Weierstrass Institute for Applied Analysis and Stochastics

Karsten Tabelow[1], Saskia Becker[1], Siawoosh Mohammadi[2], Nikolaus Weiskopf[2], Jörg Polzehl[1]

Multi-shell position-orientation adaptive smoothing (msPOAS)

HBM 2013 - Poster #1687-MoTue

Objective of this research

We present a *noise reduction method (msPOAS) for multi-shell diffusion-weighted magnetic resonance data*. It reduces noise directly in the diffusion weighted images. Hence, msPOAS does not bias the data towards any specific model for data analysis. The procedure avoids blurring of the different structures as known for non-adaptive smoothing, like Gaussian filtering. It preserves discontinuities as observed at tissue borders instead.

Multi-shell dMRI data

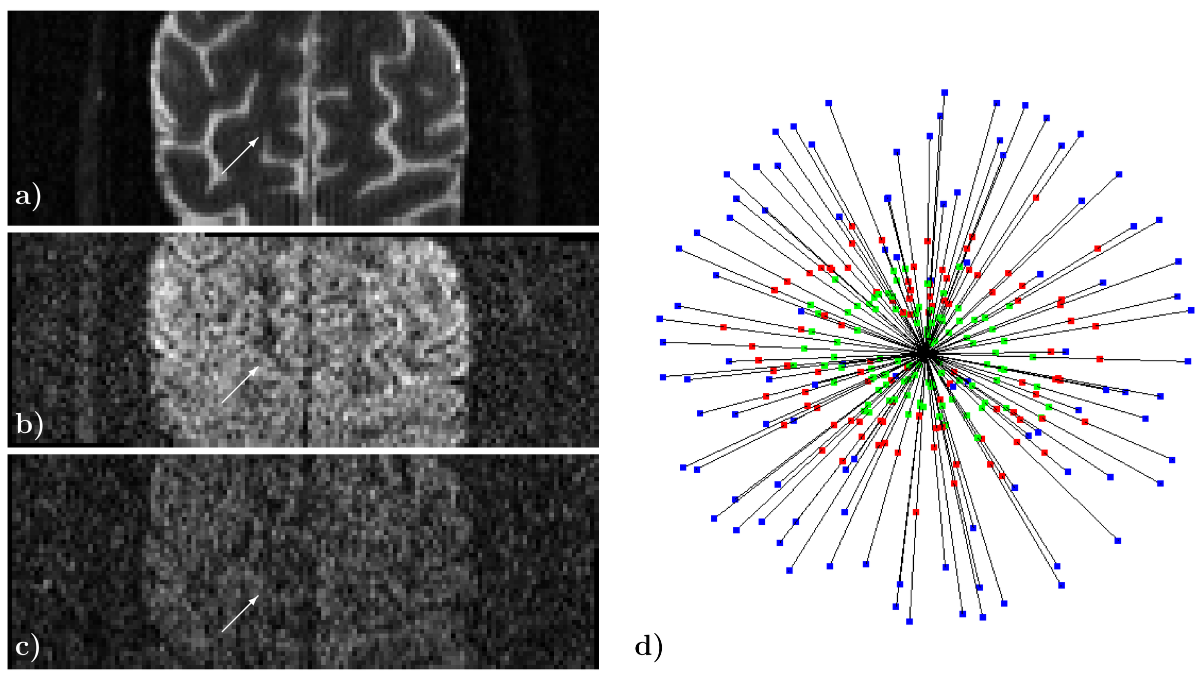


Figure 1: Slice of a) non-diffusion weighted image, b) first shell ($b = 800\mathrm{s}/\mathrm{mm}^2$) of diffusion weighted image, c) second shell ($b = 2000\mathrm{s}/\mathrm{mm}^2$) of diffusion weighted image. d) 3D image of data in one voxel.

dMRI models that require multi-shell data

- Higher order tensor models (Özarslan and Mareci 2003, Liu et al. 2003)
- Diffusion Kurtosis Imaging (DKI, Jensen et al. 2005, Tabesh et al. 2011)
- Diffusion Propagator Imaging and related (Özarslan et al. 2006, Cheng et al. 2010, Descoteaux et al. 2011)
- Multi-shell q-ball (Aganj et al. 2010)
- Nonnegative Definite EAP and ODF Estimation (Cheng et al. 2012)
- ...

