Using Bayesian priors to improve power of whole brain voxel- and connexelwise inferences

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Introduction

- Most neuroimaging studies are underpowered or in other words have small signal to Noise Rate (SNR). This is especially true for full brain connexelwise [1] analysis (see Fig. 1).
- A common way of increasing SNR is to restrict the search area with a Region of Interest (ROI).
- ROI definitions have traditionally been binary - discarding uncertainty, potentially missing strong activations outside of the ROI.
- Here we propose a probabilistic approach to ROI analysis - pROI.

Methods

We propose to formally incorporate prior knowledge into the inference process by using a Bayesian framework. The prior informs the search area, which in turn is subdivided into noise and signal. Our hierarchical model consists of two levels. On the first level we model two classes corresponding to voxels/connexels-of-interest or -of-non-interest:

\[ p(x_i) = p(m_1|x_i)p(x|m_1) + p(m_2|x_i)p(x|m_2) \]

Where \( p(m_1, i) \) are the priors on the search areas (or mixing components of the first level). They are different for each location (i), fixed, and set to values based on particular inference assumptions (previous studies, characteristics of different modalities, etc...). On the second level, the voxels-/connexels-of-interest distribution \( p(x|m_1) \) is described as a mixture of negative gamma (deactivation), Gaussian (noise), and positive gamma (activation) distributions. The location of the two gamma distribution is tied to the estimated mean of the noise component. This level is identical to the model presented in [2].

Parameters of those three distributions (and mixing coefficients) are fitted using a weighted variant of the Expectations-Maximization algorithm [3]; the entire dataset is used but influence of each voxel/connexel on the final mixture is modulated by the \( p(m_1|x_i) \) weight in the E-step:

\[ \gamma_{ik} = \frac{p(x_{i}, k)}{\sum_{I=1}^{K} p(x_{i}, I)} \]

The actual inference procedure takes two steps (see Fig. 2). First for each voxel/connexel we decide if it is of interest or non-interest, by comparing the two posterior distributions. For voxels/connexels coming from the of-interest distribution, a similar procedure is used to choose between signal and noise.

Results

To evaluate the method we have performed a series of simulations using different prior maps. On a two dimensional 100x100 array two 10x10 sources of signal were placed (see Fig. 3): one weak (effect size 9) and one strong (effect size 9). The “classical ROI” prior fails to find the second signal source, but even the most specific of the non-binary priors (with value 0.005 over the strong signal) does a reasonable job in finding both sources.

We apply the pROI method to thresholding an fMRI dataset acquired during performance of an emotional task. Subjects were exposed to negative and neutral visual imagery with varying uncertainty of the nature of the next stimulus.

Discussion

- We propose a Bayesian framework for performing ROI analysis with non binary priors.
- pROI enable researchers to explicitly encode the uncertainty about search space.
- Different sources of priors can be used and should be investigated in the future: tissue probability maps, results from different modalities, literature reviews.
- Due to its modular design, the proposed framework is flexible: second level model can be replaced with Markov Random Field or Kernel Density estimation.
- Proof of concept code is available at: https://github.com/chrisfilo/Adaptive-Thresholding/

References