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Exploiting brain critical dynamics to inform Brain-Computer Interfaces performance

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Introduction

Brain-Computer Interfaces (BCIs) constitute a promising tool for establishing direct communication and control from the brain over external effectors. However, the ideal features to design a BCI interface are unknown, since the underlying brain processes and their reflection on brain signals are poorly-understood [1]. As a result, mastering non-invasive BCI systems remains a learned skill that yields suboptimal performance in ~30% of users corresponding to the "BCI inefficiency" [2]. Measuring the dynamical features that are relevant to the execution of a task and, as a consequence, improving BCI performance remains an open challenge [1]. Functional imaging is dominated by 'bursty' dynamics, with fast, fat-tailed distributed, aperiodic perturbations, called "Neuronal Avalanches", spreading across the whole brain [3]. Neuronal avalanches spread preferentially across the white-matter bundles [4], are affected by neurodegenerative diseases [5], and evolve over a manifold during resting-state, generating a rich functional connectivity dynamics [6]. Hence, the spreading of avalanches might be a correlate of the functional interactions among brain areas and, as such, they could spread differently according to the task at hand. Therefore, they could be used to differentiate between different behaviors. To test our hypothesis, we used source-reconstructed magnetoencephalography (MEG) signals in a BCI framework, where 20 healthy subjects were compared in resting-state (RS) and while performing a motor imagery (MI) task, in order to track the dynamical features related to motor imagery.

Methods

MEG data were recorded during a BCI training session performed by a group of 20 healthy subjects (27.5 ± 4.0 years old, 12 men [7]). The participants were instructed to control the vertical position of a moving cursor by modulating their neural activity via a motor imagery task. Anatomical information was obtained from MRI imaging afterwards, whereby individual T1 were obtained and preprocessed for all participants [8]. For a complete description of the preprocessing steps, the reader can refer to Ref. [7]. Each source-reconstructed signal was z-scored (over time), thresholded, and set to 1 when above threshold, and to zero otherwise (threshold $z = |3|$). To ensure that we had adequate sampling (and, hence, time-scale separation), we have binned the data with bins ranging from 1 to 3 samples. For each binning, we measured the branching ratio and selected a binning of three samples, since in this condition we measured a branching ratio of 1, which is typical of a system operating near a critical regime. Then, an avalanche was defined as starting when at least one region is above threshold, and as finishing when no region is active. For each avalanche, we have estimated a transition matrix, structured with regions in rows and columns, where the *ij-th* entry contains the probability that regions j would be active at time $t+1$, when region i was active at time t. For each subject, we obtained an average transition matrix for the baseline condition, and an average transition matrix for the motor imagery task. For each edge, we computed the difference in the probability matrices. To statistically validate this at the individual level, we randomly shuffled the labels of the transition matrices. We then performed this procedure 10000 times obtaining, for each edge, the distribution of the differences observed given the null-hypothesis that the transition matrices would not differ in the two conditions. We used the null distribution to obtain a statistical significance for each edge, and Benjamini-Hochberg-corrected them for multiple comparisons [9], [10]. We then looked at the concordance of such matrices across subjects, and selected only those edges that were significant in a higher number of subjects as compared to what would be expected by chance, which highlighted the "task-specific" regions, which are involved the most with the MI task with respect to the Rest condition. Then, we related the differences in the transition probability (between RS and MI) corresponding to each of the edges incident upon the 'task-specific' areas to the individual BCI scores. Finally, we summed the differences over edges per each "task-related' node for each subject, and obtained the "task-specific" nodal values per subject, and related them to the corresponding difference in probabilities between the tasks to the BCI performance. BCI performance was defined as the proportion of successful trials over the session. Correlations were assessed using Spearman's analysis.

