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Improving Diffusion Tensor Estimation using Adaptive and Optimized Filtering based on Local Similarity

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Introduction

- The diffusion-weighted magnetic resonance imaging (DW-MRI or DWI) describes the neuronal pathways which are used for the communication among several centers of brain activity [1].
- The DW-MRI has an inherent low SNR due to a low signal amplitude and a pronounced thermal noise, biasing the estimation of diffusion tensors (DT) [1].
- Classic denoising techniques in DW-MRI filtering assume an equal noise distribution across the image, modifying important information (e.g. edges, structures and type of matter), leading to suboptimal filtering results.
- Methods based on local similarity have the potential to improve the estimation of diffusion information with respect to another filtering techniques [1, 2, 3].
- Moreover, adaptive and optimized filters based on local similarity can mitigate the drawbacks of having to deal with tuning the filter parameters.

Materials and Methods

Non-Local Means filter (NLM): In a 2D set of parallel images $\mathbf{u}$, the restored intensities $\hat{\mathbf{u}}(x_i)$ of the voxel x_i is given by

$$\hat{\mathbf{u}}(x_i) = \sum_{x_j \in V_i} w(x_i, x_j)\mathbf{u}(x_j). \tag{1}$$

The performance of this filter depends on the hyperparameters of the weight functions and the volume V_i. To avoid this problem, several researches have proposed the following adaptive and optimized filter techniques based on local similarity for brain imaging preprocessing:

- Adaptive and Optimized NLM filter (AONLM) [1]
- Oracle-based 3D Discrete Cosine Transform filter (ODCT) [2]
- Prefiltered Rotationally Invariant NLM filter (PRINLM) [2]
- Local PCA filter (LPCA) [3]

Diffusion Tensors (DT): Stejskal-Tanner in [4], relates the DW-MRI and DT-MRI fields by

$$S_k = S_0 \exp\left\{-b\hat{\mathbf{g}}_k^\top \mathbf{D}\hat{\mathbf{g}}_k\right\}, \tag{2}$$

where S_k and S_0 are the DW-MRI associated to the $\hat{\mathbf{g}}_k$ diffusion gradient and baseline image, respectively, and $\mathbf{D}$ is the tensor matrix. Several researches have proposed different methods for DT-MRI estimation such as linear systems [5] and methods based on least-squares (e.g. RESTORE) [6].

