The Structure of Chaos: An Empirical Comparison of Fractal Physiology Complexity Indices using NeuroKit2

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The authors made the following contributions. Dominique Makowski: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft; An Shu Te: Software, Project administration, Writing – review & editing; Tam Pham: Software, Writing – review & editing; Zen J. Lau: Software, Writing – review & editing; S.H. Annabel Chen: Supervision, Project administration, Writing – review & editing.

Abstract

Complexity quantification, through entropy, information theory and fractal dimension indices, is gaining a renewed traction in psychophsyiology, as new measures with promising qualities emerge from the computational and mathematical advances. Unfortunately, few studies compare the relationship and objective performance of the plethora of existing metrics, in turn hindering reproducibility, replicability, consistency, and clarity in the field. Using the NeuroKit2 Python software, we computed a list of 112 complexity indices on signals varying in their characteristics (noise, length and frequency spectrum). We then systematically compared the indices by their computational weight, their representativeness of a multidimensional space of latent dimensions, and empirical proximity with other indices. Based on these considerations, we propose that a selection of 12 indices, together representing 85.97\% of the total variance of all indices, might offer a parsimonious and complimentary choice in regards to the quantification of the complexity of time series. Our selection includes *CWPEn*, *Line Length (LL)*, *BubbEn*, *MSWPEn*, *MFDFA (Max)*, *Hjorth Complexity*, *SVDEn*, *MFDFA (Width)*, *MFDFA (Mean)*, *MFDFA (Peak)*, *MFDFA (Fluctuation)*, *AttEn*. Elements of consideration for alternative subsets are discussed, and data, analysis scripts and code for the figures are open-source.

Keywords: chaos, complexity, fractal, physiology, noise

Word count: 2709

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Introduction

Complexity is an umbrella term for concepts derived from information theory, chaos theory, and fractal mathematics, used to quantify unpredictability, entropy, and/or randomness. Using these methods to characterize physiological signals (a subfield commonly referred to as "fractal physiology," Bassingthwaighte et al., 2013) has shown promising results in the assessment and diagnostic of the state and health of living systems (Ehlers, 1995; Goetz, 2007; Lau et al., 2021).

There has been an exponential increase in the number of complexity indices in the past few decades (A. C. Yang & Tsai, 2013). Although these new procedures are usually mathematically well-defined and theoretically promising, limited empirical evidence is available to understand their similarities and differences (Lau et al., 2021; A. C. Yang & Tsai, 2013). Moreover, some of these methods are resource-intensive and require long computation times. This complicates their application with techniques that utilise high sampling-rates (e.g., M/EEG) and makes them impractical to implement in real-time settings - such as brain-computer interfaces (Azami et al., 2017; Manis et al., 2018). As such, having empirical data about the computation time of various complexity indices would prove useful, for instance to objectively guide their selection, especially in contexts where time or computational resources are limited.

Additionally, the lack of a comprehensive open-source and user-friendly software for computing various complexity indices likely contributes to the limited availability of empirical comparison (Flood & Grimm, 2021a). Indeed, many complexity indices are only described mathematically in journal articles, with reusable code seldom made available, therefore limiting their further application and validation (Flood & Grimm, 2021a; A. C. Yang & Tsai, 2013). And complexity measures with open-source code implementations are scattered across different packages or scripts, or embedded within a larger goal-directed framework (e.g., *HCTSA*, a time-series comparison tool, Fulcher & Jones, 2017). To address this lack of unified accessibility, we added a comprehensive set of complexity-related features to *NeuroKit2*, a Python package for physiological signal processing (Makowski et al., 2021), to provide users with a software to compute a vast amount of complexity indices. The code is designed to be as fast as possible, while still written in pure Python (with the help of standard dependencies such as *NumPy* or *Pandas*, Harris et al., 2020; McKinney et al., 2010) to maximize the re-usability, transparency, and correctness.

Leveraging this tool, the goal of this study is to empirically compare a large number of complexity indices, inspect how they relate to one another, and derive recommendations for indices selection. More specifically, we will quantify the complexity of various types of signals with varying degrees of noise using 112 of the predominantly used indices that are available for computation using *NeuroKit2*. Note that, even though it is one of the largest comparison to date to our knowledge (and covers the most commonly used metrics), this list is by no means exhaustive: new indices are being developed, such as for instance *symmetropy* (Girault & Menigot, 2022). We will then project the results on a latent space through factor analysis, and review the various indices that we find the most relevant and interesting in regards to their representation of the latent dimensions. This analysis will be complemented by hierarchical clustering.

Methods

The Python script to generate the data can be found at **github.com/DominiqueMakowski/ComplexityStructure**.

We started by generating 6 types of signals, one random-walk, two oscillatory signals made (with one made of harmonic frequencies that results in a self-repeating - fractal-like - signal), two complex signals derived from Lorenz systems (with parameters

$[\sigma = 10, \beta = 2.5, \rho = 28]$; and $[\sigma = 20, \beta = 2, \rho = 30]$, respectively) and one EEG-like simulated signal. Each of this signal was iteratively generated at 6 different lengths (ranging from 500 to 3000 by 500 samples). The resulting vectors were standardized and each were added 5 types of $(1/f)^\beta$ noise (namely violet $\beta = -2$, blue $\beta = -1$, white $\beta = 0$, pink $\beta = 1$, and brown $\beta = 2$ noise). Each noise type was added at 128 different intensities (linearly ranging from 0.001 to 3). Examples of generated signals are presented in **Figure 1**.

The combination of these parameters resulted in a total of 23040 signal iterations. For each of them, we computed 112 complexity indices, and additional basic metrics such as the *length* of the signal and its dominant *frequency*. We also included a *random* number to make sure that our our dimensionality analyses accurately discriminate this unrelated feature. The parameters used (such as the time-delay τ or the embedding dimension) are documented in the data generation script. For a complete description of the various indices included, please refer to NeuroKit's documentation at **https://neuropsychology.github.io/NeuroKit**, as well as to the data generation script.

Results

The data analysis script and the data are fully available at **github.com/DominiqueMakowski/ComplexityStructure**. The analysis was performed in R using the *easystats* collection of packages (Lüdecke et al., 2021; Lüdecke et al., 2020; Makowski et al., 2020/2022, 2020). As the results are primarily presented in a graphical way via the figures, the code to fully reproduce them is also included.

