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Percolation theory for the recognition of patterns in topographic images of the cortical activity

Francisco Gerson A. de Meneses[a,c,*], Gildário Dias Lima[a], Monara Nunes[a], Victor Hugo Bastos[a,b,c], Silmar Teixeira[a,b,c]

[a] *Neuroinnovation Technology & Brain Mapping Laboratory, Federal University of Piauí, Parnaíba, Brazil*
[b] *Master Program in Biotechnology, Federal University of Piauí, Parnaíba, Brazil*
[c] *The Northeast Biotechnology Network, Federal University of Piauí, Teresina, Brazil*

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ABSTRACT

Electroencephalogram (EEG) is one of the mechanisms used to collect complex data. Its use includes evaluating neurological disorders, investigating brain function and correlations between EEG signals and real or imagined movements. The Topographic Image of Cortical Activity (TICA) records obtained by the EEG make it possible to observe, through color discrimination, the cortical areas that represent greater or lesser activity. Percolation Theory (PT) reveals properties on the aspects of fluid spreading from a central point, these properties being related to the aspects of the medium, topological characteristics and ease of penetration of a fluid in materials. The hypothesis presented so far considers that synaptic activities originate in points and spread from them, causing different areas of the brain to interact in a diffusive associative behavior, generating electric and magnetic fields by the currents that spread through the brain tissue and have an effect on the scalp sensors. Brain areas spatially separated create large-scale dynamic networks that are described by functional and effective connectivity. The proposition is that this phenomenon behaves like a fluidic spreading, so we can use the PT, through the topological analysis we detect specific signatures related to neural phenomena that manifest changes in the behavior of synaptic diffusion. This signature must be characterized by the Fractal Dimension (FD) values of the scattering clusters, these values will be used as properties in the k-Nearest Neighbors (kNN) method, an TICA will be categorized according to the degree of similarity to the preexisting patterns. In this context, our hypothesis will consolidate as a more computational resource in the service of medicine and another way that opens with the possibility of analysis and detailed inferences of the brain through TICA that go beyond a simply visual observation, as it happens in the present day.

Introduction

Following the technological advances, computational techniques have become crucial for the interpretation and analysis of complex data, such as those generated by brain functioning and neural plasticity [1] speech recognition [2], classification of behavioral states [3,4] other issues of mental health and neural networks [5–7]. The electroencephalogram (EEG) is one of the mechanisms used to collect these complex data, applied to evaluate neurological disorders, investigate brain function and correlations between EEG signals and real or imaginary movements [8]. The Topographic Image of Cortical Activity (TICA) records obtained by the EEG [9] make it possible to observe, through color discrimination, the cortical areas that represent greater or lesser activity [10,11].

However, the search for interpretations and/or diagnoses from the computational data results from biological phenomena, it is sometimes difficult, due not always to these results, to present images with a detectable symmetry to the eyes nor in patterns of shape or color. This has led to the attempt to develop software for the analysis of signatures of these patterns [12–15], including the use of Artificial Intelligence techniques [16,17]. According to the study of [18], Artificial Neural Networks (ANN) are used for the recognition and classification of Magnetoencephalography (MEG) assays associated with the perception of different graphic objects. In this case, the objects used were Necker cubes, the comparison of mean RNA results along with their standard deviation in multiple experimental sessions allowed access to some

* Corresponding author at: Francisco Gerson Amorim de Meneses, Federal University of Piauí, Av. São Sebastião, 2819, Bairro São Benedito, Parnaíba, Piauí CEP: 64202-020, Brazil.
E-mail address: gerson@ifpi.edu.br (F.G.A. de Meneses).

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important characteristics of the interpretation of these objects, including distinguishing states of certainty and doubt in the human brain, particularizing characteristics of the decision making process. However, the work of [19] takes notes the recognition of patterns in EEG and electrocardiographic (ECG) signals of patients with focal epilepsy. We analyzed biosynthesis before the onset of seizure and in periods without seizures, the methodology used considers the generation of characteristics computed on the discrete Wavelet transform of the EEG signal and others related to the variability of the heart rate in the ECG signal. We concluded that through machine learning algorithms one can predict the outset of epileptic crisis.