Dataset experimental Background

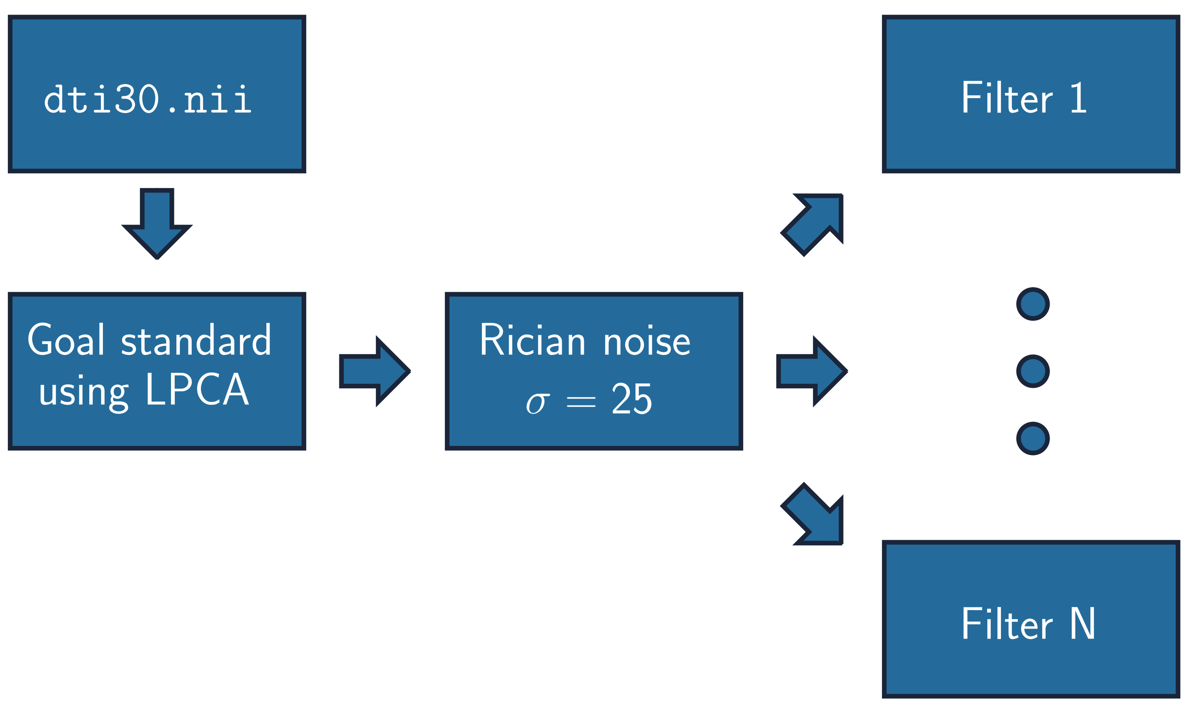

Figure : Dataset experimental Background. The `dti30.nii` is a complete set of DW-MRI images in Nifti format available at `http://www.cabiatl.com/CABI/resources/dti-analysis/`

Filtering techniques and DT estimation method

The parameters for Gaussian filter (GF) and Perona-Malik algorithm (PM) were tuned by cross-validation. For PM, we chose a monotonic function privileging wide regions. For optimized filters, we used the package for 4D-MRI proposed at `https://sites.google.com/site/pierrickcoupe`. We rely on the DT estimation method proposed by Barmpoutis in [5], and we use RESTORE algorithm to evaluate the filtering performance.