Computation Time. Firstly, one should note that the computation times presented in **Figure 2** are relative (in arbitrary units) and do not correspond to real times, as these would highly depend on the system specifications. Rather, the goal here was to convey some intuition on the differences between different classes of indices (using the same machine and the same language of implementation, i.e., Python). While it is possible that computational advances or improvements in the code efficiency might change some of these values, we believe that the "big picture" should remain fairly stable, as it is to a large extent driven by the inherent nature of the algorithms under consideration.

Despite the relative shortness of the signals considered (a few thousand points at most), the fully-parallelized data generation script took about 24h to run on a 48-cores machine. After summarizing and sorting the indices by computation time, the most striking feature is the order of magnitude of difference between the fastest and slowest indices. Additionally, some indices are particularly sensitive to the signal length, a property which combined with computational cost led to indices being 100,000 times slower to compute than others.

In particular, multiscale indices were among the slowest to compute due to their iterative nature (a given index being computed multiple times on coarse-grained subseries of the signal). Indices related to Recurrence Quantification Analysis (RQA) were also relatively slow and did not scale well with signal length.

For the subsequent analyses, we removed statistically redundant indices (which absolute correlation was equal to 1.0), such as *NLDFD* - identical to *LL*, *ShanEn (15)* - identical to *ShanEn (9)*, and *CREn (15)* - identical to *CREn (9)*. This resulting in a pool of 112 indices.

Correlation. The Pearson correlation analysis revealed that complexity indices, despite their multitude and their conceptual specificities, do indeed share similarities. They form two major clusters that are easily observable (the blue and the red groups in **Figure 3**). That being said, these two anti-correlated groups are mostly revealing of the fact that some indices, by design, index the "predictability", whereas others, the "randomness", and thus are negatively related to one another. In order to extract finer groupings, further analysis procedures are applied below.

Factor Analysis. The agreement procedure for the optimal number of factors suggested that the 112 indices can be mapped on a multidimensional space of 13 orthogonal latent factors, that we extracted using a *varimax* rotation. We then took interest in the loading profile of each index, and in particular the latent dimension that it maximally relates to (see **Figure 4**). Below are a description of factors that we found to be interpretable.

The first extracted factor is the closest to the largest amount of indices, and is positively loaded by indices that are sensitive to the deviation of consecutive differences (e.g., *LL*, *PFD (Mean)*) as well as indices that capture the amplitude of fluctuations (*DispEn (fluctuation)*, *MFDFA (Max)*). In line with this, this factor was negatively loaded by indices related to Detrended Fluctuation Analysis (*DFA*), which tends to index the presence of long-term correlations and repetitions. As such, this latent factor might be related to the predominance of short-term vs. long-term unpredictability.

The second factor was strongly loaded by by indices that measure the feature-richeness of the signal's system (as most of them operate on a state-space decomposition). It is positively related to *SVDEn* and the Kozachenko-Leonenko differential entropy (*KLEn*), and negatively with the RQA *Recurrence Rate* and *Hjorth* Complexity.

The third factor was loaded predominantlys by permutation-based metrics (*PEn*, *WPEn*, *BubblEn*, etc.). The fourth factor included multiscale indices, such as *MSWPEn*. The fifth factor was strongly loaded by signal *length*, and thus might not capture features of complexity *per se*. Indices with the most relation to it were indices known to be sensitive to signal length, such as *ApEn*. The sixth factor was loaded by indices in which the signal or the Poincaré plot was discretized via binning or gridding, respectively. The ninth factor was loaded by *EnofEn* and Kolmogorov Entropy (*K2En*). The tenth factor was loaded positively by the amount of noise, and negatively by multifractal indices such as *MFDFA*

(Width), suggesting a sensitivity to regularity. Finally, as a manipulation check for our factorization method, the random vector did not load unto any factors.

Hierarchical Clustering and Connectivity Network. For illustration purposes, we represented the correlation matrix as a connectivity graph (see **Figure 5**). We then ran a hierarchical clustering (with a Ward D2 distance) to provide additional information or confirmation about the groups discussed above. This allowed us to fine-grain our recommendations of complimentary complexity indices (see **Figure 6**).

Indices Selection. The selection of a subset of indices was based on the following considerations: 1) high loadings on one predominant latent dimension, with additional attention to the pattern of secondary loadings. For instance, an index with a positive factor 1 loading and a negative factor 2 loading could complement another index with a similar factor 1 loading, but a positive factor 2 loading. This was helped by 2) the hierarchical clustering dendrogram, with which we attempted to indices from each (meaningful) higher order clusters. Items related to clusters that we know were related to noise, length or other artifacts were omitted. 3) A preference for indices with relatively shorter computation times. This yielded a selection of 12 indices. Next, we computed the cumulative variance explained of this selection in respect to the entirety of indices, and derived the optimal order to maximize the variance explained (see **Figure 7**). The 12 included indices, representing 85.97% of the variance of the whole dataset, were:

- *CWPEn*: The Conditional Weighted Permutation Entropy is based on the difference of weighted entropy between that obtained at an embedding dimension m and that obtained at $m + 1$ (Unakafov & Keller, 2014).
- *LL*: The Line Length index stems out of a simplification of Katz' fractal dimension (*KFD*) algorithm (Esteller et al., 2001) and corresponds to the average of consecutive absolute differences. It is equivalent *NDLFD*, the Fractal dimension via Normalized Length Density (Kalauzi et al., 2009). As it captures the amplitude 1-lag fluctuations, this index is likely sensitive to noise in the series.

- *BubbEn*:
- *MSWPEn*: The Multiscale Weighted Permutation Entropy is the entropy of weighted ordinal descriptors of the time-embedded signal computed at different scales obtained by a coarsegraining procedure (Fadlallah et al., 2013).
- *MFDFA (Max)* : The value of singularity spectrum D corresponding to the maximum value of singularity exponent H.
- *Hjorth*: Hjorth's Complexity is defined as the ratio of the mean frequency of the first derivative of the signal to the mean frequency of the signal (Hjorth, 1970).
- *SVDEn*: The Singular Value Decomposition (SVD) Entropy quantifies the amount of eigenvectors needed for an adequate representation of the system (Roberts et al., 1999).
- *MFDFA (Width)*: The width of the multifractal singularity spectrum (Kantelhardt et al., 2002) obtained via Detrended Fluctuation Analysis (DFA).
- *MFDFA (Mean)* : The mean of the maximum and minimum values of singularity exponent H, which quantifies the average fluctuations of the signal.
- *MFDFA (Peak)* : The value of the singularity exponent H corresponding to peak of singularity dimension D. It is a measure of the self-affinity of the signal, and a high value is an indicator of high degree of correlation between the data points.
- *MFDFA (Increment)*: The cumulative function of the squared increments of the generalized Hurst's exponents between consecutive moment orders (Faini et al., 2021).
- *AttEn*: The Attention Entropy is based on the frequency distribution of the intervals between the local maxima and minima of the time series (J. Yang et al., 2020).

Finally, we visualized the expected value of our selection of indices for different types of signals under different conditions of noise (see **Figure 8**). This confirmed that *LL* was primarily driven by the noise intensity (which is expected, as they capture the variability of successive differences). The other indices appear to be able to discriminate between the various types of signals (when the signal is not dominated by noise).

Discussion

As the span and application of complexity science grows, a systematic approach to compare their "performance" becomes necessary to reinforce the clarity and structure of the field. The term *performance* is here to be understood in a relative sense, as any such endeavor faces the "hard problem" of complexity science: various objective properties of signals (e.g., short-term vs. long-term variability, auto-correlation, information, randomness, Namdari & Li, 2019; Xiong et al., 2017) participate in forming together over-arching concepts such as "complex" and "chaotic". Indices that are sensitive to some of these objective properties are thus conceptually linked through these over-arching framework. However, it remains unclear how these high-level concepts transfer back, in a top-down fashion, into a combination of lower-level features. As such, it is conceptually complicated to benchmark complexity measures against "objectively" complex vs. non-complex signals. In other words, we know that different objective signal characteristics can contribute to the "complexity" of a signal, but there is not a one-to-one correspondence between the latter and the former.

To circumvent the aforementioned consideration, we adopted a paradigm where we generated different types of signals to which we systematically added distinct types - and amount - of perturbations. It is to note that we did not seek at measuring how complexity indices can discriminate between these signal types, nor did we attempt at mimicking real-life signals or scenarios. The goal was instead to generate enough variability to reliably map the relationships between the indices.

Our results empirically confirm the plurality of underlying components of complexity (although it is here defined somewhat circularly as what is measured by complexity indices), and more importantly show that complexity indices vary in their sensitivity to various orthogonal latent dimensions. However, the limited possibilities of interpretation of these dimensions is a limitation of the present investigation, and future studies are needed to investigate and discuss them in greater depth (for instance, by modulating specific properties of signals and measuring their impact on these latent dimensions).

Taking into account the increasing role of complexity science as a field and the sheer number of complexity indices already published, our study aimed at empirically map the relationship between various indices and provide useful information to guide future researchers in their selection. Indices that were highlighted as encapsulating information about different underlying dimensions at a relatively low computational cost include *CWPEn*, *Line Length (LL)*, *BubbEn*, *MSWPEn*, *MFDFA (Max)*, *Hjorth Complexity*, *SVDEn*, *MFDFA (Width)*, *MFDFA (Mean)*, *MFDFA (Peak)*, *MFDFA (Fluctuation)*, *AttEn*. These indices might be complimentary in offering a comprehensive profile of the complexity of a time series. Moving forward, future studies are needed to validate, analyze and interpret the nature of the dominant sensitivities of indices groups, so that studies results can be more easily interpreted and integrated into new research and novel theories.

Acknowledgments

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References

Azami, H., Rostaghi, M., Abásolo, D., & Escudero, J. (2017). Refined composite multiscale dispersion entropy and its application to biomedical signals. *IEEE Transactions on Biomedical Engineering*, *64*(12), 2872–2879.

Bassingthwaighte, J. B., Liebovitch, L. S., & West, B. J. (2013). *Fractal physiology.* Springer.

Ehlers, C. L. (1995). Chaos and complexity: Can it help us to understand mood and behavior? *Archives of General Psychiatry*, *52*(11), 960–964.

Esteller, R., Echauz, J., Tcheng, T., Litt, B., & Pless, B. (2001). Line length: An efficient feature for seizure onset detection. *2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, *2*, 1707–1710.

Fadlallah, B., Chen, B., Keil, A., & Príncipe, J. (2013). Weighted-permutation entropy: A complexity measure for time series incorporating amplitude information. *Physical Review E*, *87*(2), 022911.

Faini, A., Parati, G., & Castiglioni, P. (2021). Multiscale assessment of the degree of multifractality for physiological time series. *Philosophical Transactions of the Royal Society A*, *379*(2212), 20200254.

Flood, M. W., & Grimm, B. (2021a). EntropyHub: An open-source toolkit for entropic time series analysis. *PLOS ONE*, *16*(11), e0259448. https://doi.org/10.1371/journal.pone.0259448

Flood, M. W., & Grimm, B. (2021b). EntropyHub: An open-source toolkit for entropic time series analysis. *Plos One*, *16*(11), e0259448.

Fulcher, B. D., & Jones, N. S. (2017). hctsa: A computational framework for automated time-series phenotyping using massive feature extraction. *Cell Systems*, *5*, 527–531. https://doi.org/10.1016/j.cels.2017.10.001

Girault, J.-M., & Menigot, S. (2022). Palindromic Vectors, Symmetropy and Symmentropy as Symmetry Descriptors of Binary Data. *Entrpy*, *24*(82). https://doi.org/10.3390/e24010082

Goetz, S. J. (2007). Spatial Dynamics, Networks and Modelling ? Edited by Aura Reggiani and Peter Nijkamp. *Papers in Regional Science*, *86*(3), 523–524. https://doi.org/10.1111/j.1435-5957.2007.00128.x

Harris, C. R., Millman, K. J., Walt, S. J. van der, Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., Kerkwijk, M. H. van, Brett, M., Haldane, A., Río, J. F. del, Wiebe, M., Peterson, P., … Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2

Hjorth, B. (1970). EEG analysis based on time domain properties. *Electroencephalography and Clinical Neurophysiology*, *29*(3), 306–310.

