

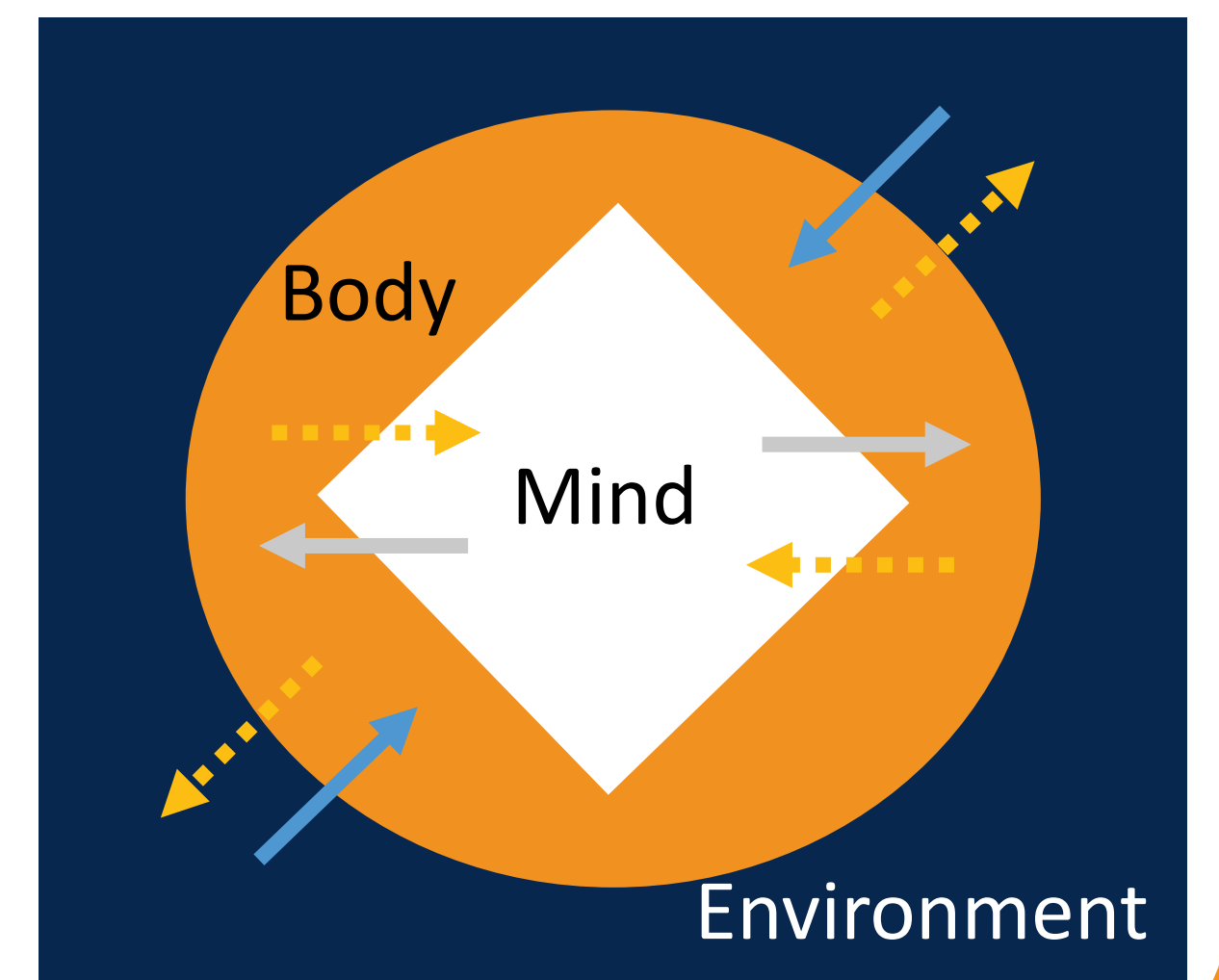
# Fractal analyses of locomotor activity data of geriatric in-patients with dementia

