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Position-orientation adaptive smoothing (POAS) at 7T dMRI

Introduction

Among other imaging artifacts noise renders subsequent analysis or medical decisions for Diffusion Magnetic Resonance Imaging (dMRI) data more difficult. Furthermore, increasing the spatial resolution of the measurement inherently decreases the signal-to-noise ratio (SNR). Attempts to achieve higher image resolution come at the expense of deteriorating image quality. Although at 7T the MR signal is much larger than at lower field strengths, significant noise still emerges at the desired high resolutions. Noise reduction is therefore essential.

Data acquisition

The MR experiment was performed on a **7T** whole body **MR scanner** (MAGNETOM 7T, Siemens Healthcare, Erlangen, Germany) equipped with gradients allowing a peak gradient amplitude of $70\,\mathrm{mT/m}$ with a maximum slew rate of $200\,\mathrm{T/m/s}$ (SC72, Siemens Healthcare, Erlangen, Germany). For signal reception a single channel transmit, **24-channel receive phased array head coil** (Nova Medical, Wilmington, MA, USA) was used. An optimized **monopolar Stejskal-Tanner sequence** (Morelli et al., 2010) was used in conjunction with the **ZOOPPA** approach (Heidemann et al., 2012) providing an **isotropic resolution of** $800\,\mu\mathrm{m}$ using the following imaging protocol parameters: 91 slices with 10% overlap, FOV $143 \times 147\,\mathrm{mm}^2$, TR $14.1\,\mathrm{s}$, TE $65\,\mathrm{ms}$, BW $1132\,\mathrm{Hz/pixel}$, ZOOPPA acceleration factor of 4.6. Diffusion weighted scans were performed with **60 directions** with a **b-value of 1000** $\mathrm{s/mm}^2$ and 7 interspersed S_0-images.