Results and Discussion

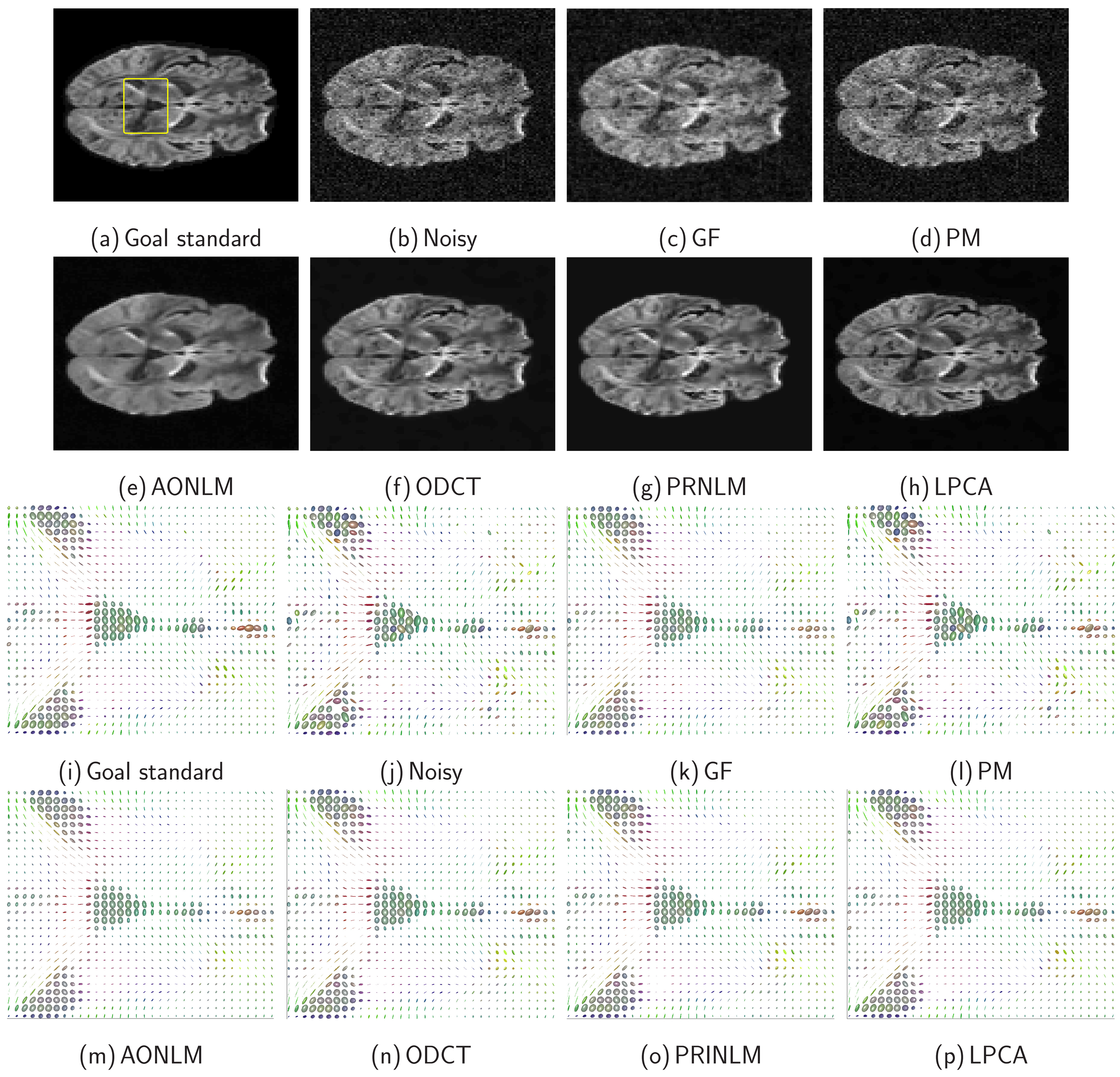

Figure : DWI and DTI results for the proposed filtering methods using the 38th direction and the 30th slide from the goal starndard. Finally we show the estimated DT-MRI from the yellow square window drawn in (a).

Table : Frobenius norm from the difference of metrics computed from the DT-MRI between the case under study and the goal standard. MD: mean diffusivity error. RA: relative anisotropy error. FA: fractional anisotropy error. Frob: Frobenius error norm.

Scheme	MD ($\times 10^{-4}$)	RA ($\times 10^{-3}$)	FA	Frob ($\times 10^{-3}$)
Noisy	0.1234 ± 0.0131	0.1912 ± 0.0190	0.0061 ± 0.0006	0.9274 ± 0.0974
GF	0.0679 ± 0.0078	0.1366 ± 0.0149	0.0060 ± 0.0006	0.5371 ± 0.0449
PM	0.1234 ± 0.0131	0.1912 ± 0.0190	0.0061 ± 0.0006	0.9274 ± 0.0974
AONLM	0.0145 ± 0.0014	0.0558 ± 0.0070	0.0058 ± 0.0007	0.1960 ± 0.0237
ODCT	0.0112 ± 0.0017	0.0448 ± 0.0059	0.0059 ± 0.0006	0.1453 ± 0.0198
PRINLM	$\mathbf{0.0090 \pm 0.0019}$	$\mathbf{0.0300 \pm 0.0040}$	0.0059 ± 0.0006	$\mathbf{0.1148 \pm 0.0239}$
LPCA	0.0104 ± 0.0017	0.0437 ± 0.0057	0.0058 ± 0.0006	0.1296 ± 0.0161
RESTORE	0.0508 ± 0.0046	0.0857 ± 0.0072	$\mathbf{0.0044 \pm 0.0005}$	0.4130 ± 0.0077

Conclusion

- Methods based on local similarity improves the performance of diffusion information but they depend on how well we tune the filtering parameters.
- Adaptive and optimized filter techniques based on local similarity, tend to remove the bias in both DWI filtering and DTI estimation by local information, showing a better performance respect to the classical filters.
- The PRINLM and LPCA filters show the best performances among the optimized filters, making them the most suitable for DWI.

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