Bibliometrics associations between EEG entropies and connections between Learning Disabilities and the Human Brain Activity

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Abstract: - In this paper we investigate the bibliometric association and connection between Electroencephalography (EEG) entropies of human brain and learning difficulties and disabilities. Learning disabilities as mathematical ancestry, attention deficit, hyperactivity disorder etc are inhibitory learning factors. In various big data bases as the biomedical databases there is an increasingly amount of data stored in, due to the breakthroughs in biology and bioinformatics. In recent years biomedical information is in the center of research growing the amount of data and thus making efficient information retrieval from scientists more and more challenging. Scientists, needs new tools and applications in order to extract scientifically important data based on experimental results and information provided by papers and journals. In this paper we use a programmable in Python tool in order to observe bibliometrics connections between EEG Entropies, learning difficulties and disabilities and the brain operation and signaling

Key-Words: - EEG Entropies, learning disabilities, bibliometrics associations.

1 Introduction

The study of the entropy of a signal [3], [22] is a study based on the theory of chaos. Techniques of this type appear to be better able to deal with stochastic systems. If a stochastic system has an entropy of zero then it is random and any increase in entropy increases randomness. Stochastic is a system that is not deterministic. A system that is described by the theory of probabilities. Entropy from the point of view of Physics is considered to be a magnitude which expresses the measure of the disorder of a system. For example, the particles constituting a vase are in a well-arranged arrangement in the space, in predetermined positions, with low movement margins therefrom. When, however, it falls and breaks, the body is led to a less organized state of its particles. Then we say that the entropy of the jar system has increased. Also, with the break, the entropy of the surrounding space also increased. Moreover, the re-creation of the jar again increases the entropy of the space, since energies are created that even put the jar particles in order, but they increase the ataxia in the surrounding space.

When used in information theory, entropy describes disorder, non-regularity, complexity, and inability to predict the characteristics of a signal Signals resulting from neural activity exhibit non-linear, chaotic behavior, and therefore the application of chaos theory to their processing process is constantly gaining ground. A very important size used to analyze such signals is the various forms of entropy. In the following paragraphs we will describe several already entropy used in study and signal analysis to extract various information.

2 Experimental and Computational Details

The entropies that will be studied in this work in order to draw and possible correlation with difficulties are :

1. Shannon Entropy
2. Sample Entropy
3. Wavelet Entropy
4. Log energy entropy
5. Threshold entropy
6. Sure entropy
7. Norm entropy
8. Kolmogorov entropy
9. Renyi entropy
10. Spectral entropy

The primary and basic goal of the system will be the ability to search for various EEG metrics supplied by the user and identify any connections or interactions with other metrics based on how frequently they are met toget her in several papers stored in PubMed central database [4].
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2.1 Methodology

Based on the principals of bibliometrics and statistics the system will take into account a series of parameters in order to create a weight-graph between metrics and learning disorders. The basic parameters will be:

- Frequency of the co-appearance of two EEG metrics in the abstracts of papers, freely available online with no restrictions
- EEG metrics Co-citation coupling [15]
- Analysis of related EEG metrics in pairs
- Analysis of the probability of relation between EEG metrics that co-exist in several papers based on the Pubmbed Central Database

2.2 High Level Design

The system will constantly poll for EEG metrics and analyze their appearance in papers stored in PubMed[4]. It will then store and link this information when it is requested by the user. For example when Shannon entropy is analyzed the system will store the PID (Paper ID) of PubMed for each paper that contains Shannon entropy. Then the same procedure is going to be followed for Sample entropy, Wavelet entropy …. Spectral entropy. The system based on the user input will construct relations between metrics following the basic principles mentioned above. This routine will be running in real time and will update the information of each entropy since the amount of papers being submitted every day could change the final graphs dramatically.

3 Experimental Results

We are going to use the findings of the previous study [medical hypothesis] to identify possible bibliographic relationship between the various EEG entropies, and Learning Disability. In order to do so, we have applied a searching mechanism via PCM of PubMed services and the results are presented in Table 2.1, 2.2 and Table 3.