Kalauzi, A., Bojić, T., & Rakić, L. (2009). Extracting complexity waveforms from one-dimensional signals. *Nonlinear Biomedical Physics*, *3*(1), 1–11.

Kantelhardt, J. W., Zschiegner, S. A., Koscielny-Bunde, E., Havlin, S., Bunde, A., & Stanley, H. E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A: Statistical Mechanics and Its Applications*, *316*(1-4), 87–114.

Lau, Z. J., Pham, T., Annabel, S., & Makowski, D. (2021). *Brain entropy, fractal dimensions and predictability: A review of complexity measures for EEG in healthy and neuropsychiatric populations.*

Lüdecke, D., Ben-Shachar, M., Patil, I., & Makowski, D. (2020). Extracting, computing and exploring the parameters of statistical models using R. *Journal of Open Source Software*, *5*(53), 2445. https://doi.org/10.21105/joss.02445

Lüdecke, D., Patil, I., Ben-Shachar, M. S., Wiernik, B. M., Waggoner, P., & Makowski, D. (2021). see: An R package for visualizing statistical models. *Journal of Open Source Software*, *6*(64), 3393. https://doi.org/10.21105/joss.03393

Makowski, D., Ben-Shachar, M., Patil, I., & Lüdecke, D. (2020). Methods and algorithms for correlation analysis in R. *Journal of Open Source Software*, *5*(51), 2306. https://doi.org/10.21105/joss.02306

Makowski, D., Lüdecke, D., Ben-Shachar, M. S., & Patil, I. (2022). *modelbased: Estimation of model-based predictions, contrasts and means* (Version 0.7.2.1) [Computer software]. https://CRAN.R-project.org/package=modelbased (Original work published 2020)

Makowski, D., Pham, T., Lau, Z. J., Brammer, J. C., Lespinasse, F., Pham, H., Schölzel, C., & Chen, S. H. A. (2021). NeuroKit2: A python toolbox for neurophysiological signal processing. *Behavior Research Methods*, *53*(4), 1689–1696. https://doi.org/10.3758/s13428-020-01516-y

Manis, G., Aktaruzzaman, M., & Sassi, R. (2018). Low Computational Cost for Sample Entropy. *Entropy*, *20*(1), 61. https://doi.org/10.3390/e20010061

McKinney, W.others. (2010). Data structures for statistical computing in python. *Proceedings of the 9th Python in Science Conference*, *445*, 51–56.

Namdari, A., & Li, Z. (Steven). (2019). A review of entropy measures for uncertainty quantification of stochastic processes. *Advances in Mechanical Engineering*, *11*(6), 168781401985735. https://doi.org/10.1177/1687814019857350

Roberts, S. J., Penny, W., & Rezek, I. (1999). Temporal and spatial complexity measures for electroencephalogram based brain-computer interfacing. *Medical & Biological Engineering & Computing*, *37*(1), 93–98.

Schölzel, C. (2019). *Nonlinear measures for dynamical systems* (Version 0.5.2) [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.3814723

Unakafov, A. M., & Keller, K. (2014). Conditional entropy of ordinal patterns. *Physica D: Nonlinear Phenomena*, *269*, 94–102.

Vallat, R. (2022). *AntroPy: Entropy and complexity of (EEG) time-series in python.* GitHub. https://github.com/raphaelvallat/antropy

Xiong, W., Faes, L., & Ivanov, P. Ch. (2017). Entropy measures, entropy estimators, and their performance in quantifying complex dynamics: Effects of artifacts, nonstationarity, and long-range correlations. *Physical Review E*, *95*(6). https://doi.org/10.1103/physreve.95.062114

Yang, A. C., & Tsai, S.-J. (2013). Is mental illness complex? From behavior to brain. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *45*, 253–257. https://doi.org/10.1016/j.pnpbp.2012.09.015

Yang, J., Choudhary, G. I., Rahardja, S., & Franti, P. (2020). Classification of interbeat interval time-series using attention entropy. *IEEE Transactions on Affective Computing*.

