Model for the organization, storage and processing of large data banks of physiological variables

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***Abstract*— The proliferation and popularization of new instruments for measuring different types of electrophysiological variables, has generated the need to store huge volumes of information, corresponding to the records obtained by applying this instruments on experimental subjects. Together with this must be added the data derived from the analysis and purification processes. Moreover, several stages involved in the processing of data, is associated with one or more specific methods related to the area of research and to the treatment at which the base information (RAW) is subjected. As a result of this and with the passage of time, various problems occur, which are the most obvious consequence of that data and metadata derived from the treatment processes and analysis, and can end up accumulating and requiring more storage space than the base data. In addition, the enormous amount of information, as it increases over time, can lead to the loss of the link between the processed data, the methods of treatment used, and the analysis performed, so that eventually all becomes simply a huge repository of biometric data, devoid of meaning and sense. Current approaches around the concept of big data, while take over the storage and other aspects such as information search mechanisms, are far from incorporating metadata about the neurophysiological and emotional records. This type of information requires the construction of chronologies of events, including the methods of processing and analysis. In addition, it is required to maintain an adequate link between those responsible for the data (those who recorded and analyzed) and subjects that are under investigation, without breaking confidentiality to which they are entitled. This paper presents an approach founded in a data model that can adequately handle different types of chronologies of physiological and emotional information, ensuring confidentiality of information according to the experimental protocols and relevant ethical requirements, linking the information with the methods of treatment used and the technical and scientific documents derived from the analysis. Because the information coming from the original data will be associated with the methods of treatment to which they were subjected and with the results stored permanently, it is not necessary to repeat analysis with equivalent requirements, ensuring a better use of CPU and memory computer resources. Consequently, the need to generate specific data model is justified by the fact that the tools currently associated with the storage of large volumes of information are not able to take care of the semantic elements that make up the metadata and information relating to the analysis of base records of physiological information.**

Index Terms-Data Models; Big Data; EEG Data Organization; fisiological information, metadata

I. INTRODUCTION

Understanding the mechanisms of human reasoning and brain functioning is a central topic in neuroscience [16] [17] [18] [29]. Technological development has multiplied alternatives of technological tools to record brain activity. In turn, the development of computers has created new opportunities for processing and analyzing the data through different tools [19] [20] [21]. Moreover, the greater availability and lower prices of technology allows researchers to access many instrumental that was previously reserved for medical specialists, allowing researchers also raised new objectives and scientific concerns.

As a result, in addition to the generation of new knowledge, there has been a huge growth in the quantity of EEG records, generating huge volumes of research data and clinical centers worldwide. The enormous size of these records, evidence that it is a collection of large volumes of data in the field of big data, which to be registered in computer systems, requires enormous storage media, which escape the most feature traditional computer systems.

The origin of the electroencephalogram, an instrument that allows the capture of signals known as EEG, date back to 1875 when Richard Caton first detected electrical activity in the brain surface of animals [22].

The expanding use of this technology beyond the traditional medical field, occurs only in the last decades together with new quantitative approaches (qEEG) allowing a deeper data comprehension beyond qualitative characterizations. [23].

The potential to use this technology spans multiple areas, such as neuromarketing [24], education [25], psychology [26], labor relations [27] and work [28].

II. PROBLEMS ON THE EEG DATA MANAGE

Regarding the different factors related to storage, organization, processing and analysis of EEG records, it is clear that this is a complex problem of data management. Indeed, the management of such data is subject to the following conditions of context:

- Constant and often excessive amount of growth data.
- Great accumulation of metadata generated in the processing and analysis of raw records.
- Loss of the meaning of information as a result of growth in the amount of data that over time hidden links between data, data processing and results.
- Current alternatives to storing and distributing data from the scope of Big Data, are still weak in their ability to include metadata and meaning.
- Many physiological data should be organized according to the time in which they originate, whether as instrumental records or as a result of processing. Therefore, proper management of the timestamps associated with the data is required.
- In order not to incur losses of information and meaning, it is required to manage data in conjunction with information on related research, researchers, experimental people, derived data and results. Moreover, it is necessary to ensure the confidentiality of information.
- Finally, it is necessary to record information about the nature of the data, their growth potential, the way they have been processed and the results of the analyzes performed.

