Optimal selection of diffusion-weighting gradient waveforms using compressed sensing and dictionary learning
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To cite this version:

HAL Id: inserm-01939066
https://www.hal.inserm.fr/inserm-01939066v2
Submitted on 30 Jan 2019

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• 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 $\gamma$ to minimize:

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

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

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 provides better estimation of microstructure parameters using CAMINO(2).

• 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, $\ell_0$-minimization)

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

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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.

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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)