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## Background

„What is the role of the body in social interaction and mental processes?“ is one of the questions central to this symposium and probably the one which is related most straightforwardly to the topics addressed in this contribution. It turns out that many physiological signals including general locomotor activity exhibit fractal characteristics appearing as a hallmark of health and indicating the ability of a living organism to maintain flexibly optimal levels of adaptability under ever-changing intrinsic and extrinsic conditions [1]. Being able to respond or engage dynamically and flexibly in social relations represents also a prerequisite for processes of synchronization. Fractal analyses may hence provide tools to get a methodological grip on apparently rather subtle aspects of human behavior along dimensions of volatility-flexibility-rigidity and/or ponderosity-effortlessness-precipitance via investigating human locomotor activity data. Here, we exemplify some of the central concepts of such analyses using locomotor activity data obtained by wrist-actigraphy from 36 geriatric in-patients diagnosed with dementia, discussing also potentials and limitations of the methods concerning diagnosis and monitoring of dementia and also beyond this specific field of eventual application.



## (Not yet) another taxonomy of (some) psychiatric disorders

Fractal analyses (see the box to the right) yielding various, associated parameters ( $\alpha, \beta, \gamma$ ) may eventually allow a taxonomy of psychiatric disorders:

	$\alpha$	$\beta$	$\gamma$
No diagnoses	$\sim 0.9$ [2]	$\beta_{con}$	$\sim 1.0$
(Alzheimer's) Dementia	$\alpha_1 \neq \alpha_2 < 0.9$ [3; here]	?	No PL <sup>a</sup> [here]
Depression	?	$\approx \beta_{con}$ [4]	$< 1.0$ [4]
Mania	?	?	$> 1.0$ [5]
Schizophrenia	?	$< \beta_{con}$ [6]	$< 1.0$ [6]
Chronic Pain	$< 0.9$ [7]	?	No PL <sup>a</sup> [8]

<sup>a</sup> is not in accordance with a power-law (PL) form of the CDD (see the box to the right of this one)

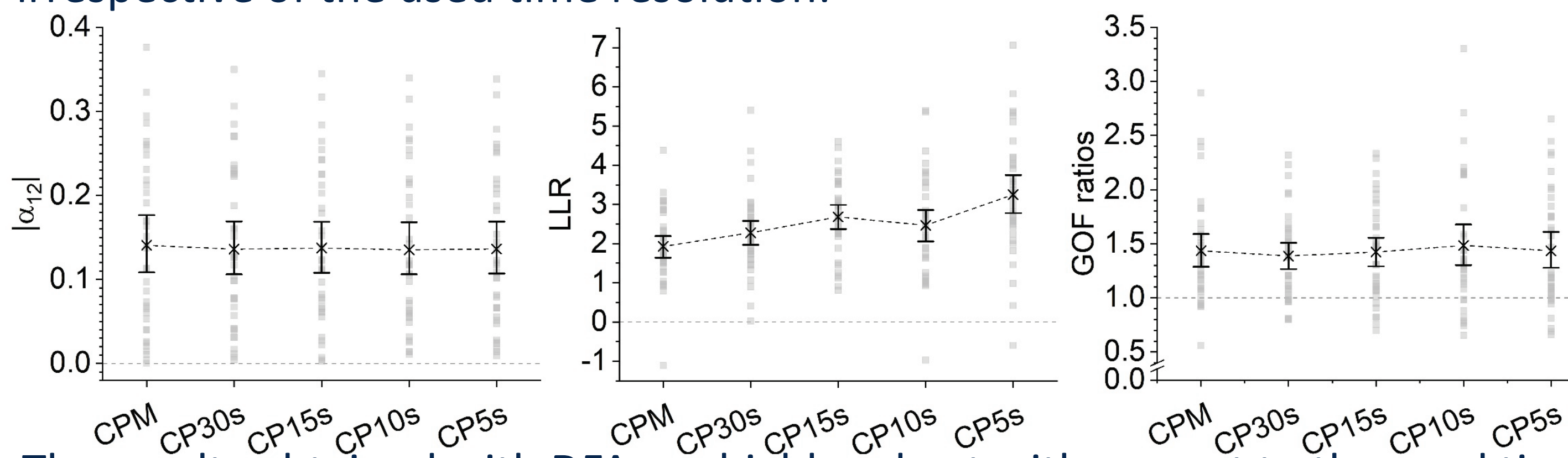
## Subjects and data acquisition

Here, we explore the fractal characteristics of locomotor activity data obtained via continuous wrist-actigraphy over the entire hospital stays of 36 geriatric in-patients (19 women; 61 – 94 years old; mean $\pm$ SD age: 81.8 $\pm$ 7.8 years) diagnosed with dementia in Alzheimer's disease, but no other enregistered diagnoses of mental or behavioral disorders or other types of dementia except for delirium superimposed on dementia. We note that besides the two mentioned diagnoses, our sample was highly heterogeneous concerning comorbidities, associated interventions such as medication and other conditions such as mobility.

