulation, do not always 'use' the full range of the measurement scale. A limited range of observed values automatically leads to lower dynamic complexity and variance compared to when the whole range is used. When we look at the distribution of answers over all items and participants, this explanation seems plausible: participants mostly rated between 3 and 5 in the recoded scale that ranges from 0 to 6 (see Figure 8).

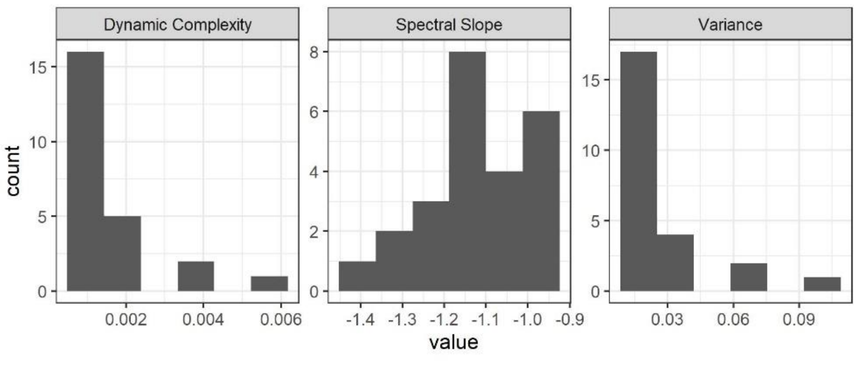

Figure 7. Spectral slopes, dynamic complexity and variance for 6 items answered by 4 participants. Dynamic complexity and variance values are medians of the values within 7-day windows per item.

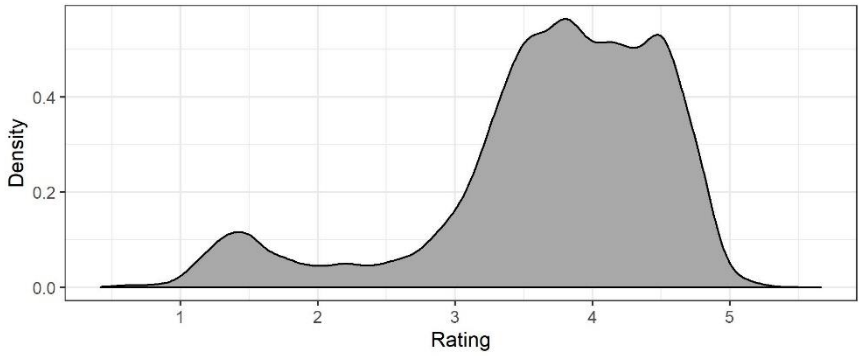

Figure 8. Density of ratings for the data from Delignières et al. (2004) rescaled to [0, 6].

Conclusion

Dynamic complexity and variance computed over small windows of size 7 are both surprisingly strongly related to spectral slopes of simulated time series. In relation to the results for simulated data, dynamic complexity and variance of observed data suggest that EMA data are not random but structured, with long-range temporal correlations, possibly pink noise, suggesting that EMA data are generated by a self-organizing complex system (in this case, an individual; Bak, 1987; Van Orden, Kloos & Wallot, 2011). Dynamic complexity and variance, however, cannot be used as a direct indicator for scaling exponents, as the way in which participant use the measurement scale heavily influences the results. Future research should explore the possibility for statistical estimation of expected spectral slopes in short EMA data based on data range and measures of local dynamic complexity and/or variance. Our findings emphasize the need for researchers to examine the temporal structure of EMA data prior to analysis, since inferences from most contemporary analysis strategies are not valid for data with long-range dependencies and we find that the absence of such dependencies cannot simply be assumed.

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