In Table 2.1 we have the co-appearances between the terms “Learning Disabilities” and “EEG_Entropies” in pairs. There are 164.377 papers for Learning Disabilities but only 317 are associated with Shannon Entropy, 1948 are associated with Sample Entropy and so on.

Table 2.1. Co-appearances between metrics (papers)

	Learning Disabilities	Shannon Entropy	Sample Entropy	Wavelet Entropy	Log energy entropy	Threshold entropy	Sure entropy	Norm entropy	Kolmogorov entropy	Renyi entropy	Spectral entropy
Learning Disabilities 164.377		317	1948	393	292	1376	180	244	141	48	795

In table 2.2. we can see the percentage of table 2.1. For example 0,24% of Learning Disabilities papers are associated with Wavelet Entropy and 0,15% of Learning Disabilities papers are associated with Norm Entropy and so on

Table 2.2. Co-appearances between metrics (papers) - present

	Learning Disabilities	Shannon Entropy	Sample Entropy	Wavelet Entropy	Log energy entropy	Threshold entropy	Sure entropy	Norm entropy	Kolmogorov entropy	Renyi entropy	Spectral entropy
Learning Disabilities 164377 papers	0,00%	0,19%	1,19%	0,24%	0,18%	0,84%	0,11%	0,15%	0,09%	0,03%	0,48%

Finally in Table 3 we can see the percentage of co - appearances of the same terms in pairs, but the percentage is in base of every Entropy.

Table 3. Co-appearances between metrics (papers) - percent

	Learning Disabilities
Learning Disabilities 164377 papers	0,00%
Shannon Entropy 5174 papers	6,13%
Sample Entropy 31009 papers	6,28%
Wavelet Entropy 2647 papers	14,85%
Log energy entropy 10382 papers	4,56%
Threshold entropy 16552 papers	21,49%
Sure entropy 2042 papers	2,81%
Norm entropy 2695 papers	3,81%
Kolmogorov entropy 1531 papers	2,20%
Renyi entropy 553 papers	0,75%
Spectral entropy 9938 papers	12,42%

For example, 6,13% of Shannon entropy papers are associated with Learning Disabilities and 14,8% of Wavelet entropy papers are associated with Learning Disabilities and so on.

3.1 Investigating the relations between metrics

The purpose of this subsection is the investigation of possible connections between Learning Disabilities and EEG Entrpy metrics. For this reason we correlate the possible connection between the mentioned metrics. By analyzing the data from Table 2.1 and 2.2 and analyzing the connections between the above mentioned metrics we obtained the following results which are depicted in Figure 1 and Figure 2.

Figure 1. Co-appearances between metrics (papers)

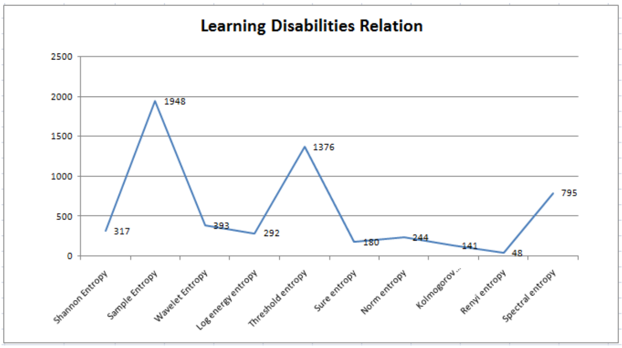
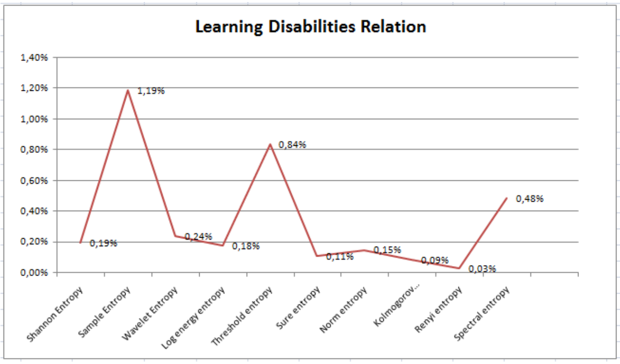