Albeit the science has advanced in the development of new tools for analysis of the patterns of neural phenomena [20–22], yet a technique for analyzing these patterns has not been developed using Percolation Theory (PT) on TICA obtained by the sign of EEG. According to [23], PT is one of the simplest and most fundamental models in the mechanics of phase transitions and statistical analyzes, showing the emergence of a component, hyperconnected percolated cluster, despite its very simple rules, PT was applied successful in describing a wide variety of natural, technological and social systems. Also on PT [24], says that: PT reveals properties on the aspects of fluid spreading from a central point, being these properties referring to the aspects of the medium, topological characteristics and ease of penetration of a fluid in materials. In this context, we present the hypothesis of the use of PT as the basis for the detection of signatures of neural phenomena in TICA. We understand that when applying the PT one can particularize models of disordered systems from their fractal structure, in this specific case, these signatures will be inferred according to the color spreading patterns in the TICA. The percolation clusters encompass different substructures, each defined by its own fractal dimension [25–27]. The PT applied to the fractal dimension calculation can categorize clusters, including segmented images [28,29]. The recognition of the pattern will be done through the application of the kNN method, which is a supervised learning technique used in the area of Data Mining (DM) and Machine Learning (ML), Artificial Intelligence (AI) subarea [30–32]. This way, a TICA is categorized by considering its fractal values and according to the degree of similarity to pre-existing TICA standards.

Therefore, we can find neural signatures in TICA provided by electroencephalographic signal analysis software. Based on our hypothesis, we can construct indirect signatures, not understood with topographic visual inspection, but rather, the light of the scattering results of the PT, identifying patterns of behavior and general properties of the TICA.

Hypothesis

The hypothesis here presented considers that synaptic activities that originate in specific points and spread from them, causing different areas of the brain to interact in a diffusive associative behavior. Electric and magnetic fields are generated by the currents that propagate through the brain tissue and produce effect on the scalp sensors [33]. Spatially separated brain areas form large-scale dynamic networks that are described by functional and effective connectivity [34]. The proposition is that this phenomenon behaves like a fluidic spreading, so we can use the PT, through the topological analysis we detect specific signatures related to neural phenomena that manifest changes in the behavior of synaptic diffusion. This signature must be characterized by the FD values of the scattering clusters. These values will be used as properties in the kNN method. The kNN works by sorting the input elements according to the data closest to their characteristics. The closest observations are defined as those with the smallest Euclidean distance to the point on consideration [35].

Our hypothesis has as base the principle of PT, which can support the process of quantification and classification of images in diagnostic support systems, with information about possible grouping characteristics (clusters) presented in images [29]. We understand that due to

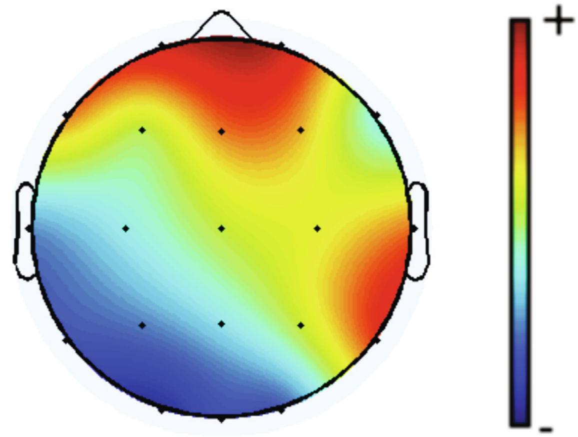

Image 1. Topographic Image of Cortical Activity (TICA) obtained with the EEGLab software. A color gradient is observed along with the variation from red to blue, representing respectively the occurrence of the highest to the lowest cortical activity.

