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

Raphaël Truffet supervised by Emmanuel Caruyer

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
- 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:

II. Data generation

- Many signals are simulated for several gradient waveforms and several microstructure parameters using CAMINO
- 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 \( \gamma \) to minimize:

\[
\sum_{j=1}^{n} \left[ \| \gamma^j - D \gamma^j \|_2^2 + \lambda \| \gamma^j \|_1 \right]
\]

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

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)
  - 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

V. Results

- Fitting error (root mean squares)
  - The criterion to optimize for the subsampling (for example, the restricted correlation matrix)
- The learning and reconstruction parameters
- The gradients given in input
- Number of samples used
- Operating point (sparsity parameter) used for reconstruction

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)