Bibliometrics EEG metrics associations and connections between military medicine and the differentiate post traumatic stress disorder (PTSD)

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Abstract: - In this paper we investigate the bibliometric association and connection between Electroencephalography (EEG) metrics of human brain and connections between military medicine and the post traumatic stress disorder (PTSD). In EEG metrics included various metrics used from scientists in order to map the brain activity. Inrecent years there has been an increasingly amount of data connect EEG metrics with PTSD and military medicine. Due to breakthroughs in biology and bioinformatics, more and more data are stored in various large databases as biomedical databases. In recent years, biomedical information has become the center of research, and its data volume has continued to grow. Therefore, obtaining effective information from scientists has become increasingly challenging. As a new scientific field of bioinformatics, new tools and applications are needed to extract important scientific data based on experimental results and information provided by papers and journals. In this paper we are going to investigate methods based in acustom made IT system, more specifically a programmable in Python toolin order to find connections between the differentiate post traumatic stress disorder and the brain operation and signaling. This IT system could become a useful tool against the struggle of scientists and medicalprofessionalsin the near future.

Key-Words: - EEG metrics, MedLine, Bioinformatics, Co-citation coupling, Bibliometrics, PubMed, Power Spectra, PTSD, ERPs, EEG Entropy, EEG Rhythms

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1 Introduction

The study of various Electroencephalography (EEG) metrics is a biometric method that can give us fairly detailed information on ongoing brain activity associated with perception, cognition and emotion [1],[2], [6], [19].

Post-traumatic stress disorder (PTSD) is a common psychiatric condition amongst active duty and ex-serving military personnel across the world, creating a significant public health challenge [[20]]. In [[25]] researchers investigate the use of resting-state electroencephalography (EEG) data to help differentiate posttraumatic stress disorder (PTSD) symptom factors. In this research there is a correlation between PTSD and EEG Rhythms (alpha, beta, delta, and theta frequency band).

In [[26]] researchers examine electroencephalogram (EEG) spectral power to study abnormalities in regional brain activity in post-traumatic stress disorder (PTSD) during sleep. According to auhtors they aimed to identify sleep EEG markers of PTSD that were reproducible across nights and subsamples of our study population.

There are various EEG-based Metrics [[6]],[[23]],[[24]] we can find in literature as cognitive state for engagement and distraction as well as a mental workload metric [17], the memory workload, sort memory capacity, various EEG entropies, power spectra (PS), coherence (ITC – InterTrial Coherence) [19], the pre-stimulus noise (PSN), signal-to-noise ratio (SNR) and EEG amplitude variance across the P300 event window (CVERP) [18], the EEG rhythms, event related potentials (ERPs) [20] etc. Some of them are connected in literature with military medicine and the differentiate post traumatic stress disorder (PTSD). Generally those metrics enable researchers to observe the unobservable brain, and incorporate a useful and reliable alternative to analyzing raw EEG data.

The study of the entropy of a signal 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.

Bioinformatics is a scientific field whose main purpose is to analyze statistical data and classify the flow of information generated by scientific experiments or laboratory work. Scientists can use various methods to analyze scientific data and evaluate huge data sets. In the past few decades, these tasks have been very difficult. On the one hand, due to limited computing power and lack of interdisciplinary fields like bioinformatics, it can be used. In the past few years, as mentioned above, a large amount of data has begun to accumulate. The main question is how to use these massive amounts of data in the future. Therefore, new technologies must be found. Several attempts have been made to extract information from various scientific papers and/or journals freely available on the Internet. We can find various techniques in this way, in the previous years as at Stapley et al [3]. In this paper the researchers have introduced term "biobibliometrics" to describe the use of bibliometric techniques on papers that are related to biological issues. We can apply the technique in a similar way for educational disorders issues. The specific implementation we can find at Stapley's could verify the bibliometrical connection between biological data as the EEG metrics, based solely on the rate of their common appearances in the abstracts of scientific papers and journals.

In this paper, we are going to investigate various methods and finally to use a custom made IT systemin order to find connections between Post-traumatic stress disorder (PTSD) and the brain operation and signaling. EEG is the main system for register the brain activity. Thus EEG is a significant medical issue. As first step we use a previous implemented IT system [[23]] [[24]] in order to search in the free full-text archive of Educational disorders, biomedical and life sciences journal literature at the U.S. in order to investigate the possible association between the selected disorders and the various EEG metrics.

The present paper is divided in the following three parts: The "methodology" in which is explained the methodology we develop. The second part concerns the "results" and the third part includes some discussion and the final conclusion

2 Experimental and Computational Details

The EEG metrics that will be studied in this work in order to draw and possible correlation with PTSD are Power Spectra (PS), ERPs, EEG Rhythms and EEG entropies. The primary and basic goal of our IT system will be the ability to search for those EEG metrics supplied by the user and identify any connections or interactions with Post-traumatic stress disorder based on how frequently they are met together in several papers stored in PubMed (US National Library of Medicine National Institutes of Health) central database [5].

