EEG Complexity Maps to Characterise Brain Dynamics during Upper Limb Motor Imagery

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Abstract— **The Electroencephalogram (EEG) can be considered as the output of a nonlinear system whose dynamics is significantly affected by motor tasks. Nevertheless, computational approaches derived from the complex system theory has not been fully exploited for characterising motor imagery tasks. To this extent, in this study we investigated EEG complexity changes throughout the following categories of imaginary motor tasks of the upper limb: *transitive* (actions involving an object), *intransitive* (meaningful gestures that do not include the use of objects), and *tool-mediated* (actions using an object to interact with another one). EEG irregularity was quantified following the definition of Fuzzy Entropy, which has been demonstrated to be a reliable quantifier of system complexity with low dependence on data length. Experimental results from paired statistical analyses revealed minor topographical changes between EEG complexity associated with transitive and tool-mediated tasks, whereas major significant differences were shown between the intransitive actions vs. the others. Our results suggest that EEG complexity level during motor imagery tasks of the upper limb are strongly biased by the presence of an object.**

I. Introduction

Understanding the neural bases of upper limb motor control is fundamental not only to give insights on the underpinning brain dynamics organisation but also to contribute to the assessment of pathological conditions (such as stroke), and pave the path towards the design of effective brain-machine interfaces, e.g., in rehabilitation. For such a challenging investigation, it is possible to consider the analysis of the electrical activity of the human cortex as the output of a nonlinear dynamical system characterised by complex dynamics [1].

Among others, entropy measures are among the most commonly used quantifiers for a dynamical system complexity. Entropy has been successfully applied to Electroencephalographic (EEG) series for the characterisation of brain dynamics in health and disease, including newborns [2], schizophrenia [3], drug abuse [4], epilepsy [5] and Alzheimer's diseases [6]. Particularly, increased EEG complexity was found during different kinds of cognitive tasks [7], [8], whereas a decreased EEG complexity has been associated with working memory tasks [9]. Furthermore, a direct relationship between the difficulty level of a cognitive task and EEG signal complexity was reported [10].

Starting from the definition of Approximate Entropy (ApEn) [11], further refinements on its calculation have been proposed. It is worthwhile mentioning the so-called Sample Entropy (SampEn) [12], Permutation Entropy [13], Conditional Entropy [14], and the more recent Fuzzy Entropy (FuzzyEn) [15], [16], whose approach relies on the use of fuzzy theory as embedded within the traditional SampEn algorithm [15]. More specifically, it is based on fuzzy membership functions, i.e., a family of exponential functions providing (fuzzy) boundary for similarity measurements, which are smooth compared with standard more rigid solutions, e.g., the Heavyside function. Furthermore, FuzzyEn was demonstrated to show better properties as continuity, less biasing, broader possibility on parameter selections, and robustness to noise in comparison with standard ApEn and SampEn [17]. Such positive aspects come with a cost, since FuzzyEn needs one additional parameter compared to ApEn and SampEn. Indeed, it is a function not only of the length of the time series, the embedding dimension, the similarity tolerance, but also the gradient of the boundary of the fuzzy membership function.

While previous studies have investigated EEG complexity changes during visual, memory, and other cognitive tasks, they failed to characterise brain complexity during motor imagery tasks especially referring to the upper limb. To this end, we studied changes in EEG complexity as estimated through FuzzyEn measures among three different classes of upper limb motor imagery tasks: *transitive* (actions involving an object), *intransitive* (meaningful gestures that do not include the use of objects), and *tool-mediated* (actions using an object to interact with another one) [18]. These movement categories were proven to be associated with distinct neuroanatomical correlates [19], [20], being especially useful for the characterisation of apraxia, i.e., a syndrome characterised by the subject's inability to perform routine gestures [21]. Furthermore, distinct neural correlates of transitive, intransitive, and tool-mediated actions have been recently identified using functional magnetic resonance imaging analysis [22].

Here, we show experimental results gathered from thirty-three healthy subjects enrolled in the frame of the European project SoftPro (Synergy-based Open-source Foundations and Technologies for Prosthetics and RehabilitatiOn), who underwent EEG acquisitions during the imagination of motor acts. Methodological details, as well as results and conclusions follow below.

