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

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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:

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 \( \mathcal{D} \) and the sparse signals \( \mathbf{y} \) to minimize:

\[
\sum_{i=1}^{N} \frac{1}{2} \| \mathbf{x}_i - \mathbf{D} \mathbf{y} \|^2 + \lambda \| \mathbf{y} \|_1
\]

\( \mathbf{x}_i \) : observed signal \( \mathcal{D} \) : dictionary \( \mathbf{y} \) : sparse representation

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

Results

- 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)

Concluding remarks

- Further work