Results

Our analysis aimed at using the spatio-temporal spreading of large aperiodic bursts of activations as a proxy for communications between pairs of regions. Within this framework, we set out to look for differences in the probabilities of one such perturbation to propagate across a given edge in the two experimental conditions (i.e. resting-state and motor imagery). Our results show that large-scale perturbations propagate differently according to the experimental condition. Fig. 1A shows the edges which consistently differ between the two conditions in a significant number of subjects. These "reliably different" edges selectively cluster on premotor regions bilaterally. In particular, the caudal middle frontal gyri bilaterally are the regions upon which edges which are different between conditions cluster the most. Premotor areas are involved in the planning of motor actions, imagining of actions, allocating executive attention [11], as well as in the selection between competing visual targets [12]. We then focused on the differences in the transition probabilities in the edges which are incident upon the regions that significantly differ between experimental conditions. For these edges, we correlated the difference in probability in each subject with the performance in the MI task, as measured using the BCI score. Fig. 1B, shows the edges which are incident upon such regions. The color code shows the corresponding correlation between such differences and BCI scores, across patients ($p<0.05$). Firstly, nearly all differences correlate positively with the performance in the task. Hence, perturbations of activity spread more often across prefrontal regions if a subject is tasked with motor imagery, as compared to resting-state. Finally, in order to help interpretation, we have moved into nodal space. To this end, we have summed the differences corresponding to all the edges which are incident upon each reliably different region (shown in Fig. 1C), obtaining an overall difference per each such node. This was then correlated with the BCI scores. Four regions showed strong direct correlation with the BCI, as shown in Fig. 1D, notably, the superior parietal lobe, which is known to be involved during motor imagery tasks [13].

Conclusions

In this work, we set out to test if neuronal avalanches would be suitable to track subject-specific changes induced by a task in the large-scale brain dynamics. Despite the fact that we selectively focus on higher-order large-scale activity (that is, discarding most of the available datavia a high threshold), we spotted a number of edges whose dynamics is affected by the execution of a motor imagery task. Our results suggest that avalanches capture functionally-relevant processes which are of interest for alternative BCI designing.

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Figure

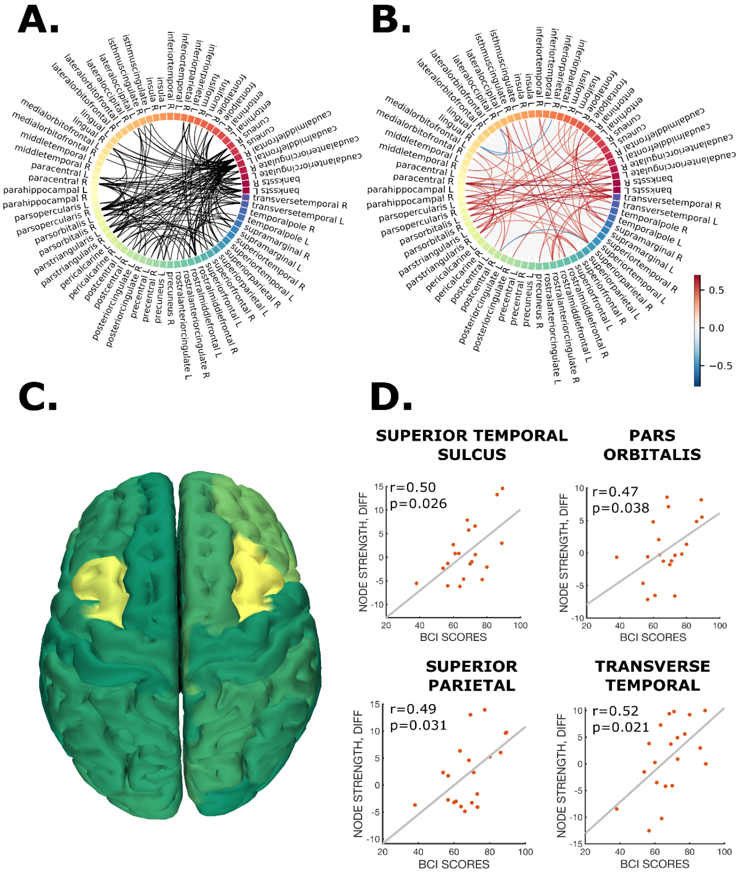

Fig. 1 Main results. (A) Edge-wise analysis - Reliable task-based interactions over the subjects ($p<0.05$, after correction for multiple comparison). (B) Edge-wise analysis - Correlation with BCI scores. (C) Node-wise analysis - Reliable nodes over the subjects. (D) Node-wise analysis - Correlation with BCI scores.

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