Optimal acquisition design for sparse reconstruction using dictionary learning in diffusion Magnetic Resonance Imaging

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inventeurs du monde numérique

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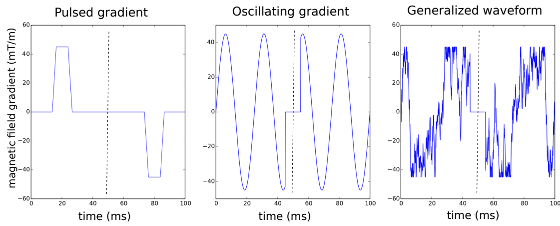
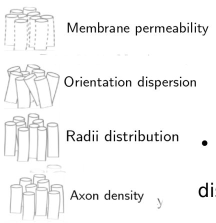
I Introduction

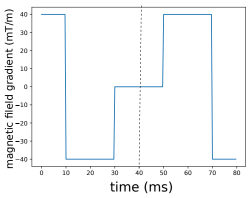
- Magnetic Resonance Imaging (MRI) is a non-invasive technique for the observation of the tissue in vivo.
- Diffusion MRI measures the movement of water molecules and gives information about white matter microstructure.
- The acquisition sequences rely on magnetic field gradients.
- While pulsed gradient waveforms are the most used because of their simplicity, it has been shown that oscillating arbitrary waveforms provide better estimation of microstructure parameters(1).
- Since every function of the time to that respect a few constraints provide a possible gradient waveform, the sampling remains largely unexploited.
- Here are several possible gradient waveforms:

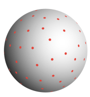


II Data generation



- Many signals are simulated for several gradient waveforms and several microstructure parameters using CAMINO(2).
- 180 different microstructure are generated with parallel fibers and different densities, radii distributions. These microstructure are rotated to represent several orientations.
- 2600 gradients are used in the simulations. Their direction is constant and they are piecewise constant with 4 steps of time.

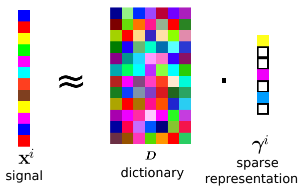




- The gradients are spread over 40 directions that cover the unit sphere.

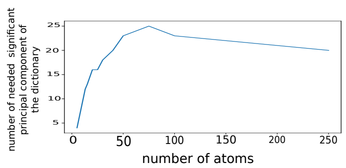
III Dictionary learning

- We want to find a sparse representation for the signal.

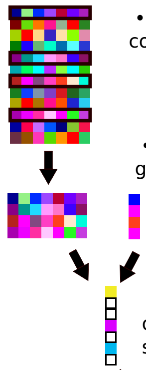


- Dictionary learning is made over the families of signals previously generated.
- The learning is made by updating alternatively the dictionary D and the sparse signals γ^i to minimize:

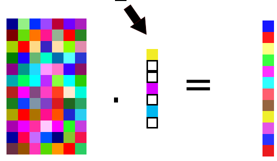
$$\sum_{i=0}^{n} \underbrace{\frac{1}{2}\left\|\mathbf{x}^i - D\gamma^i\right\|_2^2}_{\text{fidelity}} + \underbrace{\lambda\left\|\mathbf{x}^i\right\|_1}_{\text{sparsity}}$$



IV Signal undersampling

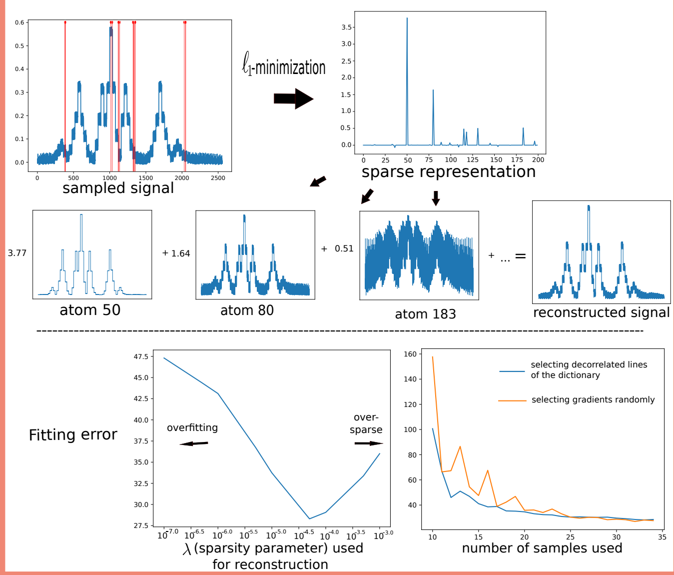


- We select some lines of dictionary (which correspond to gradients) in several ways:
  - randomly
  - uncorrelated lines (minimizing the norm of the restricted correlation matrix)
- We can restrict the dictionary to the selected gradients.
- We use only the measures associated to the selected gradients.
- We can construct a sparse signal using only a few measurements (with compressed sensing techniques, in particular, ℓ_1-minimization)



- We can reconstruct a full signal using only a few measurements

V Results



VI Concluding remarks and further work

- Encouraging results that show an efficient reconstruction
- Our gradient selection heuristic performs better than randomness (often used in compressed sensing)
- We can still improve :
  - The gradients given in input
  - The learning and reconstruction parameters
  - The criterion to optimize for the subsampling (for example, the incoherence of the columns

(1) Ivana Drobnjak, Bernard Siow, and Daniel C. Alexander. "Optimizing gradient waveforms for microstructure sensitivity in diusion-weighted MR". In: Journal of Magnetic Resonance 206.1 (2010), pp. 41-51.

(2) P. A. Cook, Y. Bai, S. Nedjati-Gilani, K. K. Seunarine, M. G. Hall, G. J. Parker, D. C. Alexander. "Camino: Open-Source Diffusion-MRI Reconstruction and Processing", 14th Scientific Meeting of the International Society for Magnetic Resonance in Medicine, Seattle, WA, USA, (2006) p. 2759.