Semi-Joint Reconstruction for Diffusion MRI Denoising Imposing Similarity of Edges in Similar Diffusion-Weighted Images

Vladimir Golkov[1,2], Marion I. Menzel[1], Tim Sprenger[1,3], Axel Haase[3], Daniel Cremers[2], and Jonathan I. Sperl[1]

[1]Diagnostics & Biomedical Technologies - Europe, GE Global Research, Garching n. Munich, Germany, [2]Department of Computer Science, Technische Universität München, Garching n. Munich, Germany, [3]Institute of Medical Engineering, Technische Universität München, Garching n. Munich, Germany

Purpose: Diffusion MRI acquisitions consist of a series of diffusion-weighted images (DWIs) of the same anatomical structure. Usually, all DWIs are reconstructed independently, without exploiting the prior knowledge of the structural similarity between DWIs. Incorporating such prior knowledge for the purpose of signal-to-noise ratio (SNR) enhancement, Haldar *et al.* [1] proposed a smoothing but edge-preserving *Joint Reconstruction* (JR) of all DWIs, where the edges are modeled by being identical among all DWIs. However, DWIs can be dissimilar since different anatomical structures are enhanced depending on diffusion weighting and diffusion direction, causing the DWIs to have quite differing edge structures. In the present work, we generalize JR to allow for individual edges in each DWI. However, the DWIs are in general too noisy to allow for reliable individual edge estimation. We therefore apply three further modifications to generalize the edge estimation, two of which take advantage of the common information contained in mutually similar DWIs, yielding *Semi-Joint Reconstruction* (SJR). Firstly, we use edge information from all DWIs weighted by their similarities to the current DWI, where the definition of similarity is based on proximity in diffusion-encoding q-space, i.e. a similar diffusion direction and weighting. Secondly, the edge estimation is done using DWIs that have been *jointly* denoised by truncated singular value decomposition (TSVD). Thirdly, we use edge detectors that are more robust to noise than the originally proposed [1] finite differences, such as wavelet- or shearlet-based edge detectors [2].

Methods: The iterative solution of JR [1] (or inhomogeneity-corrected JR [3] if multi-coil data is used) involves calculating line process values ℓ_{np} between neighboring voxels n and p which take on values in [0;1] where 0 means an edge between n and p and 1 means no edge (i.e. strong smoothing of intensities). In each iteration, the line process values ℓ_{np} are estimated from the sum of finite differnces over all Q DWIs as

$$\ell_{np} = \min\left(1, \frac{\xi}{\sqrt{\sum_{q=1}^{Q} \beta_q^2 \, e_{npq}^2}}\right),$$

where $e_{npq} = \left|\rho_p^q - \rho_n^q\right|$ is the "edge likeliness" between the voxels n and p in the DWI number q, calculated from the finite difference of their intensities ρ_p^q and ρ_p^q, the β_q are regularization hyperparameters, and ξ is the regularization (smoothing) parameter. We propose individual line process values ℓ_{npu} for each DWI (denoted by u):

$$\ell_{npu} = \min\left(1, \frac{\xi}{\sqrt{\sum_{q=1}^{Q} s_{qu} \beta_q^2 e_{npq}^2}}\right),$$

where s_{qu} denotes the similarity weighting between the DWIs q and u, that indicates how much the image contrast in the DWI q contributes to the line process value in the DWI u. DWIs with similar contrast (similar diffusion direction and weighting) should obtain higher similarity weighting than dissimilar DWIs. We therefore define

$$s_{qu} = \left(\frac{\vec{q}}{|\vec{q}|} \cdot \frac{\vec{u}}{|\vec{u}|}\right)^4 \left(1 - \big||\vec{q}| - |\vec{u}|\big|\right),$$

where $(\vec{q}/|\vec{q}|) \cdot (\vec{u}/|\vec{u}|)$ is the dot product of the diffusion directions (normalized to unit length) of the respective DWIs (yielding the cosine of the angle between them, i.e. high values for similar directions and 0 for orthogonal directions), the exponent 4 ensures positive values only (i.e. equal treatment of opposing diffusion directions) as well as sufficiently low similarity weighting for not-so-similar directions, and the factor $1 - \big||\vec{q}| - |\vec{u}|\big|$ penalizes dissimilar diffusion weighting. Replacing ℓ_{np} by ℓ_{npu} permits having individual line process values for DWIs, and the above formula for s_{qu} ensures that line process values are denoised using similar DWIs in a Semi-Joint Reconstruction framework. The contributions of similar DWIs according to s_{qu} are shown exemplarily for one u in Fig. 1.