TICA be represented by EEG power activity in specific cortical areas and visualized in color ranging from greater cortical activity (red) to lower cortical activity (blue) as seen in Image 1. Said that, PT can be used to subsidize recognition of the pattern of cortical activity, since the scattering of colors in the clusters correspond to the topological structure [36]. The PT is the simplest model of disordered systems that has fractal structure, percolation clusters encompass different substructures, each defined by its own FD [37]. A fractal measure is considered as something very irregular to fit the classical geometry [38]. In this context, the use of PT in the display of fractal structures can characterize the geometric signature [39] and categorize neural phenomena. In this case, the calculation of FD in each cluster of TICA may represent these irregular and fragmented (non-Euclidean) patterns [37]. Therefore, by analyzing the clusters through the perimetric surfaces of the TICA, we will obtain the FD of each cluster, these values will be used as properties for the use of the kNN method and through supervised machine learning to infer about the recognition of pattern of a given TICA.

Thus, the hypothesis for the development of an algorithm to obtain patterns of cortical activity with the use of PT and FD may exceed the knowledge frontier. This occurs due to the process of forming the topological structure and the distribution of colors in a TICA to present an evolution in the computational analysis of colored images from biological phenomena, as is the case of EEG data. For the viability of this process, each TICA will be represented by 3 clusters, each one prevailing one of the channels of the RGB colors system (red, green and blue) as observed in Image 2. The processing of the algorithm will start having a TICA as input (a); following by applying PT (b) the image will be segmented into three RGB clusters (c); after calculating the radius and the center of mass (d) the logarithmic properties of the radius and the center of mass will be used to obtain the values for RGB (d). The 3 fractals (e) of each TICA will be used by the kNN as parameters for the calculation of the Euclidean distance, and thus recognize the TICA pattern input.

Hypothesis evaluation

Studies demonstrate that the foundations of PT allied or not with FD provide the resources to establish standards in several areas of knowledge [40–42]. In medical science and biology, fractal properties have been reported in several cases [43]. In [44], it is observed that the percolated nature of the tumor vasculature implies that the vascular networks of the tumor have architectural obstacles inherent in the release of diffusible substances, such as oxygen and drugs. Also based on TP, another study shows that tumor diffusion and invasion of

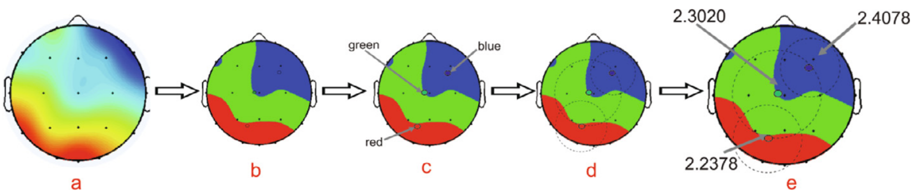

Image 2. Sequence showing the obtaining of the fractals of a TICA. By applying the kNN method, this TICA will be classified and the inference will occur according to the preexisting patterns.

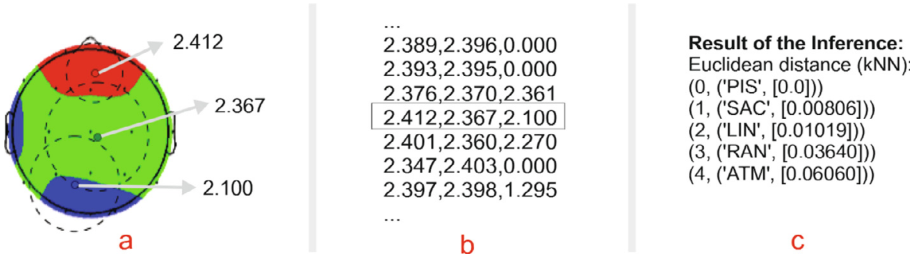

Image 3. In (a) we have the input TICA and its fractals, (b) some of the values representing the preexisting patterns and finally (c) the result of the inference through supervised learning, showing the Euclidean distance with the kNN method, classifying the entry TICA in each of the 5 proposed artifacts.