The estimates of the higher number of parameters in these models are very vulnerable to noise. $\rightarrow$ msPOAS

Data acquisition

Data has been acquired on a 3T MAGNETOM Trio scanner. Diffusion weighted images were acquired using a reduced FoV-technique as described in Heidemann(2010). The FoV was $161 \times 58\mathrm{mm}$ around the motor cortex resulting in an isotropic in-plane resolution of $1.2\mathrm{mm}$. 34 slices of $1.3\mathrm{mm}$ slice thickness were acquired. Diffusion weighted data were acquired at 2 different b-values: $b = 800\mathrm{s}/\mathrm{mm}^2$ and $b = 2000\mathrm{s}/\mathrm{mm}^2$ each with 100 gradient directions as suggested by Caruyer (2011). 21 interspersed S_0-images at $b = 20\mathrm{s}/\mathrm{mm}^2$ were acquired. One healthy male volunteer was scanned. The total scan time was $22\mathrm{min}$. Data was corrected for eddy currents and motion artifacts (Mohammadi 2010) using the ACID toolbox for SPM.

Multi-shell POAS - Algorithm

- Measurement space: $V \times G \subseteq \mathbb{R}^3 \times \mathbb{S}^2$ (*V*oxel position, *G*radient orientation)
- Data description for shells $b = b_1, \ldots, b_{\mathfrak{B}} \in B$

$$\mathscr{S} : V \times G \ni (\vec{v}, \vec{g}) \mapsto \left(S_0(\vec{v}), S_{b_1}(\vec{v}, \vec{g}), \ldots, S_{b_{\mathfrak{B}}}(\vec{v}, \vec{g})\right)^T \in \mathbb{R}^{\mathfrak{B}+1},$$

- Input: Sequence of location bandwidths $\{h\}_{k=0}^{k^*}$, balancing parameter κ, adaptation parameter $\lambda > 0$.
- Initialization: non-adaptive estimate with bandwidth h_0 (see below weights without K_{ad} term) $\tilde{S}_b^{(0)}(m) := \hat{S}_b^{(0)}(m)$ and $\tilde{N}_{m,b}^{(0)} := N_{m,b}^{(0)}$ for all $m \in V \times G_b$, $b \in B_0$.
- Iteration: For each $b \in B$ and $m := (\vec{v}_m, \vec{g}_m) \in V \times G_b$ do the following. Interpolate the missing values of $\tilde{S}_{b'}^{(k-1)}(m)$ and $\tilde{N}_{m,b'}^{(k)}$, $b' \in B \setminus \{b\}$. Then, calculate the statistical penalty

$$s_{mn}^{(k)} = \sum_{b \in B_0} \tilde{N}_{m,b}^{(k-1)} \mathscr{KL}\left(\frac{\tilde{S}_b^{(k-1)}(m)}{\hat{\sigma}}, \frac{\tilde{S}_b^{(k-1)}(n)}{\hat{\sigma}}\right), \qquad n \in V \times G_b,$$

the adaptive weights

$$\tilde{w}_{mn}^{(k)} = K_{\mathrm{loc}}\left(\delta_\kappa(m,n)/h^{(k)}\right) \cdot K_{\mathrm{ad}}\left(s_{mn}^{(k)}/\lambda\right), \qquad n \in V \times G_b,$$

the corresponding sum over the adaptive weights

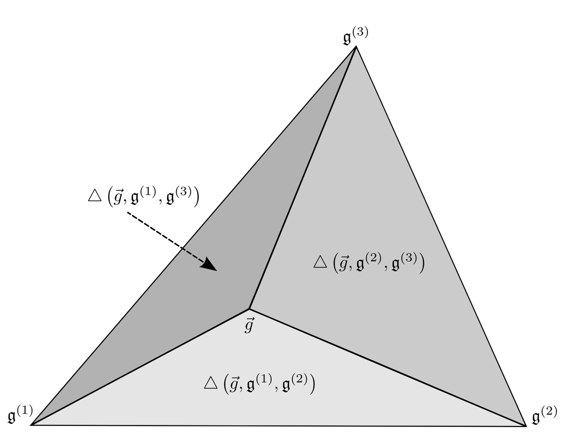
$$\tilde{N}_{m,b}^{(k)} = \max_{k' \le k}\left(\sum_{n \in V \times G_b} \tilde{w}_{mn}^{(k')}\right),$$

and the adaptive estimator

$$\tilde{S}_b^{(k)}(m) = \sum_{n \in V \times G_b} \tilde{w}_{mn}^{(k)} S_b(n) / \tilde{N}_{m,b}^{(k)}.$$