A. *Specificities of EEG data*

The application of ECG in humans, although it is conditioned to the experimental protocols of each investigation, which has management, storage and processing of data concerned, have common characteristics that can be described as follows:

1) Sequences series of values recorded during application of an electroencephalogram (EEG), can be described as a set of analog sequences, called channels, such that each channel corresponds to record one of the electrodes of the electroencephalograph. The number of channels varies according to the instrument.

2) The duration of each record depends on the experimental design and conditions. However, each channel will have the same duration as the remaining channels of the RAW register.

3) The storage format may vary depending on the instrument type. In the case of the data corresponding to this job, they are stored in EDF format [1].

4) Many individual records, such as experimental design and clinical protocol may be required. The length of each record should be as the experiment or clinical study established.

5) Due to the nature of brain activity, and the scope of the EEG technology, RAW records are not completely clean and can be affected by different perturbations, than in the clinical field are called artifacts. The most frequent disturbances are:

(a) Residual noise from the instruments.

(b) Interactions between channels, product shape propagation of brain waves.

(c) Twitching or muscle movements that distort the brain electrical signals and manifest as disturbances in the instrument signal.

B. *The EEG records and treatment in the area of Big Data*

Big Data refers to enormous amounts of unstructured data produced by high-performance applications falling in a wide and heterogeneous family of application scenarios [7]. On the other hand, the problem of big data can be discerned as two distinct problems: Big data collections and Big Data objects [8]. “There are three fundamental issue areas that need to be addressed in dealing with big data: storage issues, management issues, and processing issues” [12] and Big Data features can be summarized as follows: Data volume; Data velocity; Data variety; Data Value and Complexity [12] [10].

The problems in the area of Big Data arise mainly by the needs of scalability, the massive scale of the data, the heterogeneity of information, unstructured data and their distribution across multiple platforms. Resulting in problems of management, storage, portability and processing of information. Because data can be distributed across multiple sites, there are incompatibilities in the interfaces, in the definition and representation of data, which are often connected to the platform containing them. Furthermore, there are many metadata respect of the information and problems arise in the transmission of data over networks [8]. Moreover, "Big Data Also Brings About New Opportunities for discovering new values, Helps us to gain an in-depth understanding of the hidden values, and incurs also new challenges, for example how to effectively organize and manage such datasets" [9].

Advances in information technology (IT), the rapid growth of so-called cloud computing and the Internet of Things (IoT) [9] have increased opportunities to generate and accumulate data, exceeding the capacity of researchers and technology companies to respond to this problem with a systematic and integrated solution. Until 2003, "five exabytes (10^{18} bytes) of data were created by human. Today this amount of information is created in two days. Big Data requires a revolutionary step forward from traditional data analysis, characterized by its three main components: variety, velocity and volume [10]. For solutions of permanent storage and management of large-scale datasets disordered, distributed file systems [24] and NoSQL [25] databases are good choices [9].

McKinsey Global Institute [11], the potential of Big Data is mainly in five sectors: Healthcare, Public Sector, Retail, Manufacturing and Personal Location Data. Moreover, the research trends in the field of Big Data analytics, point to the heterogeneity of the data and subsequent incongruity that occurs in highly unstructured data; the scalability; the combination of RDBMS and NoSQL Database Query Optimization Systems Issues in HiveQ [7].

Experience with EEG records and derived information concerning this work shows that we are in the presence of a problem of massive data rather than a problem of Big Data, however, they share many of the characteristics and problems associated with big data. In fact, the volume of data not only increases, but that each action generates new records or associated metadata that systematically increase storage needs. Moreover, when there is greater availability of instrumental EEG, the growth rate of the volume of data increases linearly in proportion to the increased availability of devices.