surrounding host tissue is positively correlated with tissue homogeneity [45]. A percolation model in a square (two-dimensional) network was applied to study magnetic resonance imaging (MR) by capturing contrasts and its fractal structure, the authors concluded that the blood perfusion in a network of two-dimensional tumor vessels has a fractal structure, regardless of type and tumor size [37]. Besides, a study using FD suggests that mitochondrial inhibition may be an effective and selective therapeutic strategy in mesothelioma, and identifies mitochondrial morphology as a possible predictor of response to targeted mitochondrial inhibition [46]. Further on being a tool for the diagnosis of breast, lung and brain cancer, and one of the parameters to reflect the microstructure of a clot [47].

Until then, the percolation techniques, when applied to digital images, were limited to binary or grayscale images. In 2017, [29] they developed a method to quantify and classify color images of non-Hodgkin lymphomas (NHL) based on PT. They used the values of the ROC curve (AUC), demonstrating that percolation is suitable for application as a complementary measure for other fractal based characterization methods. In this study it was observed that the technique improves the differentiation between different classes of NHL.

Regarding kNN, several studies [48–50] present the use of the method for the classification of data related to medical science. Particularly, in relation to fractals extracted from medical images, we can mention the study of [51], in which kNN was introduced and studied as a precise method to estimate the fractal dimension of images, the proposed method was used to differentiate carotid atheromatous plaques symptomatic and asymptomatic. Also related to carotid plaques, in [52] is presented a computer-assisted system using multi-faceted texture analysis, neural network classifiers, kNN statistical classifier, and pattern recognition techniques for the automated characterization of carotid plaques recorded from ultrasound imaging. In both, good results were obtained using the kNN method.

We understand that in order to test our hypothesis, it is convenient to include 1000 (one thousand) TICA from individuals that during EEG collection will perform movements to produce artifacts: eye blinking, saccadic movement, tongue movement, atm and grinding of teeth, with a total of 200 TICA for each artifact above. There should then be 5 TICA patterns that will be used to classify the input TICA through the kNN method, as seen in Image 3.

Hypothesis consequence and discussion

Using of computational resources for diagnostic assistance is a reality that is increasingly observed today in the neurological area, recent studies support this assertion [53–56]. The use of computational resources optimizes the obtaining of diagnoses and consequently accelerates treatments, as well as the prevention of diseases. For example [57] presents a software used to investigate the utility of Diffusion Tensor Image (DTI) as a marker for white matter damage in small vessel disease and to assess its correlation with cognitive function. The study has shown promise as a useful tool to explore the mechanisms of cognitive dysfunction in this disease and has the potential to be used as a surrogate marker in therapeutic trials. Though in [58], it is presented a system of diagnosis and treatment of vision (VisDaT) that is intended to help therapists in the diagnosis and appropriate treatment of disparities of vision in children with cerebral dysfunctions. This uses a computer connected to two monitors and equipped with specialized software, the system encourages the children's vision with a dedicated stimulus and post hoc analyzes of recorded sessions that allow decisions to be made regarding future treatment. In this context, our hypothesis will consolidate as a more computational resource in the service of medicine and another way that opens with the possibility of analysis and detailed inferences of the brain through TICA that go beyond a simply visual observation, as it happens in the present day and this characterizes itself as an advantage. It should be noted, however, that in supervised machine learning systems, such as the one presented in this work with the kNN method, the success of the input TICA inference will depend on the pre-existing standards already stored.

Author contributions

Francisco Gerson A. de Meneses designed and developed the hypothesis. He wrote the initial manuscript. Silmar Teixeira, Gildário Dias Lima, Victor Hugo Bastos and Monara Nunes helped with editing, reviewing, scientific input, and final presentation.

Conflict of interests

The authors report no conflict of interest.

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