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Optimal selection of diffusionweighting gradient waveforms using compressed sensing and dictionary learning

Raphaël Malak Truffet¹, Christian Barillot¹, and Emmanuel Caruyer¹

¹Univ Rennes, CNRS, Inria, Inserm, IRISA - UMR 6074, Empenn - ERL U 1228, F-35000 Rennes, France

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Introduction

Generalized waveforms

Most of diffusion MRI studies rely on Pulsed Gradient Spin Echo sequences. However, these sequences restrict the possibilities of a more general spin echo sequence. In fact, allowing generalized diffusion-weighting gradient waveforms offers many degrees of freedom. That is why we are trying to find the waveforms that are the most interesting.

Compressed sensing

The main idea of this work is to use

- compressed sensing to choose waveforms.
- In fact, compressed sensing aims at making
- fewer measurements based on the

hypothesis that a sparse representation of the signal exists.



 40 directions covering the sphere¹.

- Acquisition parameters
- Dictionary learning

For each microstructure *i*, we have a vector *Y_i* of size
65*40=2600 signals.

 65 generalized gradient waveforms, piecewise constant with 4 steps of time and a constant direction.

 y_i

Η

 x_i

D

Synthetic signals are generated using Monte-Carlo simulations implemented in Camino².

Data generation

Microstructure parameters

- 180 sets of configuration parameters (mean radius, density...).
- Data is augmented in 100 directions using spherical harmonics.
 - The dictionary learning is performed over 80% of 180*100=18,000 vectors. It is performed with SPAMS³ and aims at solving:

$$\min_{D,x_i} \frac{1}{n} \sum_{i=1}^n \frac{1}{2} ||y_i - Dx_i||_2^2 + \lambda ||x_i||_1$$

- 1. Emmanuel Caruyer et al. "Design of multishell sampling schemes with uniform coverage in diffusion MRI". 2013.
- 2. PA Cook et al. "Camino: open-source diffusion-MRI reconstruction and processing". 2006.
- 3. Julien Mairal et al. "Online learning for matrix factorization and sparse coding". 2010.



Signal undersampling and reconstruction



Several techniques for the selection of measurements

Randomly



• Minimizing the coherence of the dictionary by minimizing $\max_{i,j} \frac{|\langle D_{\Omega,i}, D_{\Omega,j} \rangle}{||D_{\Omega,i}||_2||D_{\Omega,j}|}$ where $D_{\Omega,i}$ is th ith column of the dictionary restricted to the lines of Ω

Algorithm

- choose an initial subset Ω.
- while the correlation score decreases: find the line *j* in Ω the most correlated with the others in Ω, and replace it with the gradient not in Ω the less correlated with the remaining gradients.

return the subset Ω.

Reconstruction from a smaller sample







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Concluding remarks and further work

Results

- Encouraging results that show an efficient reconstruction.
- Our gradient selection heuristic gives a better generalization of the signal than randomness that is often used in compressed sensing.

Work in progress

 A different choice of the initial gradient waveforms (generating waveforms using Markov chains).



- Selecting only waveforms instead of selecting couples [waveform + direction] and obtain a rotation invariant scheme.
- Studying the consequences on the microstructure estimation.