Treatment, storage organization and EEG records and their analysis, share the problems inherent of Big Data, in the following aspects:

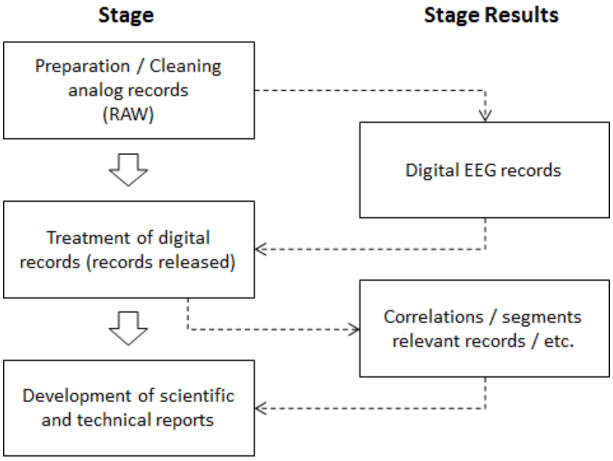
- There are differences between different instruments to capture EEG records and have a high degree of inconsistency.
- The EEG data and its derivatives within the scope of those who is called Big Data Collections [8].
- Although there storage formats for EEG records, such as the European Data Format (EDF), these records are rather unstructured nature. "In order to design meaningful analytics, it is mandatory that big data input sources are transformed in a suitable, structured format" [7].
- EEG records management and its derivatives is a data management problem high scalability. In many types of research, data usually are not discarded but remain stored for future reference, links or reviews.
- EGG data management is fully compatible with the integration of RDBMS, particularly in the management of metadata to facilitate analytical EEG records.

III. STAGES IN THE TREATMENT OF EEG RECORDS

The processing and analysis of EEG data, goes through different stages or states. Initially, after his capture, the EEG records untreated (called RAW) can contain different types of disturbances (artifacts), which should be identified and subtracted from the register, before applying methods of analysis. Then the treatment of previously released data, which will be subjected to different methods, create new records of information (in digital format), which are the input stage of analysis and preparation of scientific reports and clinical report. The different stages being experienced treatment EEG records can be seen in Figure 1.

The following sections provide a brief description of each of the stages or states of the processing and analysis of EEG registrations.

Figure 1: Steps in the treatment of EEG records.



A. *Stage data cleaning*

The aim the cleaning process is the removal of artifacts [2]. The results of the data cleaning process have important effects on EEG records both in its duration as its size. During the process, the analog sequences captured in each of the channels (RAW) are converted to digital streams. Thus, the accuracy and relevance of the digital signal generated will depend on the method parameters that are applied in the purification process.

There are different types of alternative processes for the cleaning of raw records Each EEG record may be subjected to a sequence of various cleaning methods. Some of these results will be discarded during treatment and others will be stored for later analysis. In order to properly interpret the results of the clearance records, you must record the sequence of the methods applied, and the specific values of the parameters that each of the methods was applied.

In the case of EEG records considered in this work, methods and purification processes used are the following:

1) Importing Data: Due to the Emotiv EPOC instrument records the sensor signals in 14 useful channels (called: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 , AF4), a file format of European data format (EDF), the import is done through the built-in tool BIOSIG EEGLAB [3] software. Generally, you must import all channels, but there is the possibility of importing a few.

2) Epoch's selection: It refers to select periods of records that contain events of interest to the investigation, in which people objects of study, they are subject to some kind of stimulus.

At this stage you can also perform other actions considered pre-processing such as changing the sampling rate, filter the data or re-reference them.

B. *Processing and data exploration*

It is understood by data processing, to all actions that aim to inquire into the information contained in the records or derive new information from existing data. There are different methods and techniques that can be used at this stage [4]. The specific order in which they are used, the number of times that it was applied as well as its parameters, depend on the objectives of the research and the findings that researchers performed during the same.

Processing methods according to their purpose and their effect on the data can be classified into:

1) Exploratory methods: Specifically, rather than processing methods they are techniques to explore the characteristics and peculiarities of each EEG record. Generally make use of the help of graphical tools that allow the display of one or more channels, thus forming a better impression and understanding of the records. Including loading and channel display (load and view channel locations), ERP Plotting images, and Plotting Spectra and Maps Channel [4] are frequently mentioned.

