Evidence of neural areas related to reading tasks- using Information Theory

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Abstract. To be done!

1 Experimental Set-up

This methodology has been proposed to estimate the areas with the most activity on the scalp, when tasks of reading neutral texts and motor texts are carried out, our proposal is based on the symbolization of the dynamics by means of motifs and later the estimates of permutation entropy and Renyi's Entropy. This methodology was tested on the raw data (EEG), then temporary information was included from the EEG by means of time windowing and finally information was included in time and frequency simultaneously, through the representation of Wigner-Ville.

Hyphothesis: When a person performs reading of texts containing motor verbs, there is an outstanding activity in the area of the head related to movement (Motor cortex), in comparison with the reading of neutral texts.

Our contribution: Highlight the areas of the head that are most relevant when the reading process of motor and neutral texts is done. In addition, include information from time and time-frequency in the estimation of the meaning-full areas.

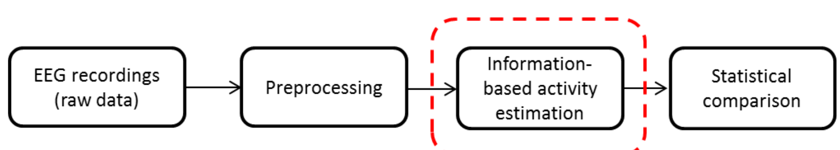

Fig. 1: *Scheme of the proposed methodology for estimating brain activity using symbolic transformation and entropy. The blocks marked in dashed lines are the subject of present study.*

Figure 1 shows the main scheme of the proposed methodology. The first task that is carried out is the preprocessing of the data, in which the interferences are eliminated and also a filtering is made between 5Hz and 45Hz. later, the symbolic transformation is carried out. Then, the brain activity estimation based on entropy is carried out, then the comparison between the estimated neuronal activity for neutral texts and for motor texts is carried out. Finally, a paired t-test is applied, and the channels in which the comparison of means is greater are taken into account, for p-values lower than $\rho = 0.05$. This study is done for the database with all the subjects and for the set of subjects with similar reading time.

1.1 Database description

The database consists of 32 subjects, of which only 26 were chosen due to acquisition problems. The recordings were measured with a BIOSEMI EEG-device of 128 channels. The sampling frequency of the device was 1KHz. Each recording of EEG was measured continuously and contains two labels belonging to two tasks and the the corresponding markers at the start of the tasks.

The first task corresponds to the reading of the *neutral text* and the second related to *motor text* reading. The task of reading neutral text corresponds to texts that contain verbs not related to movement, while the motor text includes verbs that suppose some movement, each EEG recording lasts approximately 60 seconds. All the reading tasks were carried out in silence, without the pronunciation of words and was carried out by people with different levels of education in both Spanish and English.

The signal was preprocessed in order to replace defective channels that had acquisition failures,The bad channels were replaced with spherical interpolation statistically weighted on the basis of all sensors and then the variance of the signal across trials was calculated to guarantee the stability of the averaged waveform [Courellis et al., 2016]. After this, the signal was sub-sampled, which resulted in records sampled at 256Hz. In addition, the data were taken to the same reference, using common average. Finally, all records were filtered between 5Hz and 45Hz.

1.2 k and τ selection for the symbolic transformation

The embedding dimension $k = 3$ and the time lag $\tau = 1$ was selected, which has been studied in several works [Olofsen et al., 2008,**?**],since for practical purposes $k = 3$, provides the balance between a good representation of the signal and low computational cost, because the number of permutations is increased by $k!$. In this study there were no significant spatial differences for values of $k = 4$ y $k = 5$ but the computational cost was increased. Exploratory data analysis showed that the use of longer motifs did not contribute to a better descripcion del EEG.