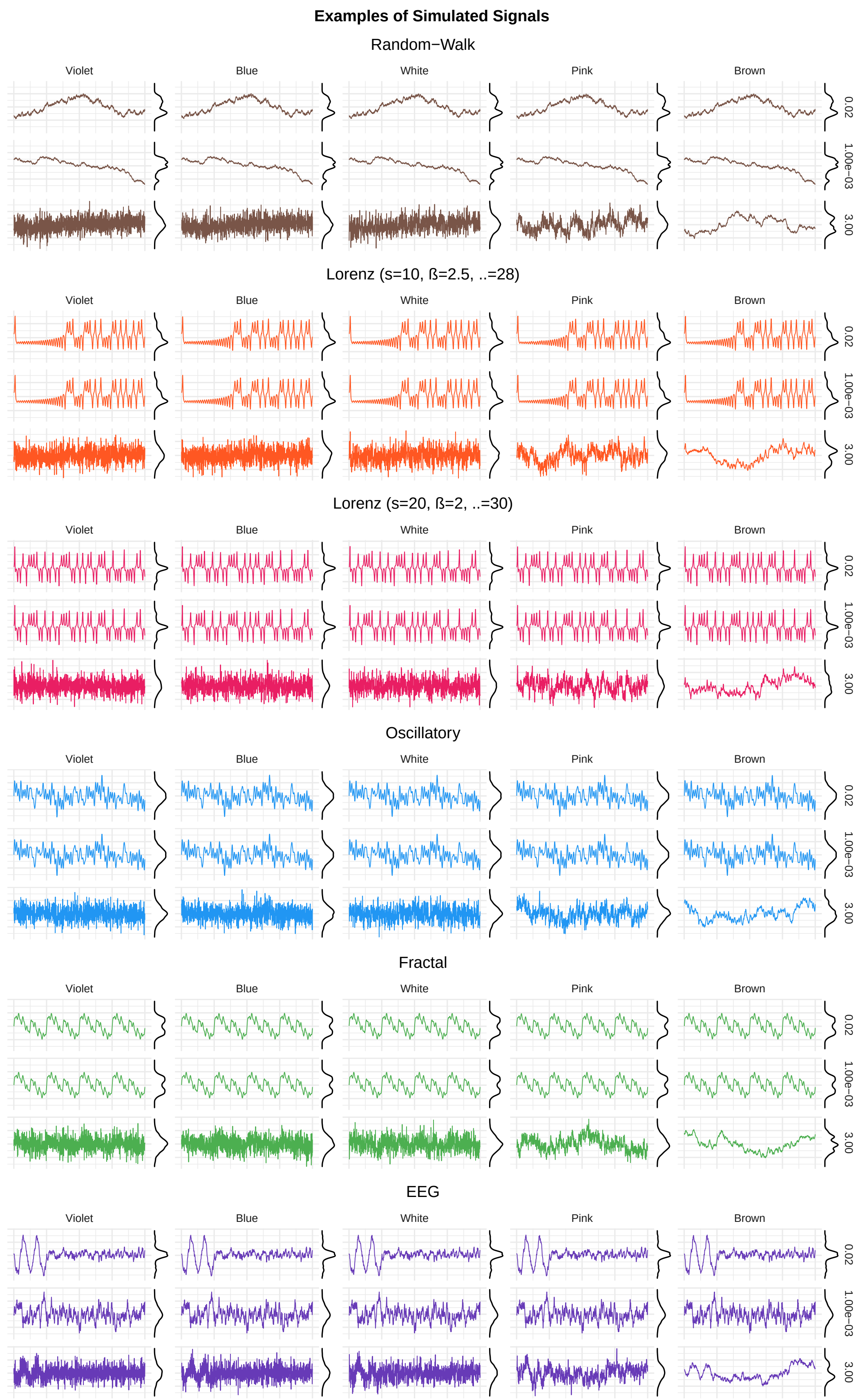

Figure 1. Different types of simulated signals, to which was added 5 types of noise (violet, blue, white, pink, and brown) with different intensities. For each signal type, the first row shows the signal with a minimal amount of noise, and the last with a maximal amount of noise.

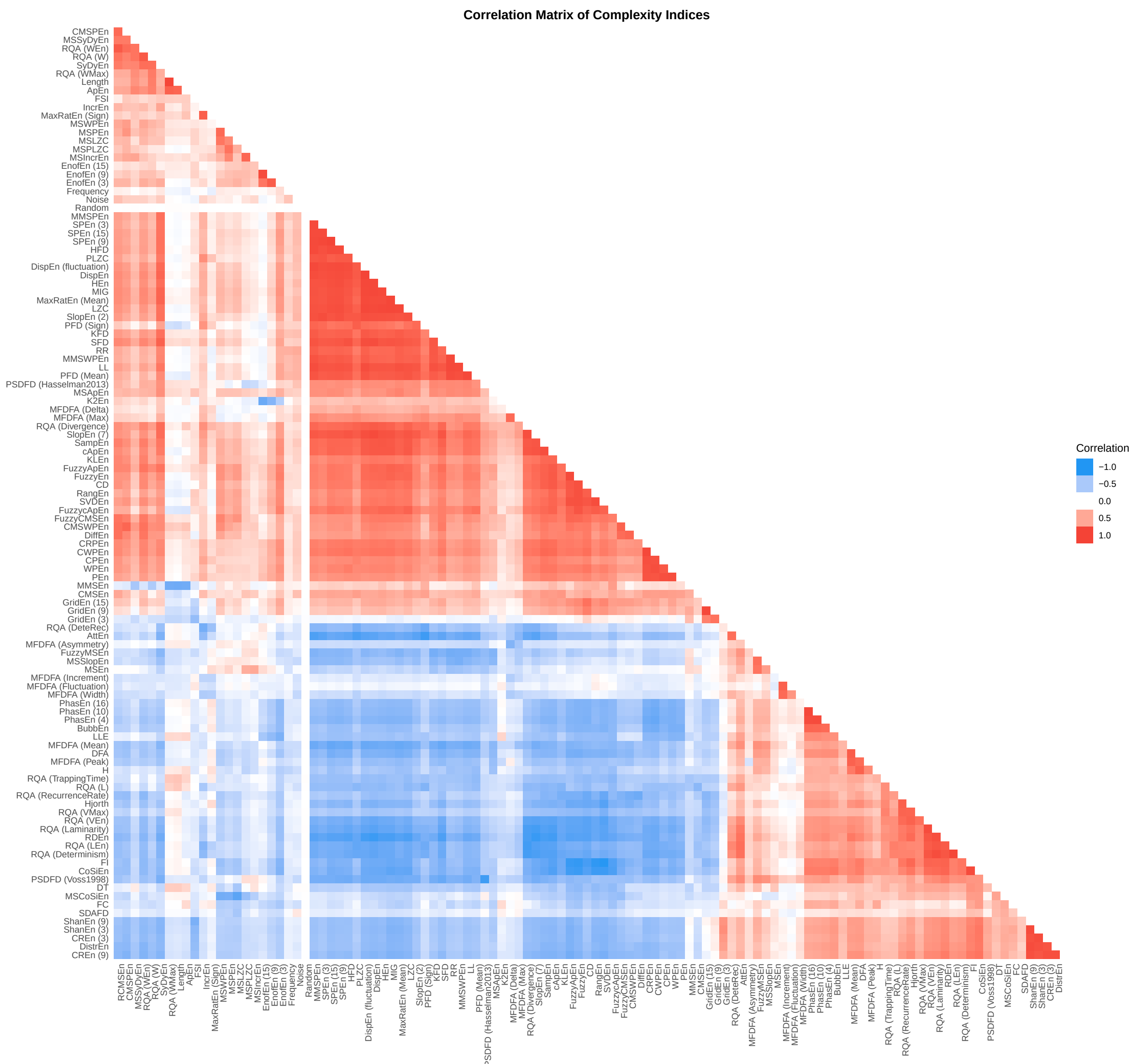

Figure 2. Correlation matrix of complexity indices.