2) Methods of processing and generation of macro data: It refers to those methods that act on the data to modify or to generate new data. Within this group are, for example, those for determining the baseline (to avoid skewed by the presence of low frequency artifacts or analysis), ICA using data decomposition [2], work with ICA components, the decomposition time / frequency [4], etc.

C. Formal organization of processing methods and technical documentation

The characterization of a processing method can be represented by a triad $(m\ ,n,\ D)$, where m is the method, n is the quantity of parameters involved in implementing the method and a vector D contains the description of the parameters. Applying a processing method on a specific EEG recording r, can be represented by $(m,\ r,\ t,\ n,\ p)$, such that the vector p contains the specific parameter values that were applied to record r at time t.

Thus, the full processing a record EEG r can be represented as the set:

$$\{\ (m_i,\ r_i,\ t_i,\ n_i,\ p_i)\ /\ i=,\ \ldots,\ k\ \}$$

That is a sequence of k methods applied in a temporal sequence $t_1,\ \ldots,\ t_k$, which denote $P(r)$.
Research process I involves the generation of one or more records for each individual S.
If we represent by $P_S(r)$ the set containing all sequences $P(r)$ associated with n EEG records applied to the subject S, a full investigation will be formed by all

$$\{\ P(r_S)\ /\ s \in I\ \}$$

which denote $I(r)$.

Finally, the results obtained from the analysis of all processing sequences contained in $P_S(r)$ and in all the research $I(r)$, give rise to many technical documents or scientific reports that should be properly cataloged and stored for any use present or future.

Scientific and clinical reports, contains the conclusions of the analysis made in the investigation and therefore should be linked to each of the records and data used in its construction.

IV. Organization, storage and processing of large data sets EEG

It needs to consider the context in which EEG records are recorded, processed and analyzed from multiple investigations; consider that the data from the processing of each of the records are in the presence of a problem of management of complex data, which also requires the coordination and integration of multiple sources of information and technologies. To keep the whole meaning of the information is necessary to include descriptive information concerning research, technical reports, and the conclusions drawn from the records and the various associations that occur between these entities.

The EEGLAB [3] [4] tool has addressed this problem from the standpoint of ease of processing and exploration of the data, but does not provide for integration into the information system of the context in which the records are generated. Neither includes information on technical documents with the conclusions drawn from his treatment.

This paper presents a conceptual model for the organization, storage and processing of EEG records (under the Model Entity / Relationship [5]), which takes over the metadata associated with the problem. Considers context information where records are generated. It takes over the need to store the associations between records, treatment, scientific papers and technical reports, which contain the findings of the analysis developed.

This proposal consists in adding information on the context in which data are generated to information concerning the organization, storage and processing of EEG records This is achieved by a technology-based relational database component, which incorporates contextual information and semantic elements that give meaning to data volumes (Figure 2). Subsequently, on this platform may implement other applications, such as web-based interfaces or other tools that use the metadata system for maintaining and managing the links between different elements of information required to manage information EEG.

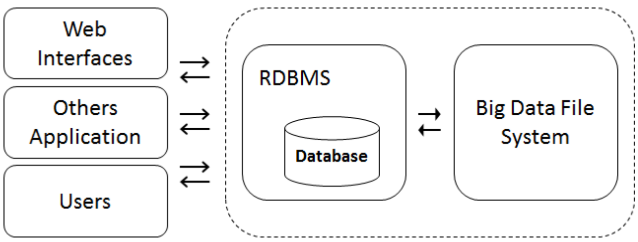


Figure 2: Interaction between system components.

The following sections describe the conceptual data model developed to meet the requirements described previously.

A. *Research, experimental situations, experimental subjects and EEG records.*

It is considered that, in general, an investigation involves different experimental situations, which are applied to different people. This creates a set of EEG records, previously has been called *I(r)*. This situation can be represented by the following scheme:

As shown in Figure 3, the association between research and experience is the type many to many, because a research may involve more than one experimental situation (experience) and in turn, a given experimental situation could be included in more of an investigation. This type of relationship is for example between experience and research in clinical studies where the same experimental situation (diagnostic procedures) is applied to many people. On the other hand, people involved in an investigation or that are subjected to a clinical procedure, they may eventually be required to participate in other research. Because this association between a people (individual) is always present around an experience in the context of a particular investigation, the relationship "includes" is considered a high-level entity which is linked to the experimental individuals, which it is also a many to many.

