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

Raphaël Truffet supervised by Emmanuel Caruyer

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 provides a possible gradient waveform, the sampling remains largely unexploited.
- Here are several possible gradient waveforms:

![Gradient Waveforms](image)

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.

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 and the sparse signals to minimize:

\[ \min_{x, \Phi} \| x - \Phi \|_2^2 + \lambda \| x \|_1 \]

Results

- The criterion to optimize for the subsampling (for example, the restricted correlation matrix)
- 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, \( \ell_1 \)-minimization
- We can reconstruct a full signal using only a few measurements

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 sub-sampling (for example, the incoherence of the columns

References: