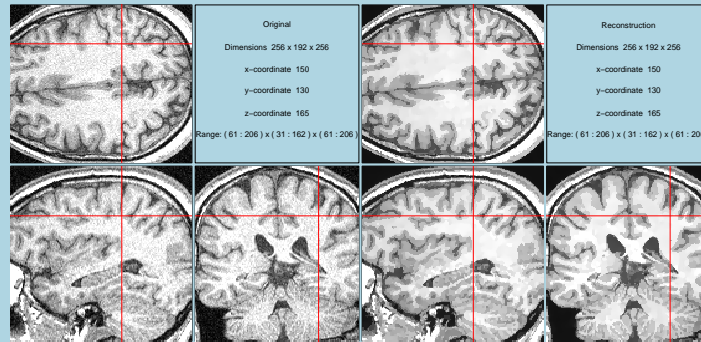


# Analyzing fMRI experiments with structural adaptive smoothing methods

## 3D medical imaging

Medical imaging includes a variety of techniques, like X-Ray, CT, and MRT. A high noise level and very low signal-to-noise ratio together with heteroskedastic tissue dependent variance is often a serious problem. Objects and signals of interest are often very weak and can hardly be detected. Methods and algorithms to handle this kind of data should be able to reduce noise while preserving important structure like edges and homogeneous regions. **Adaptive Weights Smoothing (AWS)** removes the noise without losing the structural information. This leads to substantial improvements in the analysis of various types of medical images.



Reconstruction of MR image. Left: original image, Right: result of structure adaptive smoothing

### AWS Procedure:

- ▷ **Data:**  $(X_i, Y_i), X_i \in \mathcal{X}, Y_i \in \mathcal{Y}$
- ▷ **Model:**  $Y_i \sim P_{\theta}(X_i), \theta: \mathcal{X} \rightarrow \Theta$ .
- ▷ **Structural assumption:**  $\theta(x)$  piecewise constant
- ▷ **Initialization:** global MLE

$$\hat{\theta}_i^{(0)} = \frac{1}{n} \sum_j Y_j, \quad w_{ij}^{(0)} = 1$$

- ▷ **Iteration:** adaptive weights

$$w_{ij}^{(k)} = K_I(l_{ij}^{(k)}) K_S(s_{ij}^{(k)})$$

where  $K_I, K_S$  are kernel functions and

$$l_{ij}^{(k)} = |X_i - X_j|/h^{(k)}$$

is the location penalty and

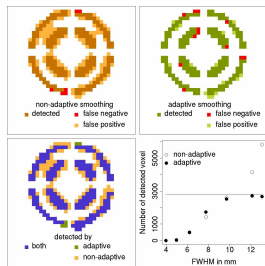
$$s_{ij}^{(k)} = \frac{1}{\lambda} \sum_l w_{il} K(\hat{\theta}_i^{(k-1)} - \hat{\theta}_j^{(k-1)})$$

the statistical penalty. New estimate

$$\hat{\theta}_i^{(k)} = \sum_j w_{ij} Y_j / \sum_j w_{ij}$$

Increase  $k$  and thus  $h^{(k)}$ .

## Structure adaptive fMRI analysis



### Data Preparation

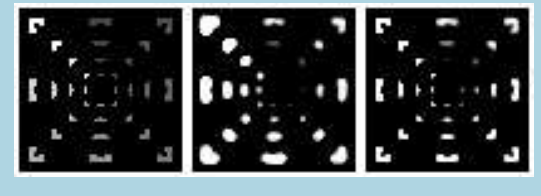
- Registration
- Motion correction
- Normalization

### Linear Model

- $Y = X\beta + \epsilon$
- prewhitening AR(1) model
- $\tilde{Y} = \tilde{X}\beta + \tilde{\epsilon}$
- estimate  $\beta$

### Smoothing / Thresholding

- structure adaptive smoothing (AWS)
- define t-statistic for a contrast
- threshold using RFT

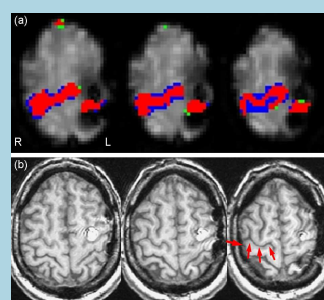


**fMRI.** In order to reduce the noise, improve signal detection and to solve the multiple test problem fMRI data is spatially smoothed. However, the common application of a Gaussian filter does this at the cost of loss of information on spatial extent and shape of the activation areas. The use of structural adaptive smoothing procedures significantly improves the information on the geometry of the activation regions with similar power of signal detection.

**Artificial dataset I (right figure).** Left: Data slice. Different shapes and sizes of activation areas are used as well as clockwise increasing signal size. Center: Signal detection in this dataset using a **Gaussian filter**. The greylevel of the voxels indicates the probability of its detection. Right: Signal detection using **structure adaptive smoothing** based on the Propagation Separation approach. The shape of the activation areas is conserved.

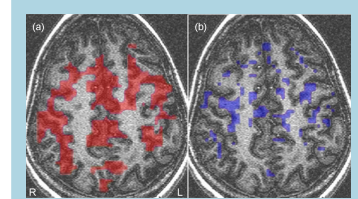
**Artificial dataset II (left figure).** Illustration of false-positive and false-negative detections with a Gaussian filter and AWS using a different artificial dataset.

## Presurgical fMRI



The goal of neuro-oncologic brain surgery is to maximize tumor resection or to perform epilepsy surgery while preserving important brain functions. Results of presurgical fMRI must be interpreted with greater care since it will strongly affect clinical decisions.

Left: Three consecutive EPI slices with functional activations (a) and corresponding anatomical images (b) of the brain of an epilepsy patient during a bilateral finger tapping task. Activations in the cortical areas of the pre- and postcentral gyrus, are better delineated in AWS (red) than in Gaussian smoothing (blue and red). Cf. red arrows.



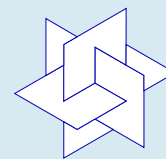
Functional activations during a bilateral finger tapping task. The activation as detected with AWS (red) delineates the gray matter regions much better than detection with Gaussian smoothing, which additionally covers also white matter areas (blue).

## Software

- **R-package** (Windows, Unix) see [cran.r-project.org](http://cran.r-project.org)

This package reads standard BRIK or ANALYZE datasets. Analysis is done with simple R-scripts. For a typical dataset it takes about 5 minutes on common hardware. No registration, motion correction, or normalization is provided. The package can write out the results as BRIK and ANALYZE file(s).

- in preparation: **amira** (TM) module
- vision: **AFNI**-plugin, **SPM** module



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## Publications

1. J. Polzehl and V. Spokoiny (2001). Functional and dynamic magnetic resonance using vector adaptive weights smoothing. *J. Roy. Statist. Soc. Ser. C*, **50**:485-501 (2001).
2. J. Polzehl and V. Spokoiny (2005). Propagation-Separation Approach for Local Likelihood Estimation. *Prob. Theory Relat. Fields*, in print (2005).
3. K. Tabelow, J. Polzehl, H.U. Voss and V. Spokoiny (2005). Analyzing fMRI experiments with structural adaptive smoothing procedures. WIAS-Preprint No. 1079.
4. K. Tabelow, J. Polzehl, A. M. Ulug, J.P. Dyke, R. Watts, L.A. Heier, H. U. Voss (2006). Accurate Localization of Brain Activity in Presurgical fMRI by Structure Adaptive Smoothing. WIAS-Preprint No. 1119.