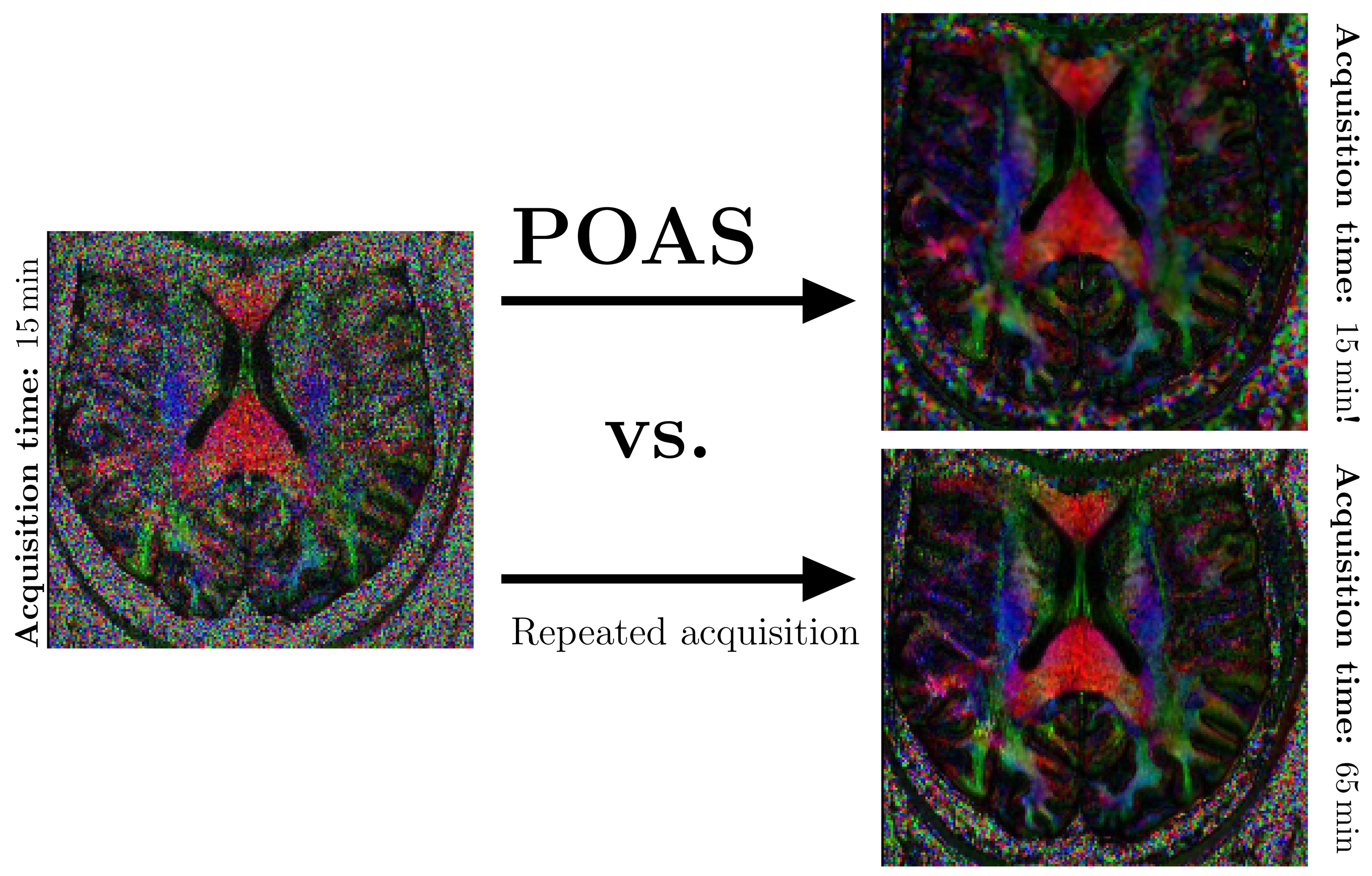


Figure: A high measurement resolution causes a higher noise level. POAS is able to reduce noise in a high resolution dMRI dataset without blurring. The original noisy data (left) can be processed using POAS yielding the result in the upper right figure. This compares well with the diffusion tensor reconstruction using 4 repeated measurements (lower right).

