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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 gives information about white matter microstructure.
• Diffusion MRI measures the movement of water molecules and field gradients.

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, $\ell_p$-minimization)
• We can reconstruct a full signal using only a few measurements

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.
• Dictionary learning is made by updating alternatively the dictionary $D$ and the sparse signals $\gamma$ to minimize:

$$\sum_{j=1}^{n} \| x_j - D \gamma_j \|_2^2 + \lambda \| \gamma_j \|_1$$

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

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)

References