**Data acquisition.** Acceleration was sampled at 30 Hz and integrated into counts per minute (CPM), i.e. it was checked if the magnitude of acceleration (corrected for gravitational acceleration  $g = 9.81 \text{ m/s}^2$ ) exceeds a predefined threshold of 0.1 g. In addition counts every 30, 15, 10 and 5 s (CP30s, CP15s, CP10s, CP5s) were computed in order to investigate the dependence of the results on temporal resolution of the assessed signals. On average, 19.7 $\pm$ 6.2 days of actigraphic recordings were analyzed, ranging from 11.6 to 39.6 days.

## Results and discussion

Both assessed measures for deviations from fractal scaling of the analyzed signals, i.e.  $|\alpha_{12}|$  for fluctuation amplitudes determined via DFA and LLR as well as GOF ratios for analysis of CDDs, result in a **significant deviation of sample means from** the respective values associated with **fractal scaling** irrespective of the used time resolution:

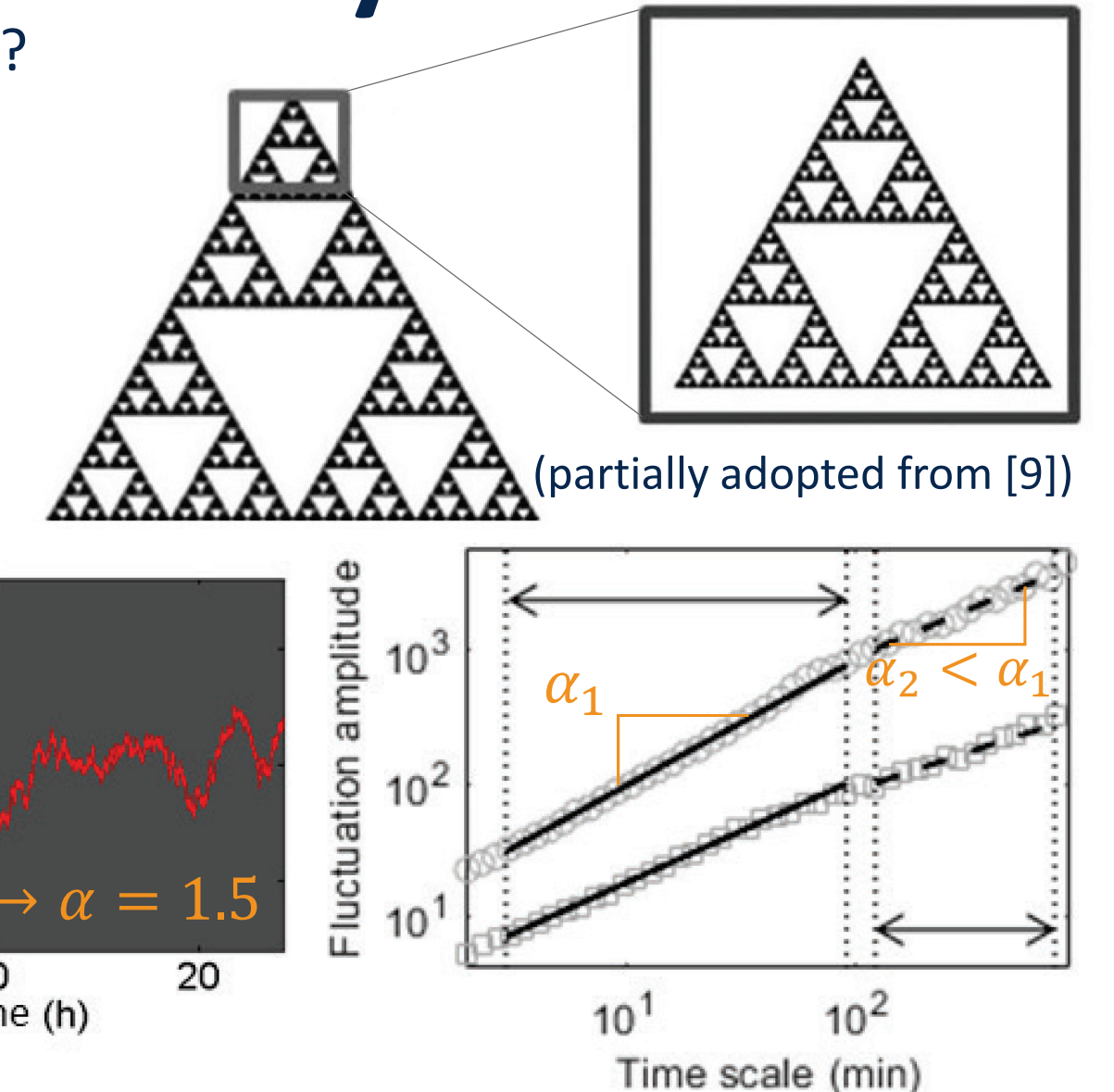


The results obtained with DFA are highly robust with respect to the used time resolution and we can add this finding to the already known robustness of the method concerning external schedules, individual average activity levels and circadian phase [2].

In contrast, individual as well as aggregated values of the quantities obtained via analysis of CDDs appear very sensitive with respect to time resolution. One reason for this could be that neither a power law nor a lognormal