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 and PTSD Co-citation coupling [15]
- Analysis of related EEG metricsand PTSDdata in pairs
- Analysis of the probability of relation between EEG metrics and PTSDdata that co-exist in several papers based on the Pubmed Central Database

2.2 High Level Design

Our IT system constantly poll for EEG metrics and analyze their appearance in papers stored in PubMed[5]. It will then store and link this information when it is requested by the user. For example when EEG PS is analyzed the system will store the PID (Paper ID) of PubMed for each paper that contains EEG PS (metric 1).Then the same procedure is going to be followed for ERPS (metric 2), EEG Rhythms (metric 3) and EEG entropies (metric 4) and finally with PTSD (metric 5). The system based on the user input will construct relations between metrics following the basic principles mentioned above. This procedure will be running in real time and will update the information of each metric since the amount of papers being submitted every day could change the final graphs dramatically.

Table 1.

	PTSD	EEG Entropy	PS	ERPs	EEG Rhythms
PTSD 59266papers		1,55%	0,74%	5,18%	1,55%
EEG Entropy 5890 papers	15,55%		21,19%	31,51%	27,03%
PS 10405 papers	4,21%	11,99%		48,55%	46,09%
ERPs 35147 papers	8,74%	5,28%	14,37%		21,61%
EEG Rhythms 17875 papers	5,12%	8,91%	26,83%	42,49%	

	PTSD	EEG Entropy	PS	ERPs	EEG Rhythms
PTSD 59266papers		916	438	3071	916
EEG Entropy 5890 papers	916		1248	1856	1592
PS 10405 papers	438	1248		5052	4796
ERPs 35147 papers	3071	1856	5052		7595
EEG Rhythms 17875 papers	916	1592	4796	7595	

Constructing relations between metrics

Metric ID	Metric ID
Metric_i	Metric_j
PID	PID
0001	0001
0003	0002
0005	0005
0006	0006
0010	0011

As seen on Table1 we could construct a relation node between metric1 and metric2 with the weight of 3.

3 Experimental Results

We are going to use the findings of our previous study [23],[24] to identify possible bibliographic relationship between the various EEG metrics, as EEG Entropy, Power Spectra (PS) and Post-traumatic stress disorder (PTSD). In order to do so, we have applied a searching mechanism based, on an IT system programmed in python, via PCM of PubMed services and the results are presented in Table 2 and Table 3.

Table 2. Co-appearances between metrics (papers)

Table 3. Co-appearances between metrics (per cent)

3.1 Investigating the relations between metrics

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

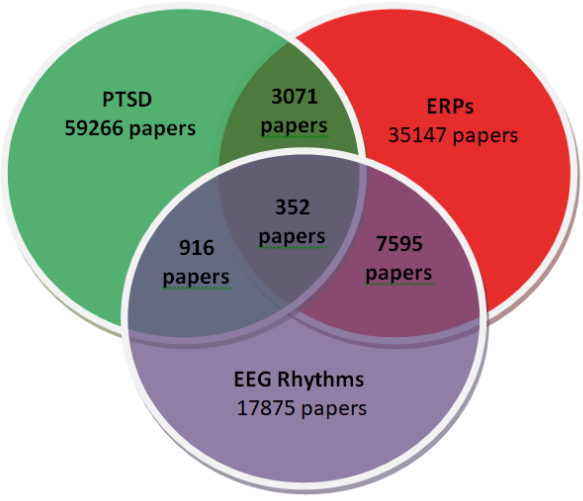

Fig. 1. The intersection between PTSD and ERPs with EEG Rhythms

According to the above results now it is possible to apply the co-citation normalization procedure [16] which is based on the following equation

$$norm = \frac{\left|in(PTSD) \cap in(ERP) \cap in(EEGRythms)\right|}{in(PTSD) \cap in(ERP)} = \frac{352}{3071} = 0.11 \quad (1)$$

$$norm = \frac{\left|in(PTSD) \cap in(ERP) \cap in(EEGRythms)\right|}{in(PTSD) \cap in(EEGRythms)} = \frac{352}{916} = 0.38 \quad (2)$$

The interpretation of this result indicates that the value 0.11 from equation (1) gives a possible bringing between PTSD and ERPs metrics at 11%and the value 0.38from equation (2) gives a possible bringing between PTSD and EEG Rythms metrics at 38%. This lead the ascertainment that a possible research in this issue obtains a higher successful rate than previous attempts.

3.2 Observing the relation between EEG metrics over time

The purpose of this subsection is the visualization of the relations we reveal in the previous subsection. Also we can draw conclusions by observing this visualization doing. In order to visualize the relation between PTSD and EEG metrics, Power Spectra, ERPs, EEG Entropies and Rhythms we are going to investigate the appearance of each metric, in PubMed Central Database, over the past 16 months with one month interval (Figure 2). We have also determined the relation between PTSD and EEG Rhythms, and between PTSD and ERPs over the period of 16 months, again with one month interval (Figure 3). All the data used to construct the graphs in figure 2 and 3 can be observed in detail in Table 3.