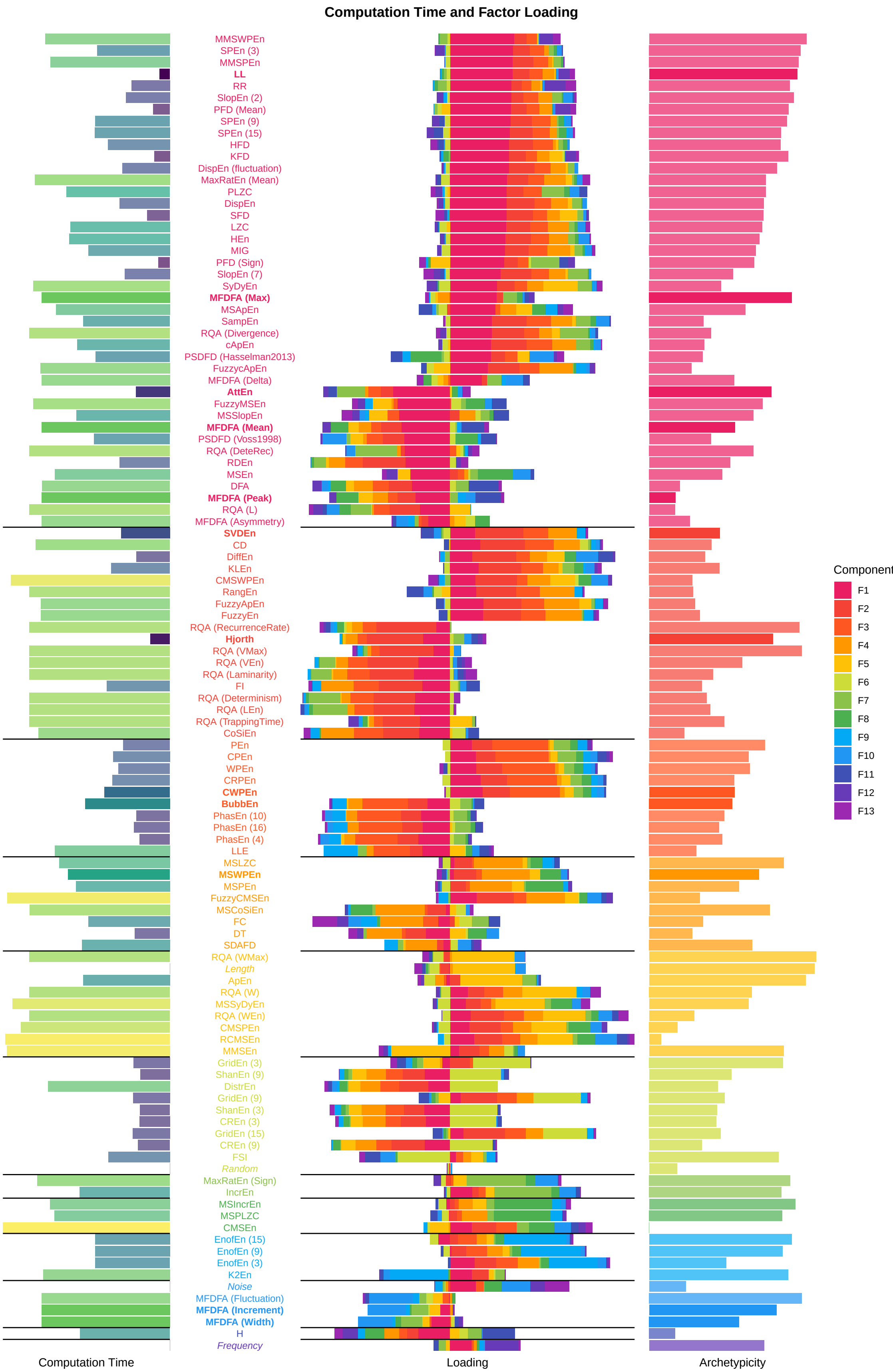

Figure 3. Factor loadings of the complexity indices, colored by the factor they represent the most (center). On the left, the median computation times and on the right, the archetypicity - the inverse of factor profile complexity, i.e., the extent to which each index is a pure representative of its dominant factor. This measure is low for indices that equally load on different factors).