B. *Methods, processing sequences and settings.*

As previously explained in Section 3.2.1, in the exploration and processing of each EEG record, you can perform a sequence of scans and applying a sequence of processing methods, each associated with a set of timestamps, represented by the following expression:

$$\{ (m_i, r_i, t_i, n_i, p_i) \,/\, i=, \ldots, k \}$$

These timestamps introduced natural chronological order that besides being a historical record of the treatment records, allows us to analyze the strategy analysis and correct it, if necessary. This situation can be represented by the diagram in Figure 4. The application of different methods results in the generation of new data records, which add to existing records. This situation is collected as a reflexive relationship between a high-level entity called "applies" and the entity called "registration" (see Figure 4).

Figure 4: Relationship between methods, sequences and settings.

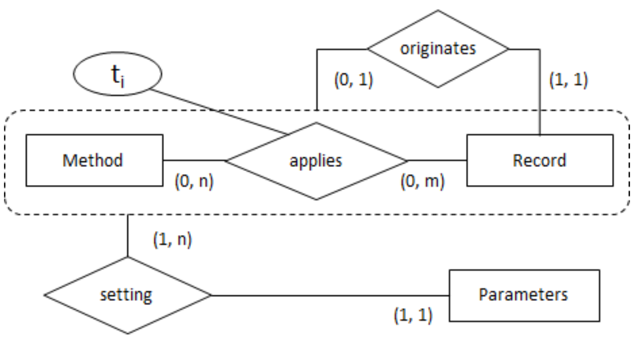
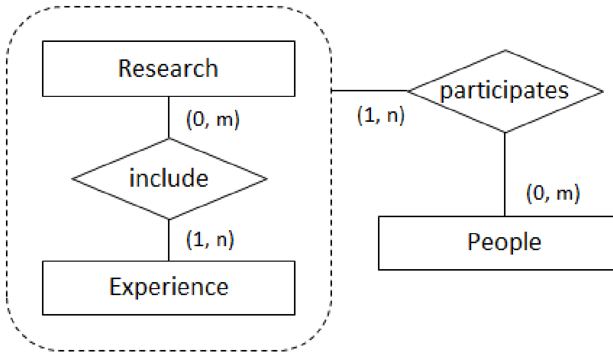


Figure 3: Relationship between research, experimental situations (experiences) and people (individuals).



C. *Management of technical reports.*

It is considered that, in general, an investigation involves different experimental situations, which are applied to different people. This creates a set of EEG records, previously has been called *I(r)*. This situation can be represented by the following scheme:

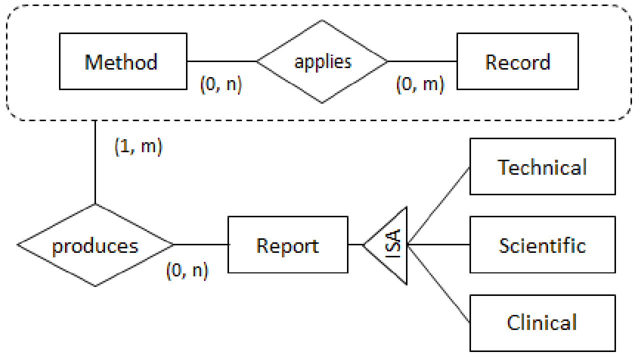
The processing of EEG records, either through exploratory methods or data processing allows to obtain derived information that is the basis of the conclusions contained in the technical and scientific reports. The preparation of the documents can take information from many records corresponding to a specific research process or multiple investigations, reason that is it necessary to link the EEG records all the scientific / technical reports involved.

A data model level, this situation is reflected in the following manner:

D. *Overview of the model for the management, storage and processing of EEG records.*

Integrating all requirements and model components described in the preceding paragraphs, the conceptual data model is presented in Figure 6. In this scheme attributes have not been incorporated, in order to not affect the understanding of it.

Figure 5: Linking methods, records and technical reports / scientists.