This research has received funding from the European Union's Horizon 2020 Research and Innovation Programme under Grant Agreement No.688857 (SoftPro).

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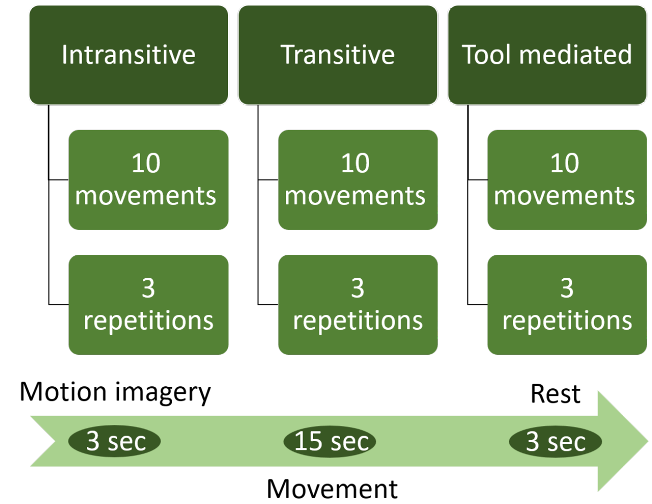

Fig. 1: Logic scheme of the experimental protocol timeline comprising 3 repetitions of 10 transitive, intransitive, and tool-mediated movements. Each task included a first motor imagery phase, an actual movement recording, and a final resting state.

Fig. 2: Exemplary experimental set-up. The subject is equipped with high resolution EEG sensors and active optical markers for motion tracking.

II. Methods

A. Experimental dataset

Thirty-three healthy volunteers (26.6 years on average, 17 females, all right handed) were recruited among the students of the University of Pisa. All experimental procedures were approved by the local ethical committee. Each subject repeated 30 tasks related to imaginary and actual movements of the right upper limb three times, therefore performing a total of 90 tasks.

An operator was appointed to instruct the subject by mimicking the action to be performed. Each task comprised the following three phases (see Figure 1): first, the subject was asked to imagine a specific upper limb movement for 3s; then, the subject was asked to actually perform the movement. Finally, 3s resting state completed the task.

As mentioned in the Introduction, in this study we grouped the different motor tasks into three different categories, depending on the kind of interaction with objects: (i) *transitive* tasks involving the use of an object. (e.g., reach and grasp an apple, and mimic biting); (ii) *intransitive* for object-free movements (e.g., point with the index to the in-front wall); and (iii) *tool-mediated* for actions in which an object was used to interact with another one (e.g., reach and grasp a pen, write a line and put the pen in a pencil-case).

Throughout the experiment, 128-channels EEG signals were continuously acquired using the Geodesic EEG Systems 300 (Electrical Geodesics, Inc.) with a sampling rate of 500 Hz, being synchronised with the optical registration of the upper limb movements. Kinematic recordings were performed using a commercial system for 3D motion tracking with active markers (Phase Space). Ten stereo-cameras working at 480Hz tracked 3D position of markers fastened to supports rigidly attached to upper limb links. An exemplary experimental set-up is shown in Figure 2. In this study, the first 3s of imaginary movements of the upper limb were retained for further analyses.

B. EEG analysis

The EEG processing chain comprised data filtering, segmentation, artefact detection and removal, data re-referencing, and bad channels interpolation. The EEG signals were filtered by means of an 8th-order band-pass finite impulse response filter with Butterworth approximation and cut-off frequencies of 0.5 Hz and 45 Hz. Afterwards, each signal was segmented into time windows corresponding to the start and end of each motor imagery sub-task of each repetition. An independent component analysis (FastICA) was applied in order to decompose the signals into independent components and detect those related to eye-blinks, heart and muscles electrical activity, head and arm movements by visual inspection. The visual inspection was performed by an expert researcher. The mean of all the EEG channels was used to re-reference each signal from each EEG channel. Finally, corrupted channels, defined as signals with clearly artefacted dynamics including high-frequency noise, were interpolated using spherical interpolation from the closest non-corrupted channels. Most of the aforementioned processing stages were implemented using the EEGLAB toolbox routines for Matlab 2017b [23].

