

Accelerated diffusion spectrum imaging in the human brain using compressed sensing

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Introduction: In diffusion spectrum MR imaging (DSI)¹⁻⁴, the information encoded in q-space⁵ can be separated into angular and radial components. The angular component reflects the underlying tissue anisotropy, while the radial component provides information about the characteristics of diffusion (i.e. Gaussian, non-Gaussian, kurtosis⁶) or degree of restriction. To better elucidate this information, the Fourier transform of the q-space data (denoted as the propagator⁵, which yields the displacement probability) is typically employed. The high dimensionality of DSI (3D in spatial and 3D in q-space) can lead to very long acquisition times, severely limiting its application *in vivo*. We propose to accelerate DSI through the application of compressed sensing (CS)⁷ in the three q-space dimensions. To first approximation the signal in q-space can be regarded as Gaussian, which admits a sparse representation in the wavelet domain. Using various under-sampling schemes, we investigated CS for DSI on simulated fiber crossings, on bovine tongue, and on the brains of healthy volunteers. CS reconstructions of under-sampled data sets were compared to fully sampled datasets with respect to orientation distribution function (ODF) and radial measures such as diffusion coefficient or kurtosis.

Theory and methods: According to Stejskal and Tanner⁸ and using the kurtosis expansion⁹, the MR q-space signal can be expressed as a function of b-values:

$$\ln[S(b)] = \ln[S(0)] - b \sum_{i=1}^3 \sum_{j=1}^3 n_i n_j D_{ij} + \frac{1}{6} b^2 D^2 \sum_{i=1}^3 \sum_{j=1}^3 \sum_{k=1}^3 \sum_{l=1}^3 n_i n_j n_k n_l W_{ijkl} \quad (\text{Eq. 1})$$

where $S(b)$ denotes the MR signal in q-space, and $S(0)$ is the MR signal in the absence of diffusion encoding gradients along gradient directions n . This equation has a diffusion tensor term (linear in b), which spans a symmetric 3×3 matrix of the diffusion tensor D_{ij} (6 independent elements) and a kurtosis tensor term (quadratic in b), which spans a $3 \times 3 \times 3 \times 3$ matrix (15 independent elements). The MR signal amplitude $S(q)$ as a function of b-value in q-space is related to the spin displacement (r) probability or diffusion propagator $P(r)$ by the Fourier transform (F).

$$S(q) = S_0 \int P(\vec{r}) \exp(i\vec{q} \cdot \vec{r}) d^3 r = S_0 F[P(\vec{r})] \quad (\text{Eq. 2})$$

The integration over a set of radial reconstructions of the diffusion propagator $P(r)$ is denoted as the ODF. It inherently retains only the angular component of diffusion information, while sacrificing the radial component. The latter can be evaluated with measures such as diffusion coefficient or kurtosis, which provide scalar measures for the shape of the q-space signal.

Results: Simulations of 2D diffusion propagator data for crossed fibers were performed using Matlab. A set of different under-sampling schemes (random, Poisson disk, Gaussian) with acceleration factors up to $R=8$ was tested in combination with our implementation of compressed sensing and compared to fully sampled data (ground truth). The effect of under-sampling on ODF and diffusion coefficient / kurtosis obtained after compressed sensing reconstruction was evaluated. DSI experiments on bovine tongue and healthy volunteers were performed using a 3T GE MR750 scanner (GE Healthcare, Milwaukee, WI) using single-shot echo planar imaging (TE = 130 ms, TR = 3 s). A single slice in k-space was acquired (bovine tongue: $64 \times 64 \times 1$, FOV = 25 cm, slice = 4 mm; brain: $64 \times 64 \times 1$, FOV = 25 cm, slice = 4 mm) and for each image pixel, the q-space was sampled in 2D (bovine tongue: b-max = 10,000 s/mm^2 , 33×33 q-space without corners; brain: b-max = 10,000 s/mm^2 , 25×25 q-space fully sampled without corners and 37×37 under-sampled with $R=2.3$ and $R=4$, Gaussian under-sampling scheme). Total acquisition times were 22 min for bovine tongue and 22 min ($R=2.3$) and 12 min ($R=4$) respectively for brain. Fully sampled datasets were reconstructed using the modulus Fourier transform (Eq. 2); under-sampled datasets were reconstructed using compressed sensing. Radial diffusion information was determined through fitting of the experimental data or reconstructed data to (Eq. 1). ODF were normalized by subtracting the isotropic part of the ODF for each individual pixel and scaling the resulting anisotropic part for all pixels jointly (for display purposes only).