This data model aims to implement a database (with documentary features), to incorporate contextual information and references to the physical location where the data is stored (URL). Specifically, the purpose of the database is as follows:

1) Integrate records and metadata to facilitate the analytics EEG records and derived data.

2) Establish a catalog of EEG records, scientific and technical documents as well as from the investigation.

3) Allow the generation of a system capable of recording the activities of research centers and evolve if necessary.

4) Allow the development of tools for analysis and processing of data, which are made in the context of the system, automatically integrating partial and final results of interest to research centers.

E. Logical Design.

To facilitate the implementation of the model in any relational platform and therefore the portability of applications that make use of it, in Figure 7 shows the logical design of the conceptual model. The logic model includes only part of the attributes that are required for its implementation, in order to highlight the most important features of the research data and scientific / technical reports, which must be r managed through this database.

V. CONCLUSIONS

The growing need to store large amounts of information relating to various areas of human and scientific work, has prompted different approaches and approaches related to the storage of information, is now called Big Data. Although these proposals address many of the problems associated with the storage, access and distribution of information on computer media, they do not have sufficient tools to manage the semantic elements of the stored information, which is specific to each problem type. In the case of EEG records and

Figure 6: System Overview

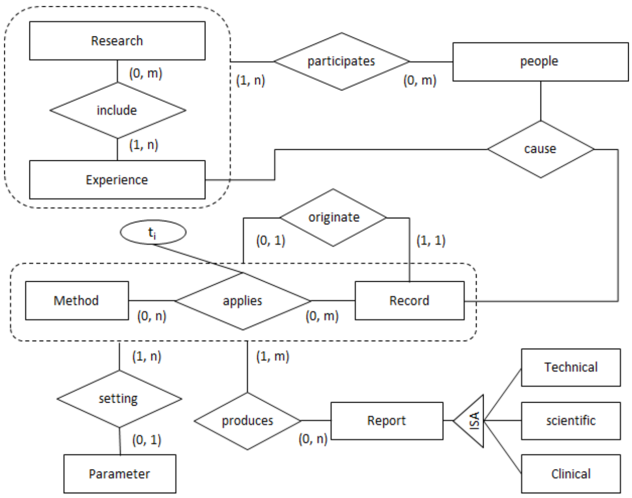
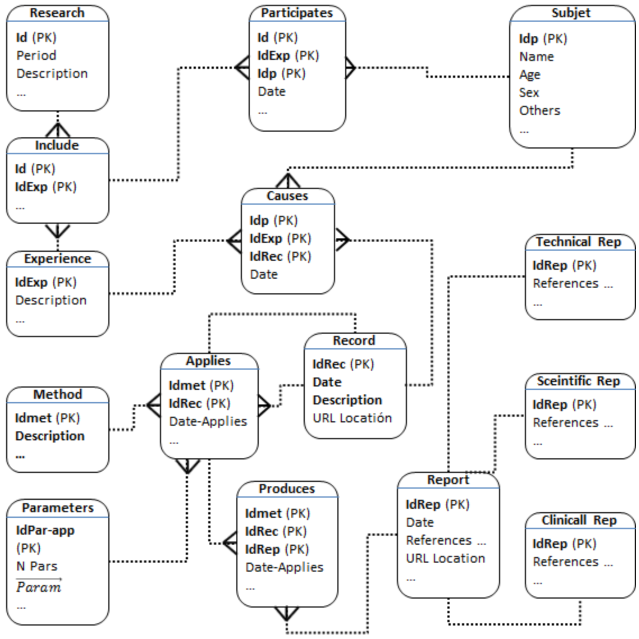


Figure 7: Relational implementation of the conceptual model



technical and scientific reports, it is required of mechanisms for the organization, storage and processing of data, allowing the integration of the various elements of information contained in the records and mainly those generated from their treatment.

Current developments in the area of storage [13] [14] provide an alternative for managing large volumes distributed in different storage media, which however are limited by the heterogeneity of the different types of data. Proposals made in this document provide a solution for these semantic constraints in the context of specific data, by integrating other technologies, such as database services (DaaS) [15] [7], which also allow manipulation of metadata and integrate different types of information, enabling the development of applications and interfaces that automate the recording and metadata generation. In addition, the technology database allows inherit mechanisms to ensure the confidentiality of information regarding experimental subjects, the analysis and conclusions of the records, research and researchers.

