

Effect of Low Sampling Frequency and Bandwidth of Idiographic Ecological Momentary Assessment On Recurrence Quantification Analysis

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Introduction

Ecological momentary assessment (EMA) has made it possible to construct time series on the basis of self-report scales, where one can map idiographic, within-person fluctuations of psychological constructs in a systematic manner (Conner et al. 2009). Data collected using these methods have been shown to display all markers of complex dynamics, which means that the future of the data generated using these methods is only predictable in the short-term, and that observations are dependent on the state of the system and its externalities at earlier timepoints (Olthof, Hasselman, and Lichtwarck-Aschoff 2020). Traditional statistical methods are often used to analyze data that is generated using EMA, but these methods are not suitable to capture complex temporal idiographic patterns (Jenkins et al. 2020; Olthof et al. 2020).

Time-dependent idiographic dynamics have historically been neglected within psychology (Molenaar 2004). This led researchers to import techniques from complex dynamical systems theory, which is an area of mathematics that concerns itself with the study of time-dependent dynamics of systems. Recurrence quantification analysis (RQA) is one of those methods. Applying the method identifies recurrent patterns, or repetitions, in a time series (Webber Jr and Zbilut 2005). It derives several indicators of the stability, predictability, and the dynamical behavior of a psychological construct on the basis of these recurrent patterns. These methods were developed under the assumption that measurements can be retrieved at great frequency and at high resolution, to an extent that is impossible in psychology. It relies on the admission of tests taken several times a day, meaning that the sampling frequency is limited (Haslbeck and Ryan 2022). Moreover, the psychological constructs that are measured using EMA cannot be measured without relying on ordinal self-report

questionnaires. Therefore, systematic study of the consequences of these limitations on RQA is needed.

For the purposes of this project, we assume that the underlying psychological construct is a continuously changing dynamical value (Boker 2002), and that EMA output values are accurate ordinal, low sampling frequency attempts to measure continuous underlying dynamical processes. This is an idealized assumption to study the consequences of low sampling frequency and data bandwidth, and does not take into account other possible challenges to validity (Stinson, Liu, and Dallery 2022; Maul, Torres Irribarra, and Wilson 2016).

The current project

The research question is “*At what point does decreased data quality limit the ability of EMA to capture idiographic dynamics using RQA?*”. We present an analysis pipeline consisting of multiple stages. We will use the `DynamicalSystems.jl` and `Statistics.jl` julia-packages to simulate the toy model and perform the analysis (Bezanson et al. 2017; Datseris 2018; Datseris and Parlitz 2022). We hope (and hypothesize) that the trajectory of the indicators when the quality is lowered has some degree of predictability, so that we can make reliable inferences from lower quality data.

Stage 1: Data generation

In the first stage, we use a toy model to simulate the data based on the $3 + 1$ *dimensions model* introduced by Gauld and Depannemaecker (2023). This model captures clinical observations found in psychiatric symptomology by modeling internal factors (y), environmental noise (z), temporal specificities (f), and symptomatology (x) using coupled differential equations. Symptomatology will be the outcome variable of this study. By changing all four of these coefficients systematically, we aim to model a large variety of possible trajectories, and we save each one of these models as a separate time series. For the purpose of our study, we redefine “symptomatology” as any dynamical fluctuations of psychological constructs.

Stage 2: Binning data and removing time points

Now, we aim to systematically reduce the quality of the data. We bin a range of the width of the data into n intervals of equal length, where n stands for the number of bins. We also vary the minimum (min) and maximum (max) value of this range to simulate ceiling and floor-effects. Moreover, we remove time points from the data by keeping the first and every k^{th} observation of the simulated data. We systematically decrease the number of bins, the range, number of time points, and re-analyze the data.

Stage 3: Data analysis

We will judge the sensitivity of the data by calculating summary statistics and recurrence indicators (recurrence rate, determinism, entropy of the distribution) for each time series in each state of degradation. We judge the sensitivity of the data to degradation by looking at the change in values for each of the indicators, where the intact dataset is used as the baseline. We will then map the changes in the indicators as the difference for that indicator between the baseline and at n , min , max , and k .

Ethical approval and proof of concept

The project has been approved by the ethical committee. The target journal is *Frontiers in Psychology*, section Quantitative Psychology and Measurement.

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