- Stopping: Stop if $k = k^*$, else set $k := k+1$.

Interpolating missing values



Spherical interpolation

$$\mathscr{S}_b(\vec{v}, \vec{g}) := \sum_{l=1}^{3} c_{(b,\vec{g})}^{(l)} S_b(\vec{v}, \mathfrak{g}_{(b,\vec{g})}^{(l)})$$

with

$$c_{(b,\vec{g})}^{(l)} := \frac{\mathrm{area}(\triangle(\vec{g}, \mathfrak{g}_{(b,\vec{g})}^{(l_1)}, \mathfrak{g}_{(b,\vec{g})}^{(l_2)}))}{\mathrm{area}(\triangle(\mathfrak{g}_{(b,\vec{g})}^{(1)}, \mathfrak{g}_{(b,\vec{g})}^{(2)}, \mathfrak{g}_{(b,\vec{g})}^{(3)}))}$$

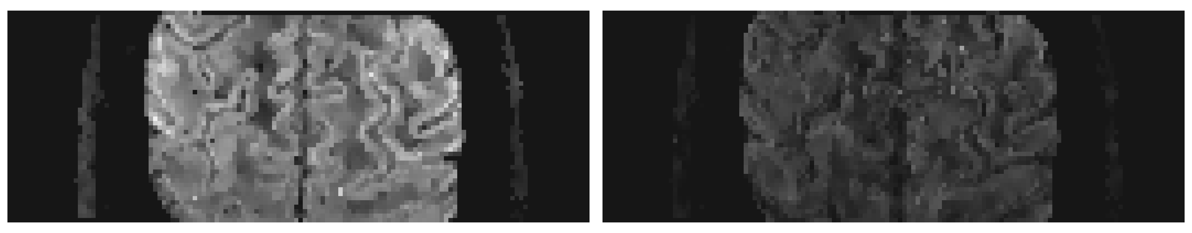


Figure 2: Diffusion weighted data on the two shells from Figure 1b)+c) after reconstruction using msPOAS. The smoothed b0 image is not shown here.