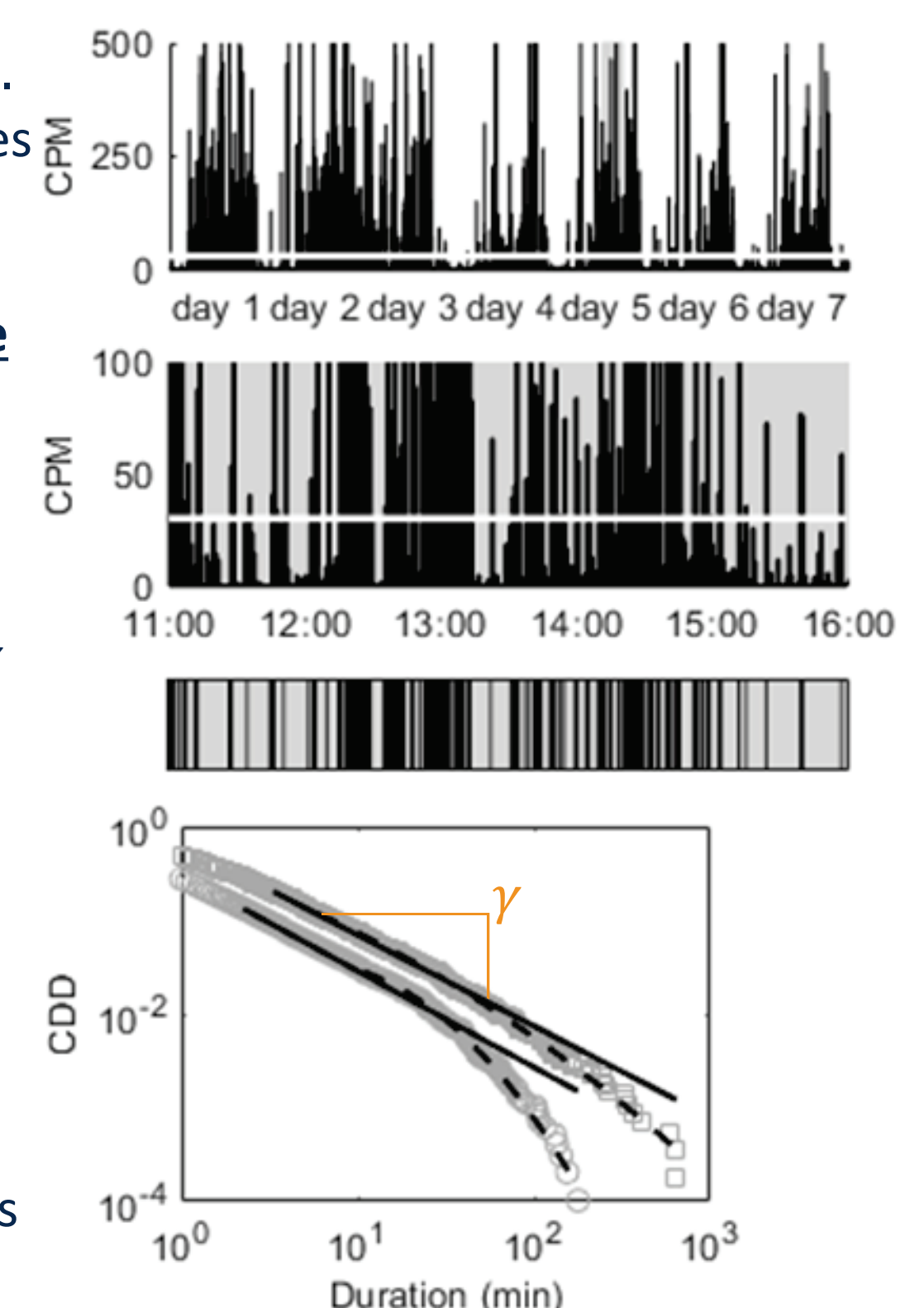
## Two types of fractal analyses

What are fractals, fractal analyses or how long is a coast line? Unfortunately, the somewhat unsatisfactory answer to the last question is: it depends on the scale of measurement. Indeed, the relation between length,  $L$ , and measurement scale,  $s$ , gives more information than any length at any given scale. For (most) fractals, this relation is given by  $L(s) \sim s^d$  with  $d$  also known as the scaling exponent.



**Detrended fluctuation analysis (DFA)** allows to assess temporal correlations of activity fluctuations. In short, the signal is centered with respect to its mean, integrated and decomposed into disjoint time windows of various lengths. For each of those windows, the root-mean-square residuals from a trend fitted to the integrated signal are computed. Taking the average of the residuals over all windows and repeating the procedure for the various considered window sizes the yields the fluctuation amplitude  $F(m)$  as a function of the time scale  $m$ .

Fractal scaling is indicated by a power-law form, i.e.  $F(m) \sim m^\alpha$ . Significantly different scaling exponents  $\alpha_1$  and  $\alpha_2$  at time scales below 1.5 hours and beyond 2 hours, respectively, indicates a break-down of fractal scaling over the whole time range. The procedure for the **analysis of (complementary) cumulative distributions of low-activity period durations (CDDs)** is depicted to the right. The activity signal is decomposed into periods of low (below overall mean) and high (above overall mean) activities. CDDs,  $P(x \geq d)$ , were then calculated and fitted (via maximum-likelihood estimation) to a power-law,  $d^{-\gamma}$  with scaling exponent  $\gamma$ . To assess how well the CDDs can be represented by power laws, they were also