Discussion and conclusions: In the simulated fiber experiments, we compared different under-sampling schemes and evaluated the compressed sensing reconstruction performance on the reconstructed orientation distribution function (Fig.1). Our analysis demonstrates that the main features of ODFs are retained up to an under-sampling factor of $R=4$, while for higher accelerations, the shape of the ODFs gradually degrade, leading to ambiguities in assigning major orientations of diffusion. The comparison of different under-sampling schemes (random, Poisson disk and Gaussian) revealed that for q-space data sets (which have nearly Gaussian shape) the Gaussian under-sampling scheme performed best. This observation was confirmed in experiments on bovine tongue and *in-vivo* human brain, which means that even in the presence of noise, compressed sensing with acceleration factors up to $R=4$ can be used to reconstruct ODFs reliably (Fig. 1b-e) and to retain fitted diffusion coefficients. Fig 1b-e depicts the pronounced left-right anisotropy for the central corpus callosum region, while pixels within ventricles and grey matter appear isotropic. Fiber crossings can also be observed clearly both in brains and bovine tongue (data not shown). A regularization of the fitting procedure to compute kurtosis reliably is currently under study. We have shown that CS can be effectively employed to shorten the acquisition times of DSI to reasonable durations, which can be tolerated by volunteers and patients. Shortening DSI acquisitions significantly by means of CS would open up the door to new contrasts that are truly based on underlying tissue properties.

References:

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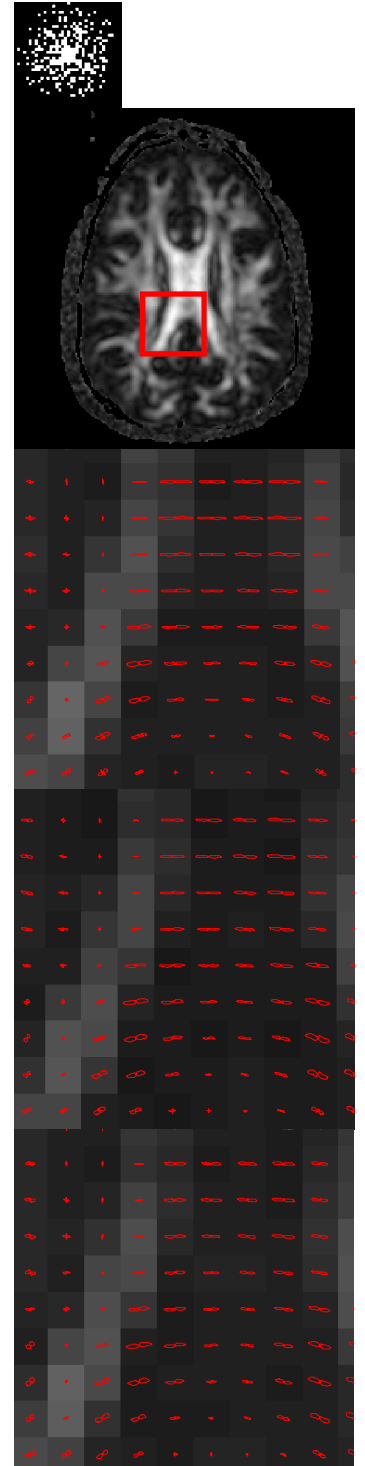


Fig.1: a) Gaussian sampling q-space pattern ($R=4$); b) fractional anisotropy map; enlargements of c) fully sampled acquisition ($R=1$, 25×25) d) under-sampled acquisition of higher resolution q-space dataset ($R=2.3$, 37×37); e) under-sampled acquisition of higher resolution q-space dataset ($R=4$, 37×37)