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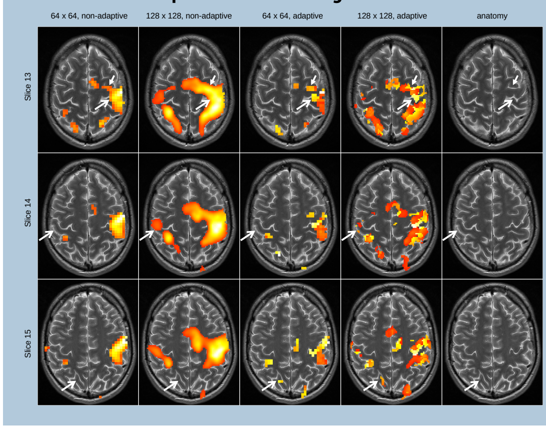
Structural adaptive smoothing methods for high resolution fMRI

Increasing the spatial resolution in functional Magnetic Resonance Imaging (fMRI) inherently lowers the signal-to-noise ratio (SNR). In order to still detect functionally significant activations in high-resolution images, spatial smoothing of the data is required. However, conventional non-adaptive smoothing comes with a reduced effective resolution, foiling the benefit of the higher acquisition resolution. Here, we demonstrate that a structural adaptive fMRI analysis is capable to reveal finer activation structure in fMRI at higher resolutions even when the lower SNR requires to detect signals at all.

Why it works

- ▷ Alternative to non-adaptive smoothing in the general linear modeling workflow
- ▷ Sequential multiscale procedures that adapts to underlying unknown structures
- ▷ Avoids loss of spatial resolution due to smoothing
- ▷ Compensates increased noise level caused by higher resolution
- ▷ Increases both specitivity and sensitivity of decisions

Structural adaptive smoothing



Workflow:

- ▷ Linear modeling / parameter estimation
- ▷ Structural adaptive smoothing of parameters or contrasts
- ▷ Signal detection / thresholding by Random Field Theory

Figure 1: Three slices through the primary motor area with varying matrix size and smoothing method. Multiple test corrected p = 0.05. Arrows: Structures only visible in high-resolution images and well aligned with the cortical grey matter. Image orientation R-L.

Sequential algorithm:

- ▷ Initialization: $\theta_i = \gamma_i$ - contrast from linear model, scale h_1, $k = 1$.
- ▷ Generate weighting scheme $\forall i, j$

$$w_{ij} = K_s\left(\frac{\mathcal{K}(\theta_j, \theta_i)}{\lambda \sigma_i^2}\right) K_l\left(\frac{|i-j|}{h_k}\right)$$

- ▷ Compute new (smoothed) parameter estimates

$$\theta_i = \frac{\sum_j w_{ij}\gamma_i}{\sum_j w_{ij}}$$

- ▷ Iterate: $k := k+1$, $h_k = c_h h_{k-1}$. If $h_k > h_{max}$ stop, else continue with second step.

Artificial data

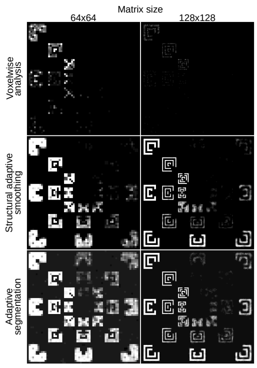


Figure 2: Signal detection probablilities for artificial phantom data.

Adaptive segmentation

Advantages

- ▷ combines smoothing and signal detection in one step
- ▷ provides sequential multiscale test for signals exceeding a minimal size
- ▷ does not rely on a local constant assumption under the alternative
- ▷ motivated as generalization of multiscale tests

$$T(\Gamma) = \max_{h\in\mathcal{H}} \max_{i \in V} \frac{\theta_i^{(h)} - \delta}{\sqrt{\mathbf{D}\theta_i^{(h)}}} - C(h)$$

$$C(h) = \sqrt{\beta \log \frac{cK}{h^3}} + \frac{2\log \beta \log \frac{cK}{h^3}}{\sqrt{\beta \log \frac{cK}{h^3}}}$$