fitted using lognormal distributions and the ratios of goodness of fits (GOFs) via the Kolmogorov-Smirnov-distance metric were computed as well as the log-likelihood-ratios (LLRs) of the obtained likelihoods for the two distributions. Highest complexity in physiological signals is typically represented by power laws, and loss of it is expected to result in a shift towards less heavy-tailed distributions [10].



distribution can provide optimal fits to the empirical data. Comparing the CDDs of patients diagnosed with psychotic or bipolar disorder yielded the result that different psychopathological states may be related to different, specific functional forms of CDDs which were, in the considered cases, not represented by simple power laws [11].

Further research will also be required to scrutinize whether and how much of the found deviations from fractal characteristics may be traced back to (a) the presence, severity and specific form of dementia, (b) comorbidities and their associations with pain [7, 8], (c) effects of interventions including especially medication, and also how these possible causal factors may interact. However, taking together our results with the outcomes of earlier investigations [2, 3, 12], we arrive at the conclusion that the fractal characteristics at least as quantified in terms of parameters obtained via DFA might very well provide diagnostically useful information in neuropsychiatric contexts and that our naturalistic study can add some credibility to the ecological validity of those parameters. Together with more conceptual groundwork, further investigations could clarify also general relations and interactions between the various functional, neural systems associated with the organization of human motor activity. Read more in Ref. 13.

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