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Optimal selection of diffusion-weighting gradient waveforms using compressed sensing and dictionary learning

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 that respect a few constraints provide 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.

![Data Generation](image)

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 $\gamma$ to minimize:

$$\sum_{i=1}^{n} \|x_i - D\gamma_i\|^2 + \lambda \|\gamma_i\|_1$$

$$\text{over} \gamma \text{ and sparsity}$$

- The dictionary learning is performed by the tool SPAMS in python.

![Dictionary Learning](image)

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)
  - minimizing the coherence
- 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

![Signal Undersampling](image)

Results

- The criterion to optimize for the subsampling (for example, the incoherence of the columns)
- The learning and reconstruction parameters
- The gradients given in input
- The criterion to optimize for the subsampling

![Results](image)

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)