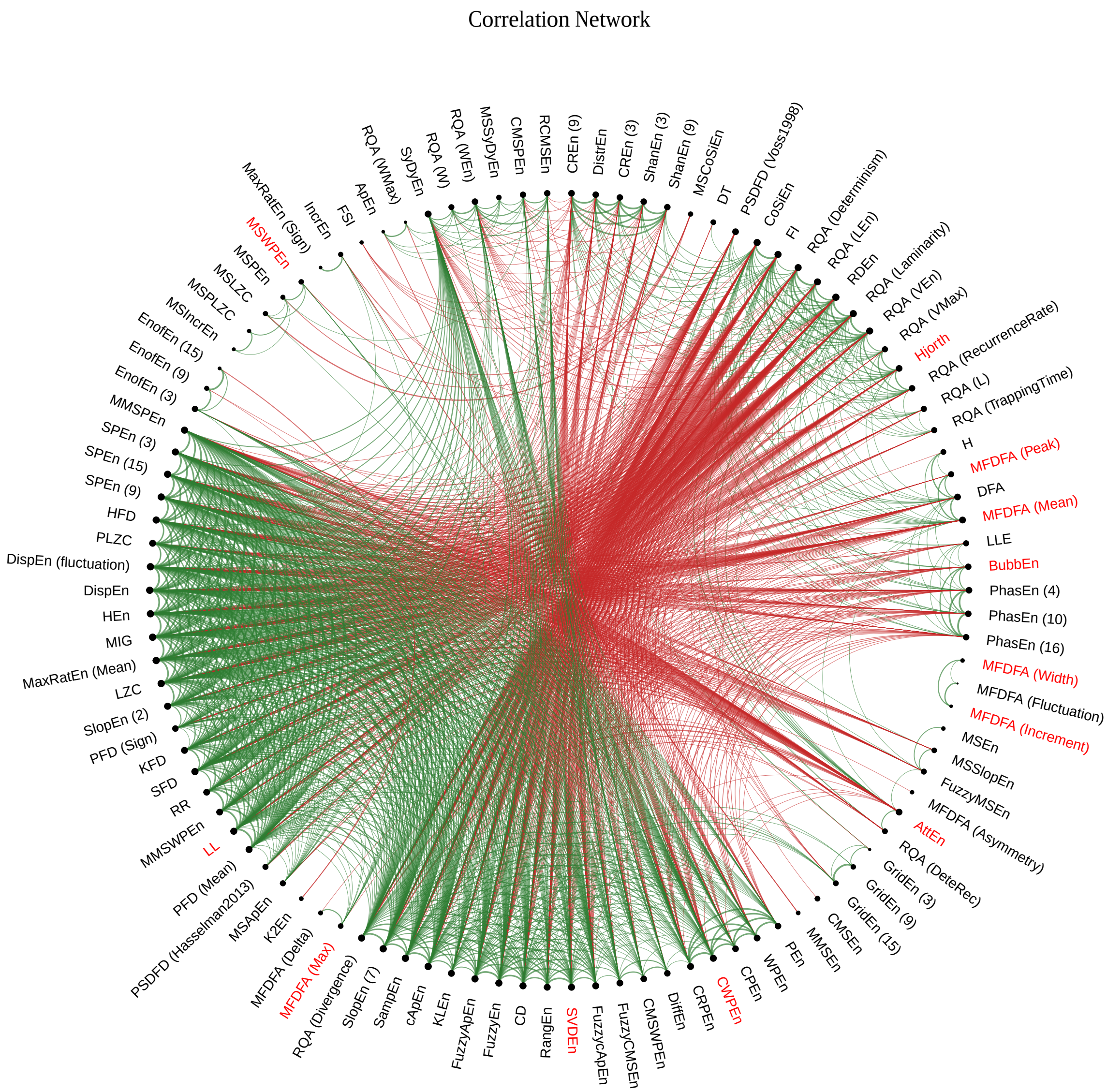

Figure 4. Correlation network of the complexity indices. Only the links where |r| > 0.6 are displayed.

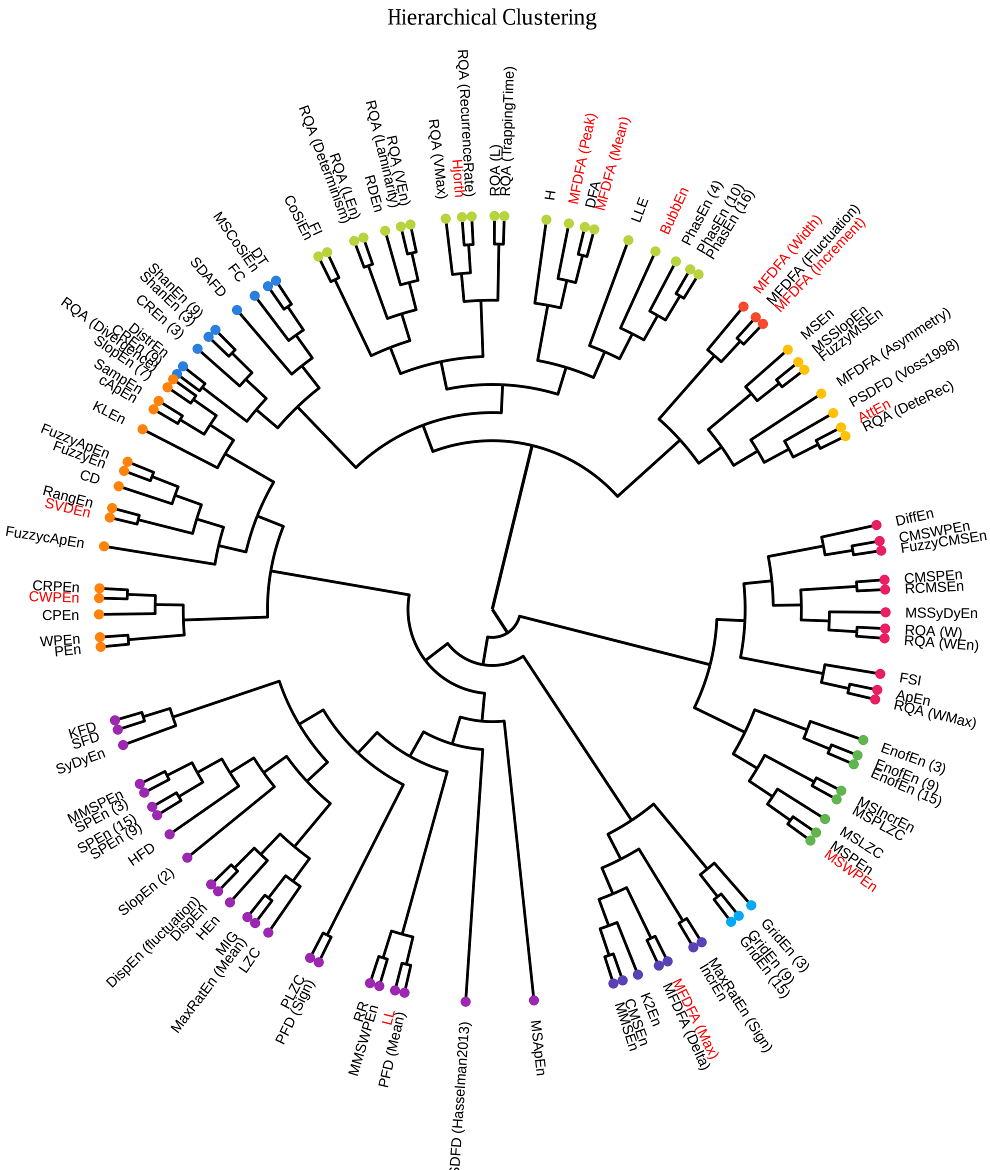

Figure 5. Dendrogram representing the hierarchical clustering of the complexity indices.

