6th International Conference on Nanotechnologies and Biomedical Engineering
Proceedings of ICNBME-2023, September 20–23, 2023, Chisinau, Moldova
Volume 2: Biomedical Engineering and New Technologies for Diagnosis, Treatment, and Rehabilitation

A Less Common Algorithmic Complexity Approach to EEG Signal Processing for Machine Learning

Victor Iapascurta

https://doi.org/10.1007/978-3-031-42782-4_20

Abstract

Electroencephalography (EEG) is a widely used neuroimaging technique that records the electrical activity of the brain. EEG analysis provides valuable insights into brain dynamics and understanding of neural processes. As EEG data analysis relies heavily on signal processing and statistical analysis, it is crucial to have a robust framework for analyzing EEG data that produces reliable results. One very useful framework for EEG data analysis is the use of algorithmic complexity measures. Algorithmic complexity is a measure of the complexity of a given sequence of data such as the EEG waveform. It provides a way to quantify the amount of randomness and predictability within EEG data. Along with traditional complexity measures like Sample Entropy, Hurst Exponent, Multiscale Entropy, etc., there is a less-known approach involving Kolmogorov-Chaitin algorithmic complexity, which is a mathematical approach used for measuring the complexity of a string of information. It is based on the idea that a complex string of information cannot be compressed or represented by a simpler algorithm. The advantages of using Kolmogorov-Chaitin complexity include its objectivity, non-linearity, ability to capture content and robustness. This paper presents the basics of the later approach and shows how it can be used for machine learning on EEG data.

Keywords: signal processing, electroencephalography, Kolmogorov-Chaitin algorithmic complexity, machine learning

6th International Conference on Nanotechnologies and Biomedical Engineering
Proceedings of ICNBME-2023, September 20–23, 2023, Chisinau, Moldova
Volume 2: Biomedical Engineering and New Technologies for Diagnosis, Treatment, and Rehabilitation

References

1. Subha, D.P, Joseph, P.K., Acharya, R.U., Lim, C.M.: EEG signal analysis: a survey. J. Med. Syst. **34**,195–212 (2010)
2. Kamel M., Saeed Malik, A., (eds.): EEG/ERP Analysis: Methods and Applications. 1st ed., Boca Raton, New York: CRC Press Taylor & Francis Group (2015)
3. Zenil, H.: A review of methods for estimating algorithmic complexity: options, challenges, and new directions. Entropy **22**(6), 612 (2020). https://doi.org/10.3390/e22060612
4. Delgado-Bonal, A.,Marshak, A.: Approximate entropy and sample entropy: a comprehensive tutorial. Entropy **21**(541), 2–37 (2019). https://doi.org/10.3390/e21060541
5. Mielniczuk, J.,Wojdyllo, P.: Estimation of hurst exponent revisited. Comput. Stat. Data Anal. **51**(9), 4510–4525 (2007)
6. Gao, J., Hu, J., Liu, F.,Cao,Y.: Multiscale entropy analysis of biological signals: a fundamental bi-scaling law. Front. Comput. Neurosci. **9**, 64 (2015). https://doi.org/10.3389/fncom.2015.00064
7. Yakovleva, T., et al.: EEG analysis in structural focal epilepsy using the methods of nonlinear dynamics (Lyapunov exponents, Lempel-Ziv complexity, and multiscale entropy). Hindawi Sci. World J. (2020). https://doi.org/10.1155/2020/8407872
8. American Epilepsy Society Seizure PredictionChallenge (2014).www.kaggle.com/c/seizureprediction
9. Zenil, H, Kiani, N.: instrs.: Algorithmic Information Dynamics: A Computational Approach to Causality and Living Systems from Networks to Cells MOOC by Complexity Explorer, Santa Fe Institute, Santa Fe, NM (Jun 12, 2018 to Oct 13, 2018). www.complexityexplorer.org/courses/63-algorithmic-informationdynamics-acomputational-approach-to-causality-and-livingsystems-from-networks-to-cells-2018
10. Zenil, H.: Towards demystifying shannon entropy, lossless compression, and approaches to statistical machine learning. In: Proceedings of the International Society for Information Studies 2019 summit, University of California, Berkeley, vol. 47, no. 1, p. 24 (2020). https://doi.org/10.3390/proceedings2020047024
11. Zenil, H., et al.: The Online Algorithmic Complexity Calculator (OACC) v3.0. Algorithmic Dynamics Lab, Science for Life Laboratory (SciLifeLab), Unit of Computational Medicine, Center for

Molecular Medicine at the Karolinska Institute in Stockholm, Sweden (2018). www.algorithmicdynamics.net/software.html

12. Zenil, H., et al.: A decomposition method for global evaluation of Shannon entropy and local estimations of algorithmic complexity. Entropy **20**(8), 605 (2018). https://doi.org/10.3390/e20080605

13. Soler-Toscano, F., Zenil, H., Delahaye, J.-P., Gauvrit, N.: Calculating kolmogorov complexity from the output frequency distributions of small turing machines. PLoS ONE **9**(5), e96223 (2014). https://doi.org/10.1371/journal.pone.0096223

14. Delahaye, J.-P., Zenil, H.: Numerical evaluation of algorithmic complexity for short strings: a glance into the innermost structure of randomness. Appl. Math. Comput. **219**(1), 63–77 (2012). https://doi.org/10.1016/j.amc.2011.10.006

15. Iapascurta, V.: Block decomposition method and traditional machine learning for epileptic seizure prediction. In: 26th InternationalWorkshop on Cellular Automata and Discrete Complex Systems AUTOMATA 2020, Stockholm, Sweden (2020). https://www.automata2020.com/videos--material.html

16. Iapascurta, V.: Combining algorithmic information dynamics concepts and machine learning for electroencephalography analysis:what can we get?.Complex Syst. **31**(4), 389–413 (2022). https://doi.org/10.25088/ComplexSystems.31.4.389

17. Wolfram Research, Inc., Wolfram Alpha Notebook Edition, version 13.2, Champaign, IL (2022)