C. Fuzzy Entropy

In order to calculate the FuzzyEn measure of a N-point time series $u(i) : 1 \leq i \leq N$, the series phase space has to be reconstructed using a specific embedding dimension m. The distance d_{ij}^m between two vectors in the phase space is defined as follows:

$$d_{ij}^m = \max_{k \in (0,m-1)} \left\{ \left| u(i+k) - \mathbb{E}\left[u(i)\right] - \left(u(j+k) - \mathbb{E}\left[u(j)\right]\right) \right| \right\} \quad (1)$$

where $(i, j = 1 : N - m, j \neq i)$, and $\mathbb{E}$ is the Expectation operator. The similarity degree D_{ij}^m, in the phase space, is defined using the fuzzy membership function $\mu(d_{ij}^m, n, r)$, as shown in eq. 2:

$$D_{ij}^m = \mu(d_{ij}^m, n, r) = exp\left(\frac{-(d_{ij}^m)^n}{r}\right) \quad (2)$$

where n, r are the gradient of the boundary and the width of the exponential function, respectively.

Thus, the FuzzyEn of a time series with a sequence length of N can be formulated as follows:

$$FE(m, n, r, N) = \lim_{N\to\infty}[\ln \phi^m(n, r) - \ln \phi^{m+1}(n, r)], \quad (3)$$

where the ϕ function is defined as:

$$\phi^m(n, r) = \frac{1}{N - m}\sum_{i=1}^{N-m}\left[\frac{1}{N - m - 1}\sum_{j=1, j\neq i}^{N-m} D_{ij}^m\right] \quad (4)$$

Of note, a non proper choice of the m and r values can lead to information loss, or a sensible increasing in noise sensibility [24], [25]. In this study, as per [25], the value of m was chosen equal to 13 and $r = \rho \cdot SD$, where ρ is the chosen tolerance, in this case 0.2, and SD is the standard deviation of the signal, as suggested by [24].

D. Statistical analysis

Aiming at investigating differences in EEG complexity between the three groups of movements (transitive, intransitive, and tool-mediated), a multi-vector statistical test has been applied for FuzzyEn samples gathered from each EEG channel. In this preliminary study, we did not account for intra-group differences, and considered the average value of EEG FuzzyEn per subject among all motor imagery tasks belonging to the same class. Since the distribution of the FuzzyEn samples was non-Gaussian ($p < 0.001$ from Kolmogorov-Smirnov test with null hypothesis of Normally distributed samples), a Friedman non-parametric test for paired data was applied on the three groups of movements.

Then, a post-hoc analysis using Wilcoxon signed tests was performed to investigate paired differences between movement classes. The significance threshold was decreased following a Bonferroni correction rule ($\alpha_{post-hoc} = \frac{\alpha}{number-of-comparisons}$).

III. Results

A. Topographic Entropy Maps

Figure 3 shows the EEG FuzzyEn topographic maps calculated for the 89 channels over the scalp. Values were averaged across the estimates gathered from 33 subjects, consistently grouped for each of the three classes of movements.

Specifically, the midline area of the cortex, in both central and parietal regions, showed the minimum values of FuzzyEn at each class of actions, while brain activity over the lateral cortices were associated with a higher complexity. The intransitive and transitive imaginary movements were associated with higher entropy values over the right temporal lobe, whereas tool-mediated imaginary movements were associated with higher complexity over the right parietal cortex. Furthermore, the tool-mediated class showed also a significant complexity decrease over the left-frontal region.

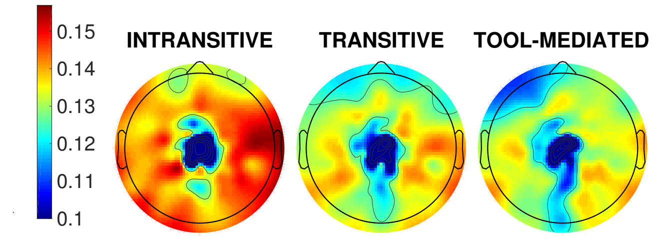

Fig. 3: Topographic maps of EEG Fuzzy Entropy estimates for each class of movement.