In this scenario the data model proposed is able to leverage solutions in the field of Big Data, incorporating semantic elements that enable researchers and technical staff not to lose control over data and new knowledge derived from them. The data model becomes a significant interface between the information processing methods, facilitating data analysis and generation of conclusions. Moreover, the increased availability of metadata and recording timestamps on different moments related to the processing, analyzing and drawing conclusions, promote more efficient use of computing resources by decreasing the need to reprocess data unnecessarily when those results are registered for the system level.

Finally, the use of technologies of conventional databases available in the field of free software or proprietary contributes to greater integration of information value in the new scenario underlying the current developments in the field of human computer interfaces in science and Medicine.

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References

[1] “European Data Format (EDF)”. [En línea]. Disponible en: http://www.edfplus.info/. [Accedido: 17-nov-2015].

[2] T.-P. Jung, C. Humphries, T.-W. Lee, S. Makeig, M. J. McKeown, V. Iragui, y T. J. Sejnowski, “Removing electroencephalographic artifacts: comparison between ICA and PCA”, 1998, pp. 63–72.

[3] A. Delorme y S. Makeig, “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis”, Journal of neuroscience methods, vol. 134, nº 1, pp. 9–21, 2004.

[4] “EEGLAB Tutorial: Table of Contents”. [En línea]. Disponible en: http://sccn.ucsd.edu/eeglab/eeglabtut.html.

[5] Chen, Peter (March 1976). "The Entity-Relationship Model - Toward a Unified View of Data". ACM Transactions on Database Systems 1 (1): 9–36.

[6] E. F. Codd, “A relational model of data for large shared data banks”, Communications of the ACM, vol. 13, nº 6, pp. 377–387, 1970.

[7] A. Cuzzocrea, I.-Y. Song, y K. C. Davis, “Analytics over large-scale multidimensional data: the big data revolution!”, en Proceedings of the ACM 14th international workshop on Data Warehousing and OLAP, 2011, pp. 101–104.

[8] M. Cox y D. Ellsworth, “Managing big data for scientific visualization”, en ACM Siggraph, 1997, vol. 97, p. 21.

[9] M. Chen, S. Mao, y Y. Liu, “Big Data: A Survey”, Mobile Networks and Applications, vol. 19, nº 2, pp. 171–209, abr. 2014.

[10] S. Sagiroglu y D. Sinanc, “Big data: A review”, en Collaboration Technologies and Systems (CTS), 2013 International Conference on, 2013, pp. 42–47.

[11] J. Manyika, M. Chui, B. Brown, J. Bughin, R. Dobbs, C. Roxburgh and A.H. Byers, "Big data: The next frontier for innovation, competition, and productivity", McKinsey Global Institute, 2011.

[12] S. Kaisler, F. Armour, J. A. Espinosa, y W. Money, “Big Data: Issues and Challenges Moving Forward”, 2013, pp. 995–1004.

[13] Zikopolous Paul, Deroos Dirk, Deutsch Tom, Lapis George, Understanding Big Data: Analytics for Enterprise Class Hadoop and Streaming Data, McGraw-Hill, 2012.

[14] “HPCC Systems”. [Online]. https://hpccsystems.com/.

[15] H. Hacigümüs, B. Iyer, y S. Mehrotra, “Providing database as a service”, en Data Engineering, 2002. Proceedings. 18th International Conference on, 2002, pp. 29–38.