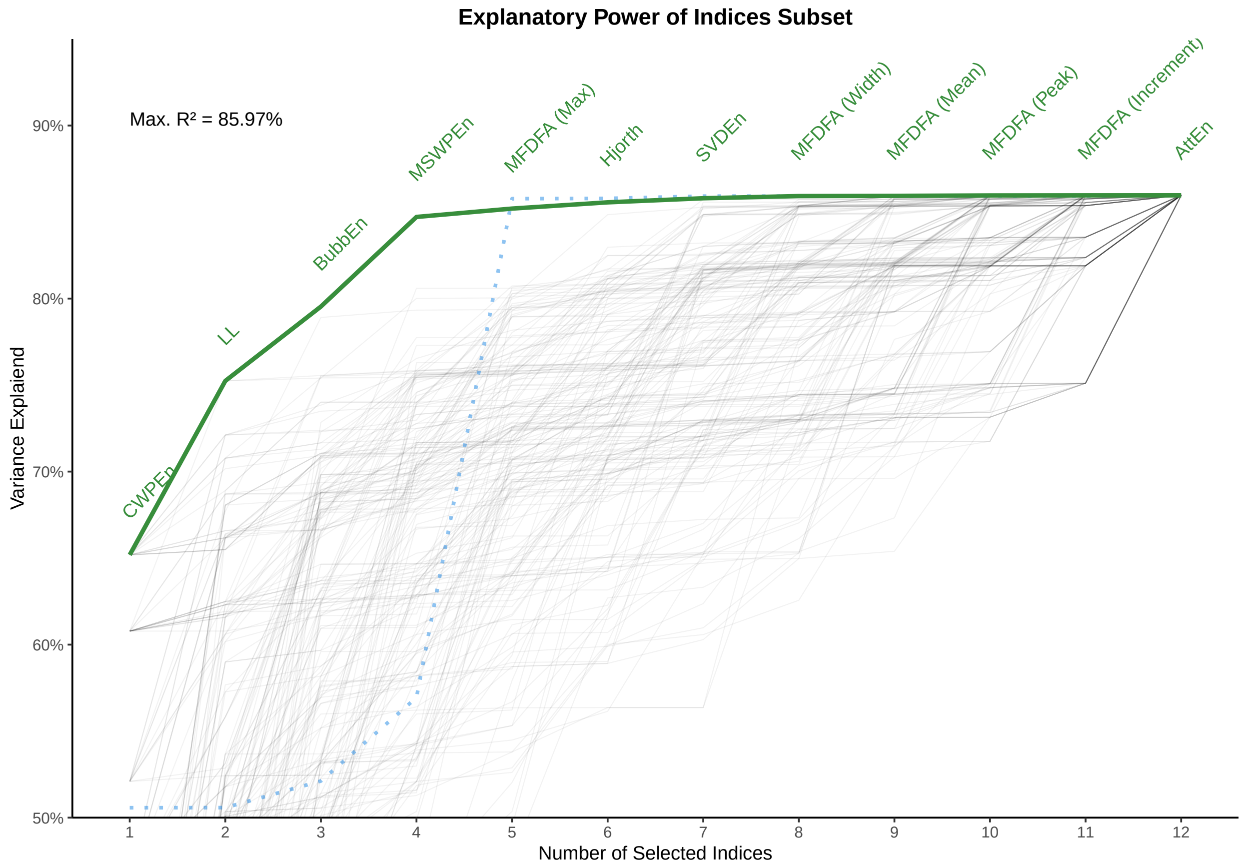

Figure 6. Variance of the whole dataset of indices explained by the subselection. Each line represents a random number of selected variables. The green line represents the optimal order (i.e., the relative importance) that maximizes the variance explained. The dotted blue line represents the cumulative relative median computation time of the selected indices, and shows that MFDFA and multiscale indices are the most costly algorithms.

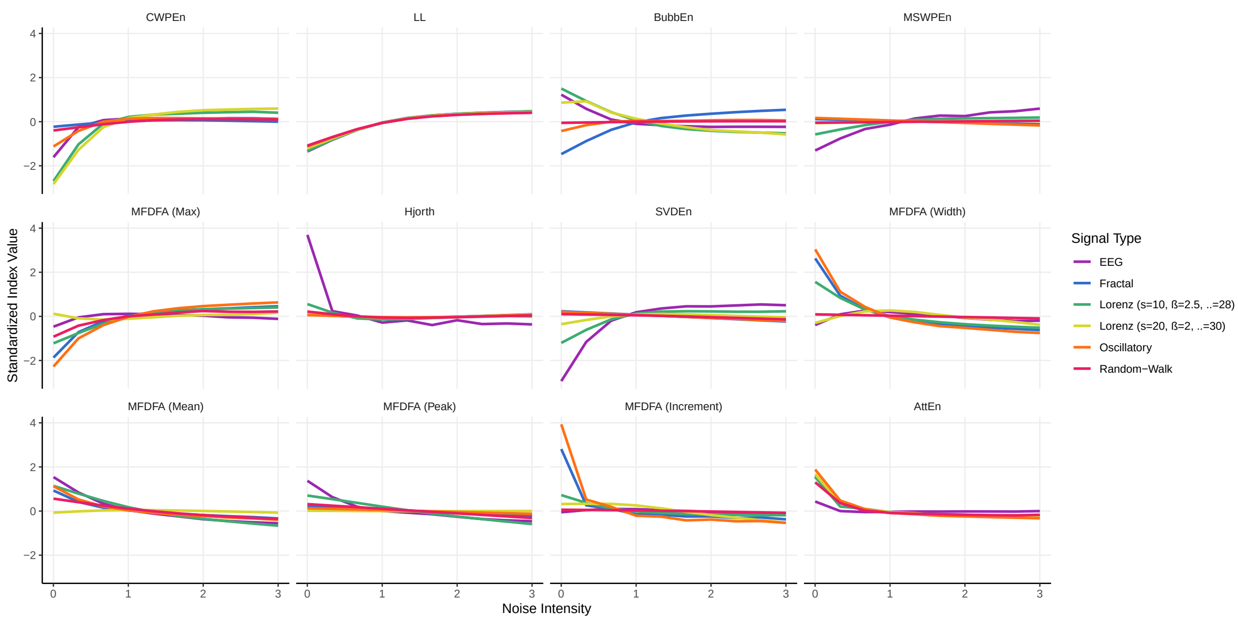

Figure 7. Visualization of the expected value of a selection of indices depending on the signal type and of the amount of noise.