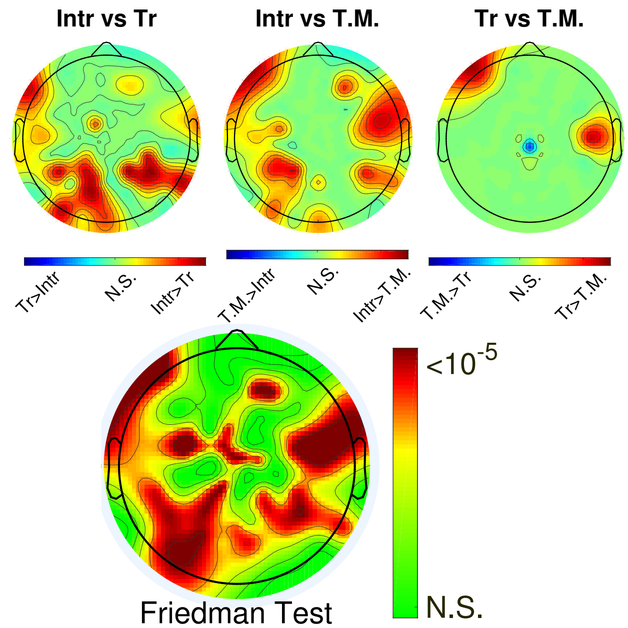

Fig. 4: p-values topographic maps showing results from a 3-class Friedman test (bottom topoplot), and 2-class Bonferroni-corrected Wilcoxon non-parametric tests for intransitive (Intr), transitive (Tr), and tool-mediated (T.M.) paired comparisons.

B. Statistical Analyses

Results from a Friedman non-parametric test (see Figure 4) demonstrated that brain complex dynamics associated with 59 out of 89 channels significantly changes between the three classes of movement (p-value < 0.05). Particularly, left and right temporal cortices, as well as the dorso-parietal and fronto-temporal cortices showed significant differences with $p < 0.05$. A post-hoc analysis revealed few significant differences between transitive and tool-mediated imaginary tasks, especially localised over the right-temporal and left-frontal regions. Conversely, several significant differences were found in comparing EEG complexity between intransitive vs. transitive, and intransitive vs. tool-mediated imaginary tasks. The former comparison showed differences over the dorso-parietal cortex, and occipital and anterior temporal cortices, whereas the latter comparison showed differences over the temporal and dorso-parietal cortices.

IV. Discussion and Conclusion

In this preliminary study, we investigated EEG complexity changes during motor imaginary tasks. To this aim, thirty-three young healthy subjects were asked to imagine different upper limb movements. These movements were grouped into three categories, namely transitive, intransitive, and tool-mediated movements [18] according to the kind of interaction with objects. For the estimation of the brain complexity level, we applied a recently proposed definition of FuzzyEn, which has been demonstrated to outperform other kinds of entropy measures for applications involving short time series corrupted by noise [17].

As motor imagery tasks affect motor cortex dynamics, results showed a clear reduction of the cortical complexity level over the central cortex and midline brain regions, as expected, quite independently from the kind of action. On the other hand, upper limb imaginary movements induced a high EEG complexity level over the right tempo-parietal lobe, i.e., the ipsilateral motor region, which is known to be associated with the representation of the human hand in the cortex [26].

Concerning the statistical comparison between the three classes of action, results showed clear significant differences between intransitive vs. transitive and tool-mediated tasks, i.e., between motor imagery tasks involving vs. not involving the use of an object through the upper limb. This result suggests that the complexity of brain dynamics, in case of imaginary movement of the upper limb, is more affected by the (imaginary) presence of an object than by the specific kind of interaction with the object itself.

Interestingly, some of the cortical regions highlighted as significant by our statistical analyses were also identified as crucial brain areas characterising transitive, intransitive, and tool-mediated tasks in a former functional neuroimaging study involving healthy volunteers [22]. Specifically, brain activity from the left parietal lobe was proved to discriminate between intransitive and tool-mediated, whereas the occipital area contributed in discerning between intransitive and transitive actions (see Figure 4 for a direct comparison with [22]).

Future endeavours will be directed to exploiting this knowledge towards novel and reliable brain-machine interface applications driven by EEG complexity during motor imagery tasks. More specifically, perspective robotics applications may exploit brain complexity levels to trigger grasping actions and object interaction in neuroprosthetic applications. Furthermore, differences and similarities in brain complex dynamics between real and imaginary upper limb movements, as well as related gender differences will be investigated.

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