POAS - Algorithm for $k = 1, \ldots, k^\star$

$$\hat{S}^{(k)}_{g_1} := \sqrt{\sum_{g_2 \in \mathbb{R}^3 \times \mathbb{S}^2} w^{(k)}_{g_1 g_2} S^2_{g_2} \Big/ \sum_{g_2} w^{(k)}_{g_1 g_2}}$$

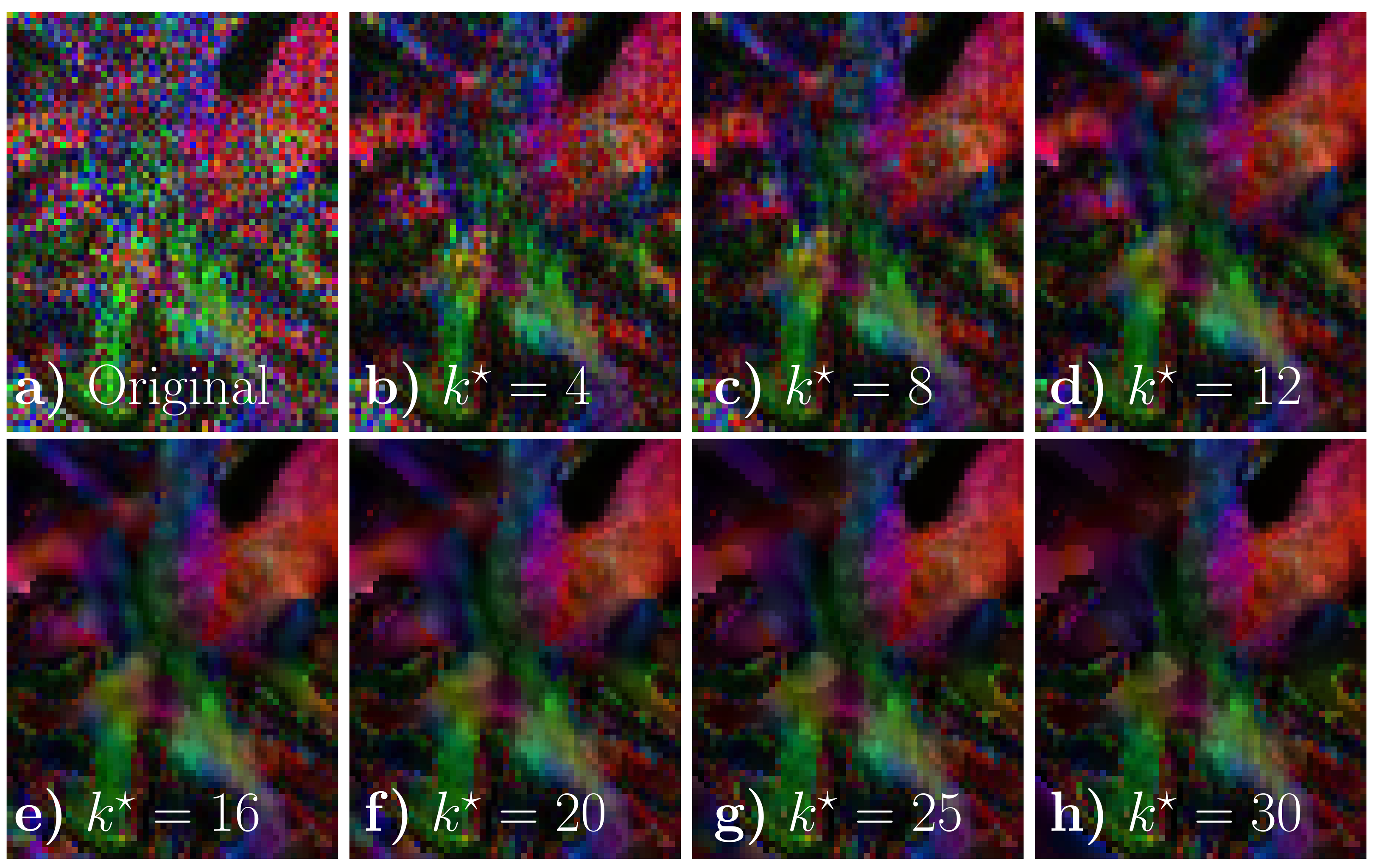
$$w^{(k)}_{g_1 g_2} := K_{loc}\left(\frac{\Delta_{\kappa(\vec{b}_1,k)}(g_1,g_2)}{h(\vec{b}_1,k)}\right) K_{st}\left(s^{(k)}_{g_1 g_2}/\lambda\right)$$