Figure 2. Co-appearances between metrics (papers) - present



According to the above results we can export a stronger relationship between Learning Disabilities and the three of ten entropies. Sample entropy with 1948 papers, Threshold entropy with 1376 papers, and Spectral entropy with 795 papers

Now it is possible to apply the co-citation normalization procedure [16] among those four metrics which is based on the following equation

$$norm = \frac{\left| in(Sample) \cap in(Threshold) \cap in(Spectral) \right|}{in(LearningDisabilities)} = 0.0205 \quad (1)$$

The interpretation of this result indicates that the value 0.0205 gives a possible bringing between the three entropies and the Learning Disabilities at 2,5% and this lead the ascertainment that a possible research in this issue obtains a higher successful rate than previous attempts.

4 Results and Discussion

The bibliometric approach we presented in this paper, between Learning disorders and Human brain via EEG Entropy metrics, could provide a very important tool for the scientific community, improving connections between learning disabilities and human brain EEG entropies. In this paper we showed that the EEG Sample, Threshold and Spectral Entropy metrics play a bigger role than the other entropies, regarding the identification of possible relation between EEG and learning disorders. Through this paper we showed that if we study the graphs provided we are sure that EEG entropies could be a basic link between EEG metrics affecting possibility of learning disability existence.

We have the opinion that the statistical system will become a useful tool for researchers around the world. The specific implementation will provide a mean to connect, seemingly unconnected EEG metrics.

5 Conclusions and Future Work

In this paper we approached with bibliometric terms the scientific fields of Education and Electroencephalography (EEG) metrics. More specifically we presented association and communication between human brain Learning disorders and EEG entropies. We used EEG Entropies, as Shannon Entropy, Sample Entropy, Wavelet Entropy, Log energy entropy, Threshold entropy, Sure entropy, Norm entropy, Kolmogorov entropy, Renyi entropy and Spectral entropy.

As a conclusion we can conclude with that, via this paper we provide with a very important tool the scientific community, improving connections between learning disabilities and human brain EEG metrics. In this paper we showed that the EEG entrpoy metric plays a small but not negligible role regarding the identification of possible relation between EEG and learning disorders. For this reason we believe that further pursue of this work could be made by taking into account the crucial role of the EEG entropy metric. We have the opinion that the statistical system will become a useful tool for researchers around the world. The specific implementation will provide a mean to connect, seemingly unconnected EEG metrics [23-27].

As future work, we plan to develop a parametric information system in order to automate the statistical procedure of tables 2.1, 2.2 and 3. The information system will constitute from an intelligent calculate mechanism based on Python and a graphical user interface with parameters that can automatically extract bibliometric information and statistical information from PubMed or other online databases.

References:

[1] Michael L. Metzker ," Sequencing technologies — the next generation" *Nature Reviews Genetics 11*, 31-46 ,January 2010.

[2] Jacques Cohen, "Bioinformatics—an introduction for computer scientists", *ACM Computing Surveys*, Volume 36 Issue 2,122-158,June 2004

[3] Bein B., «Entropy», *Best practice & Researche Clinical Anaesthesiology* Vol.20, No 1, pp. 101-109, ELSEVIER 2006.

[4] B.J. Stapley et al," Biobibliometrics: Information retrieval and visualization from co-occurrences of genenames in Medline abstracts", *Pacific Symposium on Biocomputing* 5:526-537 (2000)

[5] Martzoukos Y., Papavlasopoulos S., Poulos M., Syrrou M., "Biobibliometrics & gene connections",*IISA*2015

[6] Poulos M. and Stefanidis V. , "Synchronization of Small Set Data on Stable Period", *2nd International Conference Mathematics and Computers in Science and Industry*, Malta, 2015.

[7] Baars, B. J., Gage, N. M., (2010), *Cognition, Brain, and Consciousness: Introduction to Cognitive Neuroscience*, Elsevier, 2nd Edition.

[8] Hodgkinson, Colin A., Mary-Anne Enoch, Vibhuti Srivastava, Justine S. Cummins-Oman, Cherisse Ferrier, Polina Iarikova, Sriram Sankararaman, et al. "Genome-Wide Association Identifies Candidate Metrics That Influence the Human Electroencephalogram." *Proceedings of the National Academy of Sciences* 107, no. 19 (2010): 8695–8700.