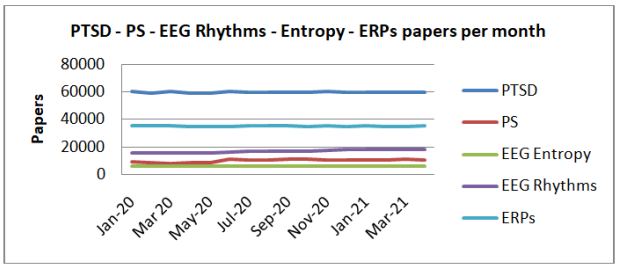

Fig. 2 Appearances of Power Spectra, EEG Rhythms and ERPs in PubMed Central over the past 16 months.

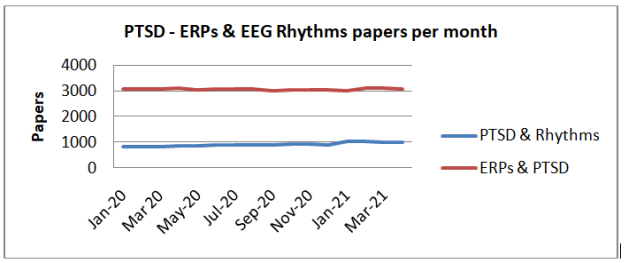

Fig. 3 Number of co-appearances between EEG Rhythms and Power Spectra and between EEG Rhythms and ERPs in PubMed Central over the past 16 months.

Table 4. Appearance and co-appearances of PTSD, Power Spectra (PS), EEG Entropies, EEG Rhythms and ERPs

	PTSD	PS	EEG Entropy	EEG Rhythms	ERPs	PTSD & Rhythms	ERPs & PTSD
Jan-20	59821	8970	5919	15786	35234	820	3081
Feb-20	59265	8708	5761	15839	35343	831	3072
Mar 20	59845	8044	6056	15828	35372	814	3066
Apr-20	59241	8908	5859	15908	35121	849	3096
May-20	59316	8693	5881	15959	35010	840	3030
Jun-20	59865	10686	5887	16226	35218	885	3058
Jul-20	59668	10396	5725	16720	35308	899	3052
Aug-20	59438	10203	6080	16743	35446	876	3077
Sep-20	59709	10748	5769	16852	35249	888	3005
Oct-20	59713	10941	5850	17100	35168	932	3021
Nov-20	59945	10302	5841	17456	35333	933	3035
Dec-20	59537	10313	6063	17925	35181	900	3029
Jan-21	59734	10411	5765	17897	35457	1045	3000
Feb-21	59673	10117	5865	17994	35048	1043	3087
Mar-21	59654	10849	5862	17811	35147	1005	3100
Apr-21	59621	10132	5715	17762	35425	1005	3060

As we can observe in Figures 2 and 3 there is a noticeable increase in EEG rhythms appearances in journals, Power Spectra appearance rates seem to be stable and there is a slight increase in the appearances of ERPs. We can also notice that there is a slight increase of the bio-bibliometric relation between PTSD and EEG Rhythms. Finally we identify an almost stable relation between PTSD and ERPs.

4 Results and Discussion

The bibliometric approach we presented in this paper, between Post-traumatic stress disorder (PTSD) and Human brain via EEG metrics, could provide a very important tool for the scientific community, improving connections between learning disabilities and human brain EEG metrics. In this paper we showed that the EEG Rhythms metric plays a crucial role regarding the identification of possible relation between EEG and PTSD. Through this paper we showed that if we study the graphs provided we are sure that EEG Rhythms could be the common link between EEG metrics affecting possibility of learning disability existence. Thus we believe that further pursue of this work could be made by taking into account the crucial role of the EEG Rhythms 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 PTSD and EEG metrics.

5 Conclusions and Future Work

In this paper we approached with bibliometric terms the scientific fields of military medicine and Electroencephalography (EEG) metrics. More specifically we presented association and communication between post-traumatic stress disorder (PTSD) and human brain through various EEG metrics. We used EEG Entropies, Power Spectra, Event Related Potentials, EEG Rhythms Oscillations. As a conclusion we can conclude with that, via this paper we provide with a very important tool the scientific community, improving connections between post-traumatic stress disorder (PTSD) and human brain EEG metrics. In this paper we showed that the EEG Rhythms metric plays a crucial role regarding the identification of possible relation between EEG and PTSD. Based on the graphs provided we are fairly sure that EEG Rhythms could be the guide and the common link between EEG metrics affecting possibility of learning disability existence. For this reason we believe that further pursue of this work could be made by taking into account the crucial role of the EEG Rhythms 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 PTSD and EEG metrics.

As future work, we plan to develop a parametric information system in order to automate the statistical procedure of tables 2, 3 and 4. 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.

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