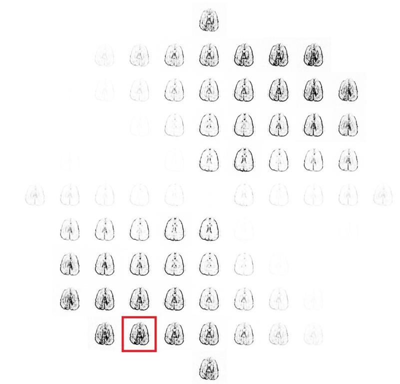

Figure 1. Contribution from each DWI (4-D slice of DSI data shown) to the edge map of the marked DWI (bottom left, q=(4,0,-2)).

To further denoise the ℓ_{npu} maps, we propose replacing $e_{npq} = \left|\rho_p^q - \rho_n^q\right|$ by $e_{npq} = \left|\hat{\rho}_p^q - \hat{\rho}_n^q\right|$, where the $\hat{\rho}_p^q$ and $\hat{\rho}_n^q$ are obtained from DWIs denoised by TSVD [4,5]. Further denoising of ℓ_{npu} is achieved by replacing the finite differences by the estimates of corresponding derivatives yielded by shearlet-based edge detectors [2] applied to TSVD-denoised DWIs.

For experimental validation, healthy volunteer 11^3 diffusion spectrum imaging [6] (DSI) data were acquired on a 3T GE MR750 clinical MR scanner (GE Healthcare, Milwaukee, WI, USA) using a single channel Tx/Rx head coil (data set #1, b_{max}=2000mm/s², TE=96ms, TR=3s, 128x128, FOV=24cm, slice=4mm) and a 32-channel head coil (data set #2, NEX=4, b_{max}=8000mm/s², single spin echo, TE=124.3ms, TR=1.6s, 96×96, FOV=24cm, slice=2.5mm).

Results and Discussion: Reconstruction results and edge maps (data set #1) are shown in Fig. 2. Both JR and SJR yield denoised images. However, the underlying edge maps in JR contain false positives and false negatives due to averaging over dissimilar DWIs, whereas edge maps are individual for each DWI in SJR. Root-mean-squared error (RMSE) of DWI intensity (data set #2) is shown in Fig. 3. Both JR and SJR outperform standard reconstruction. SJR does not outperform JR, but it is more stable to the choice of regularization parameter ξ.

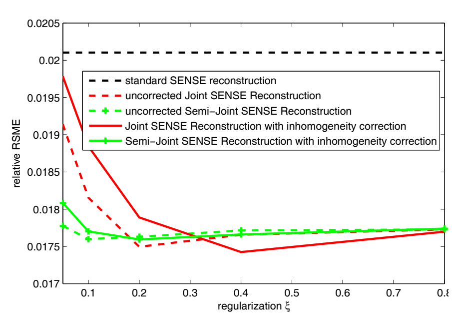

Figure 3. Error in DWI intensity for standard SENSE reconstruction, JR, and SJR. (ground truth: average of 3 other repetitions)

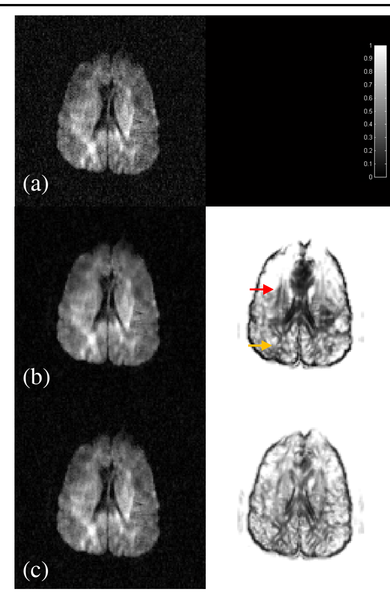

Figure 2. One single-coil DWI (q=(4,0,-2)) for compared reconstruction methods (left column) and corresponding line process value map (right column). **(a)** Standard reconstruction: noisy; no line process applied. **(b)** JR: false positives and false negatives (arrows) in edge map due to averaging over dissimilar DWIs. **(c)** SJR: denoised images while preserving individual edges.

References: [1] Haldar et al., MRM 2012. [2] Schug et al., Proc. SPIE 8058, 2011. [3] Golkov *et al*., ESMRMB 2013, #153. [4] Oros-Peusquens & Shah, ISMRM 2013. [5] Golkov et al., ESMRMB 2013, #23. [6] Wedeen et al., MRM 2005. **Grant support:** Deutsche Telekom Stiftung.