- K_{loc} and K_{st} are *kernel functions*.
- $\Delta_\kappa(g_1,g_2)$ is a *discrepancy* in $\mathbb{R}^3 \times \mathbb{S}^2$.
- $\{\kappa(\vec{b},k)\}$ relates distances in $\mathbb{R}^3$ and $\mathbb{S}^2$.
- $\{h(\vec{b},k)\}$ sequence of *bandwidths*.
- $s^{(k)}_{g_1 g_2}$ is a *statistical penalty* defined by

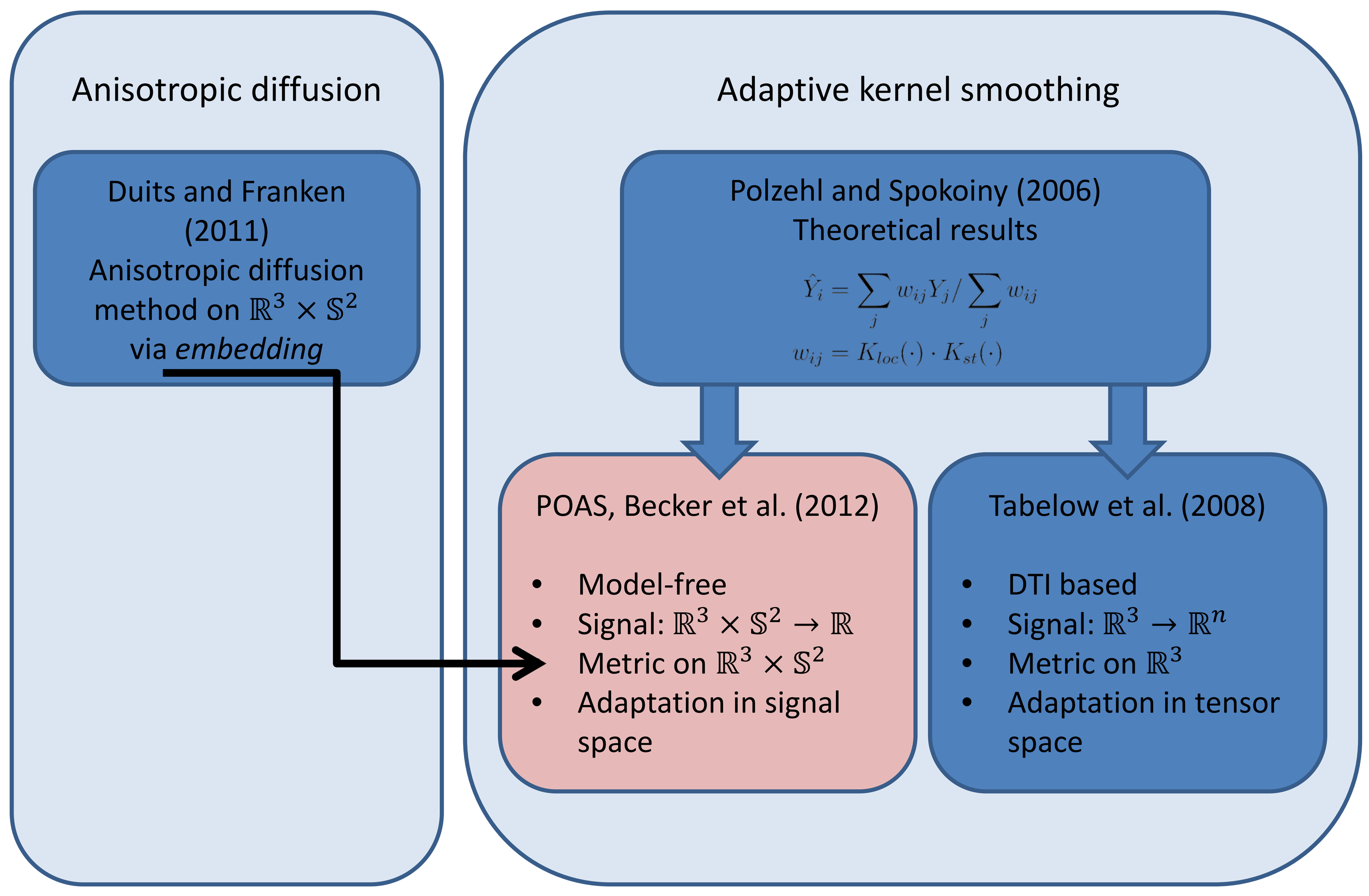
  $$s^{(k)}_{g_1 g_2} := \mathscr{K}\left(\frac{\hat{S}^{(k-1)}_{g_1}}{\hat{\sigma}}, \frac{\hat{S}^{(k-1)}_{g_2}}{\hat{\sigma}}\right) \cdot \sum_{g_2} w^{(k-1)}_{g_1 g_2}$$

  with the Kullback-Leibler distance $\mathscr{K}$ between two non-central χ-distributions.
- λ is the *adaptation parameter*, chosen by a *propagation condition* (data-independent).

Dependence on the maximal number of iteration steps $k^\star$



Related works



Conclusions

Our position-orientation adaptive smoothing algorithm (POAS) for dMRI data has several advantages:

- POAS **uses the special geometry of the measurement space** $\mathbb{R}^3 \times \mathbb{S}^2$ (voxel space and diffusion-gradient directions).
- POAS is designed to be adaptive to the fine anisotropic structures observed in dMRI by using a statistical penalty. This ensures propagation within homogeneous compartments and separation between distinct compartments **avoiding blurring at structural borders**.
- The improved quality of the data after smoothing can be used for further analysis or in clinical context for **a reduction of number of diffusion weighting gradients and hence acquisition time**.
- The proposed algorithm **does not rely on the tensor model or other higher order models for the dMRI data**. Therefore, after using the method for smoothing the diffusion weighted images any model can be applied to the data.
- The method has an intrinsic stopping criterion, which means that **most of the parameters of the method have only minor influence on the results**, while the bandwidth parameter $k^\star$ is limited only by the available computational power and the desired smoothness in homogeneous regions.

Further reading

Structural adaptive smoothing methods for DW-MRI

- S.M.A. Becker, K. Tabelow, H.U. Voss, R.M. Heidemann, A. Anwander, J. Polzehl (2012), 'Position-orientation adaptive smoothing of diffusion weighted magnetic resonance data (POAS)', *Med. Image Anal.*, http://dx.doi.org/10.1016/j.media.2012.05.007
- 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 (2011), 'Beyond the Gaussian Model in Diffusion-Weighted Imaging: The package dti', *J. Statist. Software*, vol. 44, issue 12, pp. 1–26. (Explaining the usage of the package for HARDI)
- J. Polzehl, K. Tabelow (2009), 'Structural adaptive smoothing in diffusion tensor imaging: The R package dti', *J. Statist. Software*, vol. 31, issue 9, pp. 1–23. (Explaining the usage of the package for DTI)
- Download: `http://cran.r-project.org/web/packages/dti/index.html`

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