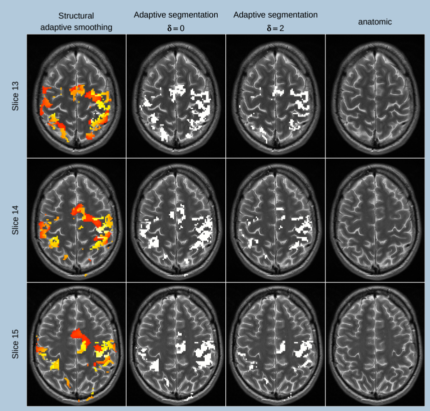
$$\theta_i^{(h)} = \sum_j K\left(\frac{|i-j|}{h_k}\right)\gamma_i / \sum_j K\left(\frac{|i-j|}{h_k}\right)$$

$\mathcal{H}$ - sequence of bandwidths, β depends on df.

Algorithm

- ▷ Initialization: $\theta_i = \gamma_i$ - contrast from linear model, scale h_0, $k = 1$, $\zeta_i = 0$ - segmentation
- ▷ Generate weighting scheme w_{ij} $\forall i, j$, adaptive if $\min(\zeta_i, \zeta_j) = 0$, else nonadaptive.
- ▷ Compute new (smoothed) parameter estimates
- ▷ If $\frac{\theta_i^{(h)} - \delta}{\sqrt{\mathbf{D}\theta_i^{(h)}}} - C(\tilde{h}_i) > \tau$ set $\zeta_i = 1$.
- ▷ Iterate: $k := k+1$, $h_k = c_h h_{k-1}$. If $h_k > h_{max}$ stop, else continue with second step.

Figure 3: Comparison of structural adaptive smoothing, adaptive segmentation for minimum signal size $\delta = 0$ and $\delta = 2$ for high resolution data ($\alpha = 0.05$).



Software

Within the project many software packages are developed for evaluation and for usage withing the (Neuro)imaging community.

Download at:
http://cran.r-project.org
http://www.nitrc.org

The Structural Adaptive Smoothing Software family in R

Most software is provided as packages for the *R Language for Statistical Computing* (http://cran.r-poject.org), easy to use and integrate.

- ▷ **adimpro** (Image processing tools)
- ▷ **aws** (General structural adaptive smoothing)
- ▷ **fmri** (Structural adaptive analysis)

```
> data <- read.AFNI("file.BRIK")
> hrf <- fmri.stimulus(107, c(18,48,78), 15)
> x <- fmri.design(hrf)
> spm <- fmri.lm(data, x)
> spms <- fmri.smooth(spm, hmax=3)
> pv <- fmri.pvalue(spms)
> plot(pv)
```

- ▷ **dti** (Structural adaptive DTI analysis), **Poster #257 F-AM**

Package *fmri*:

Features

- ▷ fMRI data import/export.
- ▷ fMRI analysis (linear model, ...)
- ▷ GUI for easy handling
- ▷ Structural adaptive smoothing
- ▷ 2D and 3D visualization
- ▷ Publication-ready images

Perspectives

- ▷ Group analysis.
- ▷ Motion correction.
- ▷ . . .

Plugin *aws4SPM*:

- ▷ Integrates structural adaptive smoothing into the SPM workflow
- ▷ Download at: http://www.wias-berlin.de/software/aws4SPM/

Publications

[1] Polzehl, J. and Tabelow, K. (2007). fmri: A package for analyzing fmri data. *RNews*, 7:13–17.

[2] Polzehl, J. and Tabelow, K. (2009). fmri signal detection by structural adaptive segmentation. Manuscript in preparation.

[3] Tabelow, K., Piëch, V., Polzehl, J., and Voss, H. (2008). High resolution fmri: Overcoming the signal-to-noise problem. *Journal of Neuroscience Methods*, 178:357–365.

[3] Tabelow, K., Polzehl, J., Ulug, A., Dyke, J., Watts, R., Heier, L., and Voss, H. (2008). Accurate localization of brain activity in presurgical fmri by structure adaptive smoothing. *IEEE TMI*, 27:531–537.

[4] Tabelow, K., Polzehl, J., Voss, H. U., and Spokoiny, V. (2006). Analysing fMRI experiments with structure adaptive smoothing procedures. *NeuroImage*, 33(1):55–62.

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www.matheon.de www.wias-berlin.de/projects/matheon_a3/ **Poster #275 F-PM** (DTI)

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