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Detecting task-based fMRI compliance using plan abandonment techniques

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Introduction

Task-based fMRI is a powerful approach to understand brain processes for a certain task. However, fMRI images are usually preprocessed hours, days or even months after the scan. During the functional image preprocessing stage, defects in images are detected and, in some cases, cannot be corrected. For example, technical problems with the scanner or lack of collaboration from the subject to perform the given tasks. For these cases it is necessary to realize a new scan. In order to mitigate lost scans due to patient non-compliance, we need an approach to detect such noncompliance during the scan.

Approach

In this Brainhack project, we aim to detect if a subject is following the given task and provide an almost real-time feedback to the researchers to make a decision during the exam if the subject is not collaborating. This is necessary to be performed in order to avoid loss of data, in which the images are typically processed and quality assessed at another day. We will focus on task where there are no button responses from the subject, hence relying solely in the BOLD signal if the subject is collaborating. To do so, we use plan abandonment techniques [1] a sub-area of Artificial Intelligence. For a given fMRI paradigm, a plan should be created and compared with the subject's brain activation during the scan using recognition methods. To use plan abandonment techniques, we need to discretize and formalize the fMRI and construct a expected plan based on the hypothesized paradigm using this formalization. To evaluate the compliance with a specific paradigm, we aim to use real-time fMRI methods to retrieve BOLD signals of brain regions that are supposed to be active in a particular time range. In order to tolerate fluctuations of the BOLD signal, we aim to use the methods that detect non-compliance using a threshold from the expected activation.By doing so, it is possible to detect if a subject is following the paradigm given a specific stimulus type, such as visual or auditory stimulus. The brain state of each stimulus type will be mapped based on atlas from the literature. For example, to cover motor activations,

Brodmann area 4 will be mapped with a state *motor_actv*. Thus, for a paradigm that works with motor tasks, the plan must contain *motor_actv* for the given time that the task occurs.

Discussion

The formalization of brain states strongly depends on the discretization of specific region states, which might vary from subject to subject. In order to normalize the signals, a previous tuning phase is required with simple paradigms, depending on which paradigm will be executed. During the scan, an online normalization must be made to a standard space, such as the MNI brain space. This real-time processing is required to map expected active regions to the previously selected brain areas from an atlas.

The usage of real-time fMRI methods aggregates to our approach since the tuning and pursuance recognition can be made during the exam. Such real-time fMRI methods can also monitor movements during the scan in order to identify if there is too much subject movement. In the case of fMRI paradigm abandonment, the paradigm can be adapted to induce or interest the subject in a way that the subject proceeds with its tasks, using methods such as demonstrated by [2]. Neurofeedback can be used to sustain the subject's interest by letting the paradigm be more challenging, requiring more attention and collaboration from the patient, such as the paradigm from [3].

Conclusions

This project is in its initial phase. Real-time fMRI methods are being tested, using AFNI's provided tools. In order to use plan abandonment techniques, the next step is to formalize basic stimuli types based on mapped regions. By using these formalizations, paradigms can be converted to a problem of plan abandonment and it becomes possible to evaluate the participation of a subject during the scan.

Availability of supporting data

More information about this project can be found at: https://github. com/brainhack-poa/fmri-plan-recongnition.

Competing interests

None.

Author's contributions

RFP and FM develop the project, and RFP, ASH, FM, ARF, and AB wrote the report.

Acknowledgements

Report from 2015 Brainhack Americas (MX). The authors would like to thank the organizers and attendees of Brainhack MX and the developers of AFNI.

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Self-Organization and Brain Function

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Introduction

Self-organization is a fundamental property of complex systems, describing the order spontaneously arising by the local interactions of the system components not mediated by top-down inputs. Though, self-organizing systems typically possess a large number of components and exhibit complex dynamics, their evolution is deterministic and governed by a small number of order parameters. This property was used to model the self-organization of the ocular dominance columns of the striate cortex in patterns of neighboring stripes [1] which respond preferentially to inputs from the left or the right eye. In this model the self-organization across ocular dominance and orientation preference layers was coupled, were both layers were modeled with the Swift-Hohenberg eq. [2] We reduce the model complexity by including only the cortical dominance layer and investigate the parameter dependency of the self-organization with a Matlab implementation.

Approach

The Swift-Hohenberg eq. [2] was used to model the self-organization of the ocular dominance columns. There are two order parameters in this equation, the first one determines the spatial wavelength (λ) of the stripes and the second one the branchiness (ϵ) of the pattern. is the Laplace operator.

$$\partial_t \psi(x, y, t) = \left[\varepsilon - \left(\Delta + \frac{4\pi^2}{\lambda^2} \right)^2 \right] \cdot \psi - \psi^3 \tag{1}$$

The algorithm used to generate the results has been modified from an open source script [http://nile.physics.ncsu.edu/hon292a-f08/]. The Swift-Hohenberg equation was solved by applying periodic boundary conditions after a Fourier transform to k space, which simplifies the computation of the solution.

Results

Figures 16 (a), (b) and (c) shows the temporal evolution of the solution to the Swift-Hohenberg equation for random initial conditions (a), constant ϵ and time increasing from (a) to (c). In (c), (d) and (e) three solutions with different ϵ are shown. The branchiness increases with ϵ from (c) to (e). The wavelength (λ) was set to the same value in all figures and the pattern in (d) is similar to the ocular dominance layers found in the visual cortex.

Conclusions

A simple model suffices to study basic properties of ocular dominance self-organization. Possibly, a combination of models for selforganization in neighboring cortical layers would allow to investigate even higher organizational principles of the cortex [1] e.g.~the coordination between ocular dominance layers, orientation layers, and cytochrome oxidase.

Availability of supporting data

More information about this project can be found at: http://brainhack.org/self-organization-and-brain-function. Further data and files supporting this project are hosted in the GigaScience repository: https://github.com/Brainhack-Proceedings-2015/Pfan_HBM_SOBF.

Competing interests

None.

Author's contributions

JPP, RCM, LCTH, and DD performed the project and wrote the report.

Acknowledgements

The authors would like to thank the organizers and attendees of the 2015 OHBM Hackathon. This work was supported by generous donations from individuals to the Center for Investigating Healthy Minds, founded and led by Dr.~Richard J. Davidson.

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