[16] B. B. Biswal, M. Mennes, X.-N. Zuo, S. Gohel, C. Kelly, S. M. Smith, C. F. Beckmann, J. S. Adelstein, R. L. Buckner, S. Colcombe, A.-M. Dogonowski, M. Ernst, D. Fair, M. Hampson, M. J. Hoptman, J. S. Hyde, V. J. Kiviniemi, R. Kotter, S.-J. Li, C.-P. Lin, M. J. Lowe, C. Mackay, D. J. Madden, K. H. Madsen, D. S. Margulies, H. S. Mayberg, K. McMahon, C. S. Monk, S. H. Mostofsky, B. J. Nagel, J. J. Pekar, S. J. Peltier, S. E. Petersen, V. Riedl, S. A. R. B. Rombouts, B. Rypma, B. L. Schlaggar, S. Schmidt, R. D. Seidler, G. J. Siegle, C. Sorg, G.-J. Teng, J. Veijola, A. Villringer, M. Walter, L. Wang, X.-C. Weng, S. Whitfield-Gabrieli, P. Williamson, C. Windischberger, Y.-F. Zang, H.-Y. Zhang, F. X. Castellanos, y M. P. Milham, “Toward discovery science of human brain function”, Proceedings of the National Academy of Sciences, vol. 107, nº 10, pp. 4734–4739, mar. 2010.

[17] A. Paul Alivisatos, Miyoung Chun, George M. Church, Ralph J. Greenspan, Michael L. Roukes, and Rafael Yuste, “The Brain Activity Map Project and the Challenge of Functional Connectomics”, Neuron 74, June 21, 2012.

[18] Monti, M. M., Parsons, L. M., & Osherson, D. N. (2009). The boundaries of language and thought in deductive inference. Proceedings of the National Academy of Sciences, 106(30), 12554-12559.

[19] Evan Heit, Brain imaging, forward inference, and theories of reasoning, Frontiers in Human Neuroscience, January 2015, Volume 8, Article1056.

[20] Vinod Goel, Brian Gold, Shitij Kapur, and Sylvain Houle, The seats of reason? An imaging study of deductive and inductive reasoning, NeuroReport 8, 1305–1310 (1997)

[21] Ranjit A. Thuraisingham, Georg A. Gottwald, On multiscale entropy analysis for physiological data, Physica A: Statistical Mechanics and its Applications, Volume 366, 1 July 2006, Pages 323–332.

[22] Hass LF (2003) Hand Berger (1873-1941), Richard Caton (1842-1926), and electroencephalography. Journal of Neurology, Neurosurgery and Psychiatry 74 (1):9. doi:10.1136/jnnp.74.1.9.

[23] (Kececi H, Y Degirmenci (2008). Quantitative EEG and cognitive evoked potentials in anemia. Clinical Neurophysiology 38(2): 137-143. doi:10.1016/j.neucli.2008.01.004.).

[24] Rami N. Khushaba, Chelsea Wise, Sarath Kodagoda, Jordan Louviere, Barbara E. Kahn, Claudia Townsend., Consumer neuroscience: Assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking, Expert Systems with Applications 40 (2013) 3803–3812.

[25] Díaz, Hernán, L. Cañete, F. Palominos, C. Costa y F. Córdova., Neurotechnologies for Education Improvement: Self-Knowledge After Opening the Black-box, Conference Proceedings of the International Symposium Research and Education in Innovation Era. ISREIE, 4th Edition Arad. Journal Plus Education, ISSN: 1842-077X, E-ISSN (online) 2068 – 1151 Vol VIII (2012), No. 2, pp 44 - 52

[26] Paul Howard-Jones, Andrew Pollard, Sarah-Jayne Blakemore, Peter Rogers, Usha Goswami, Brian Butterworth, Eric Taylor, Aaron Williamon, John Morton and Liane Kaufmann, Neuroscience and Education: Issues and Opportunities, TLRP Teaching and Learning Research Program; ESRC Economic and Social Research Program. University of London ISBN: 0-85473-741-3.

[27] Maria Kozhevnikov, Cognitive Styles in the Context of Modern Psychology: Toward an Integrated Framework of Cognitive Style, Psychological Bulletin, Vol. 133, No. 3, 464 – 481

[28] Matthew D. Lieberman, Social Cognitive Neuroscience: A Review of Core Processes, Annu. Rev. Psychol. 2007. 58:259-289. Downloaded from arjournals.annualreviews.org

[29] Raja Parasuraman, George Mason and Glenn F. Wilson, Putting the Brain to Work: Neuroergonomics Past, Present, and Future, Human Factors, Vol. 50, No. 3, June 2008, pp. 468–474. DOI 10.1518/ 001872008X288349.