[9] Dumermuth, G., Molinary, L., (1987), *Spectral Analysis of EEG Background Activity, In Handbook Methods of Analysis of Brain Electrical and Magnetic Signals*, A. S. Gevins (ed.) (Amsterdam: Elsevier).

[10] Sommer BJ, Barycki JJ, Simpson MA. *Characterization of human UDP-glucose dehydrogenase*. J Biol Chem 2004;279:23590.

[11] Marcel, S., Milln, J. del R., (2007), Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation. Pattern Analysis and Machine Intelligence, *IEEE Transactions on 29*, 743 - 752.

[12] Dougherty MK, Morrison DK. *Unlocking the code of 14-3-3*. J Cell Sci 2004;117:1875–84.

[13] Hirsch L. J., Richard P., Brenner R.P., (2010), *Atlas of EEG in Critical Care*, Wiley-Blackwell..

[14] Percival, D. B., Walden, A. T., (1993), Spectral *Analysis for Physical Applications Multitaper and Conventional Univariate Techniques*, Cambridge, England: Cambridge University Press

[15] Henry Small," Co-citation in the scientific literature: A new measure of the relationship between two documents", Volume 24, Issue 4, pages 265–269, July/August 1973.

[16] Fang Li et al.," Applying Association Rule Analysis in Bibliometric Analysis-A Case Study in Data Mining" , *Proceedings of the Second Symposium International Computer Science and Computational Technology*(ISCSCT '09),Huangshan, P. R. China, 26-28,Dec. 2009, pp. 431-434.

[17] Gerald Matthews, Lauren Reinerman-Jones, Julian Abich IV, Almira Kustubayeva, "Metrics for individual differences in EEG response to cognitive workload: Optimizing performance prediction", *Personality and Individual Differences*, Volume 118, 1 November 2017, Pages 22-28

[18] Anderson S. Oliveira,Bryan R. Schlink,W. David Hairston, Peter König, and Daniel P. Ferris, "*Proposing Metrics for Benchmarking Novel EEG Technologies Towards Real-World Measurements*", frontiers in Human Neuroscience

[19] Stefanidis V., Anogianakis G., Evangelou A., Poulos M., «*Learning Difficulties Prediction using Multichannel Brain Evoked Potential Data*», IEEE Proceedings, MCSI, pp. 268-272, 2016.

[20] Agatha Lenartowicz, and Sandra K. Loo, "*Use of EEG to Diagnose ADHD*", Curr Psychiatry Repot 2014 Nov; 16(11): 498.

[21] Jasper HH, Solomon P, Bradley C. Electroencephalographic analyses of behavior problem children. *American Journal of Psychiatry*. 1938;95(3):641–658.

[22] «ENTROPY HANDBOOK Defnitions, Theorems, M-files» www.uivt.cas.cz/~pklan/eth.pdf

[23] Martzoukos, Y., Papavlasopoulos, S., Syrrou, M., & Poulos, M. (2015, July). Biobibliometrics & gene connections. In Information, Intelligence, Systems and Applications (IISA), 2015 6th International Conference on (pp. 1-5). IEEE.

[24] Papavlasopoulos, S., Poulos, M., Korfiatis, N., & Bokos, G. (2010). A non-linear index to evaluate a journal's scientific impact. Information Sciences, 180(11), 2156-2175.

[25] Poulos, M., Papavlasopoulos, S., Alexandris, N., & Vlachos, E. (2004). Comparison between auto-cross-correlation coefficients and coherence methods applied to the EEG for diagnostic purposes. Medical Science Monitor, 10(10), MT99-MT108.

[26] Papavlasopoulos, S., Poulos, M., & Evangelou, A. (2006). Feature extraction from interictal epileptic and non-epileptic pathological EEG events for diagnostic purposes using LVQ1 neural network. In *Mathematical Methods In Scattering Theory And Biomedical Engineering* (pp. 390-398).

[27] Papavlasopoulos, S. H., Poulos, M. S., Bokos, G. D., & Evangelou, A. (2007). Classification control for discrimination between interictal epileptic and non-epileptic pathological EEG events. *International Journal of Biomedical Sciences, 1*(1).