1.3 λ selection in Renyi's entropy

- Renyi's entropy measure is much more flexible due to the parameter λ, enabling several measurements of uncertainty (or dissimilarity) within a given distribution.
- Because H2 is a lower bound of Shannon's entropy, it might be more efficient than Shannon's entropy for entropy maximization.
- Renyi's Quadratic Entropy for $\lambda = 2$
- In particular the argument of the log of quadratic Renyi's entropy can be estimated directly from data with kernels.
- The estimation of λ entropy depends on one free parameter that needs to be estimated from the data structure and controls the bias and variance for finite datasets.

The figure 2 shows the ρ-values for different values of λ in the estimation of Renyi's entropy (for the α rhythm), it can be seen that the best λ value is 2 since the p most reliable values are presented

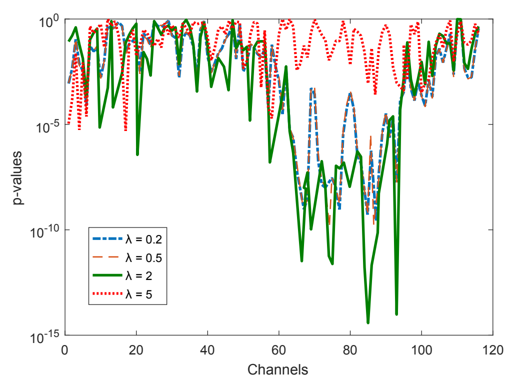

Fig. 2: *Selection of λ in the Renyi's entropy*

For the calculation of λ parameter, it was determined that the best value of H_λ is 2 with windows of 1 second and overlap of 75%, which are enough to properly encode different EEG dynamics [Olofsen et al., 2008].

2 Results

Our methodology is tested on the EEG raw data, then additional time information is included by means of a window on the EEG signal and finally time-frequency information for the selection of channels with the greatest contribution on the reading task. In all cases, the symbolic transformation is made, later the entropy calculations by means of permutation entropy and entropy of Renyi.

All the results have been calculated on the rhythms $\alpha - (8Hz - 12Hz)$ and $\beta - (13Hz - 30Hz)$ for the database with all the subjects and for the group of subjects that have reading time similar, this set is made up of 19 of the 29 subjects of the database, in this case the subjects presented in the table 1 have been selected:

DB red. Subj	3	4	5	7	8	9	10	11	12	17	18	19	20	21	23	24	25	26	28

Table 1: *Subjects with similar reading time*

All the figures are presented with topoplots and show the results of the paired t-test, in which the motor text and neutral text readings are compared; after this, the statistical correction of $\rho - values$ is performed using the FDR technique (False Discovery Rate) for controlling the effect of multiple comparisons. In all the figures of the head that will be presented in this document, the red color will represent more activity for the reading of motor text, while the blue color, will represent greater activation for the reading of neutral text, according to the results provided by the *paired t-test*.

2.1 Results for Permutation entropy- including time

When Permutation Entropy is used for α and β, including more temporary EEG information by means of the signal windowing,the results of the figures 3 and 4 are obtained, in which greater activity is presented in the parietal and occipital lobes for the reading of motor text (represented by the red color), and there is greater activity in the frontal lobe for the reading of neutral texts (marked in blue). There are no differences between the complete database and the set of subjects with similar reading time, this behavior occurs in α and β rhythms. Permutation entropy is the temporal information contained in the time series and has the qualities of simplicity, robustness, and low computational cost[Borowska, 2015]

2.2 Results for H_λ including time

if we take into account that the entropy of an EEG channel is a measure of uncertainty, where the EEG signal is considered as a random variable [Alotaiby et al., 2015], [Borowska, 2015] when we apply short-time windowing technique to EEG signals and we take into account that the EEG signal can be stationary for short segments of time, activity is found in frontal and prefrontal areas as seen in the figures 5 and 6, but during mental and physical activities this assumption is not valid[Phung et al., 2014]. Because of this, different non-linear approaches such as entropy have gained interest, because entropy is an appropriate measure of randomness, information and uncertainty [Song and Liò, 2010].