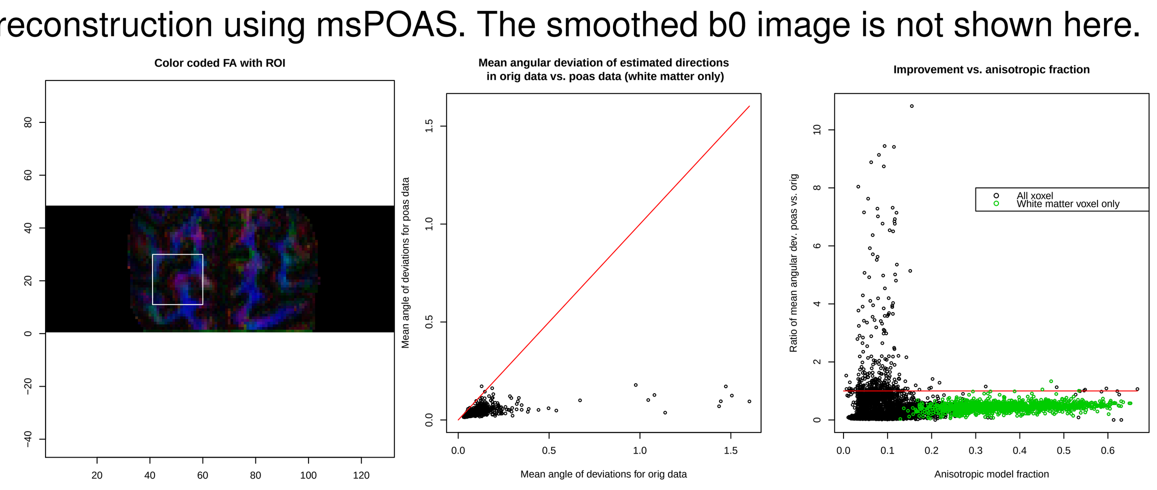


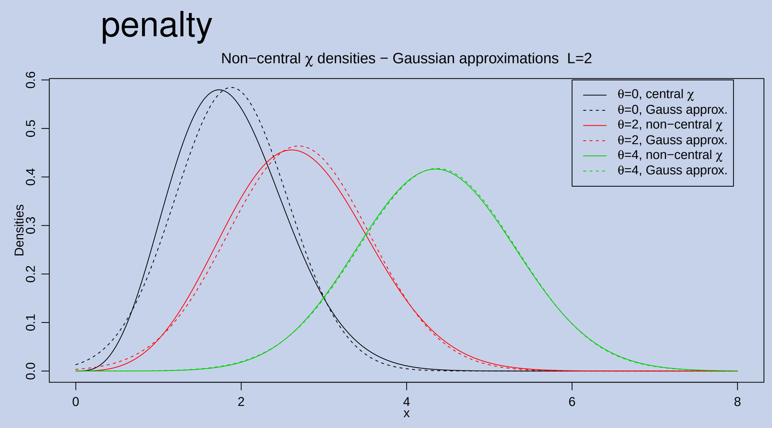
Figure 3: Improvements of the variability of the estimated direction in a 1-stick-1-ball model (Behrens et al., 2003)

msPOAS vs. POAS

- Simultaneous adaptive smoothing of data from all shells (more efficient adaptation)
- Simplified discrepancy in the measurement space

$$\delta_\kappa(m_1, m_2) := \|\vec{v}_1 - \vec{v}_2\| + \kappa^{-1} \arccos|\langle \vec{g}_1, \vec{g}_2 \rangle|$$

- Simplified approximation of the statistical penalty



Further reading

Structural adaptive methods in DW-MRI

- S. Becker, K. Tabelow, S. Mohammadi, N. Weiskopf, J. Polzehl, (2013) Adaptive smoothing of multi-shell diffusion- weighted magnetic resonance data by msPOAS, WIAS-Preprint no. 17XX. (Model-free multi-shell dMRI)
- S. Becker, K. Tabelow, H.U. Voss, A. Anwander, R.M. Heidemann, J. Polzehl, (2012) Position-orientation adaptive smoothing of diffusion weighted magnetic resonance data (POAS), *Med. Image Anal.* 16, pp. 1142–1155. (Model-free single-shell dMRI)
- K. Tabelow, J. Polzehl, V. Spokoiny, H.U. Voss (2008), 'Diffusion tensor imaging: Structural adaptive smoothing', *NeuroImage*, vol. 39, pp. 1763–1773. (Structural adaptive smoothing DTI data)

Implementation in **R**: Package **dti**

- J. Polzehl, K. Tabelow (2009), 'Structural adaptive smoothing in diffusion tensor imaging: The R package dti', *J. Statist. Software*, vol. 31, pp. 1–24. (Explaining the usage of the package for DTI)
- J. Polzehl, K. Tabelow (2011), 'Beyond the Gaussian Model in Diffusion-Weighted Imaging: The package dti', *J. Statist. Software*, vol. 44, issue 12 (Explaining the usage of the package for HARDI).

- Free download: `http://cran.r-project.org/web/packages/dti/index.html`
- Upcoming POAS4SPM toolbox for SPM at `http://www.diffusiontools.com`

For diffusion weighted data analysis with **R** see also **Poster #1455-MoTue**

Conclusions

MSPOAS is a useful method for adaptively denoising multi-shell (including single-shell) diffusion MRI data. It reduces variability of estimated model parameters. This will be most interesting at low SNR, high spatial resolution, and for using higher order data models.

This research was funded by the DFG research center MATHEON (project F10).

[1] Weierstrass Institute · karsten.tabelow@wias-berlin.de [2] Wellcome Trust Centre for Neuroimaging at UCL, ION UCL, London, United Kingdom