(a) *Permutation Entropy for all subjects.* **(b)** *Permutation Entropy for reduced group.*

Fig. 3: *Permutation Entropy for α rhythm including temporal information. Only areas corrected with 5% using FDR are presented.*

(a) *Permutation Entropy for all subjects.* **(b)** *Permutation Entropy for reduced group.*

Fig. 4: *Permutation Entropy for β rhythm including temporal information. Only areas corrected with 5% using FDR are presented.*

(a) *H_λ entropy for all subjects.* **(b)** *H_λ entropy for reduced group.*

Fig. 5: *H_λ entropy for α rhythm including temporal information. Only areas corrected with 5% using FDR are presented.*

2.3 Results for H_λ - including time-frequency

The scheme of selecting the channels, taking into account their contribution in time and frequency, allows us to refine our methodology a bit more, This scheme has been proposed in several previous works, but we have taken as reference the scheme of [Sucic et al., 2014]. With the channels that present the greatest contribution in time and frequency, the symbolic transformation and the entropy calculations are applied.

(a) *H_λ entropy for all subjects.* **(b)** *H_λ entropy for reduced group.*

Fig. 6: *H_λ entropy for β rhythm including temporal information. Only areas corrected with 5% using FDR are presented.*

It can be seen in the figures 7 and 8, the effect of taking into account the time-frequency representation of Wigner-ville, which was estimated for each channel, with 128 bins of frequency to optimize the calculation time associated with the duration of the records.
In these figures it can be seen that for the rhythms α and β there is greater activity on the frontal region, in addition there is a marked activity on the motor area (Figures 7a and 8a) when the entire database is taken into account,however, for the reduced data set, figs. 7b and 8b, it is not possible to determine significant differences for both tasks.

(a) *H_λ for all subjects.* **(b)** *H_λ for reduced group.*

Fig. 7: *H_λ for α rhythm including time-frequency information. Only areas corrected with 5% using FDR are presented.*

(a) *H_λ for all subjects.* **(b)** *H_λ for reduced group.*

Fig. 8: *H_λ for β rhythm including time-frequency information. Only areas corrected with 5% using FDR are presented.*

3 Conclusion and discussion

We propose a methodology to estimate the areas with the most activity on the scalp, when tasks of reading neutral texts and motor texts are carried out. To this end, we aim to compute the symbolic transformation upon the EEG recording and then calculate the permutation entropy and the Renyi's entropy. Nevertheless, the following aspects should be considered:

- The embodiment cognition approach to language claims that understanding words and sentences involves a mental simulation of the objects, events and actions described in the sentences, whereby, it is reasonable to think that the process of reading motor verbs may activate the premotor and motor cortex. This lends support to the neurological embodiment of theories, which defend that linguistic meaning goes beyond the activation of the Broca's and Wernicke's areas [Shebani et al., 2017], involving the activation of other regions in the sensorimotor cortex.[Moreno et al., 2013,Cowley, 2014],as seen in figure 7a.
- A better estimation of brain activity was obtained in the physiologically associated channels with reading and movement tasks, since information was included in time and frequency as can be seen in figures 7 and 8,These results are consistent with those reported in the state of the art by [Moreno et al., 2015], [Moreno et al., 2013],[Tomasello et al., 2017]. However, for the reduced data set, the results are not good, since it is reported that in this class of tasks,since the subject, task, trial, stimulus variability , could affect the selection, affect the areas involved in cognitive and motor processes [**?**], [Melloni et al., 2015].
- Another relevant aspect according to figures 5 and 6 is the comparison of different measures of entropy for the symbolic transformation; the best results were obtained with Renyi's entropy, reason for which, this measurement was used in the selected channels by time and frequency according to the representation of Wigner-Ville, as shown in figures 7 and 8.
- The clinical and theoretical implications mentioned in this study should be tested and validated in other applications and other brain pathologies.

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