Using spheres to navigate the brain ...

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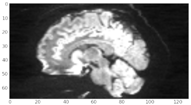
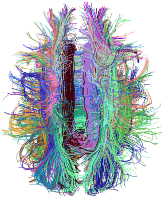
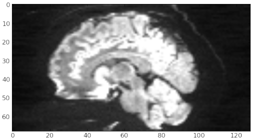
… enroute from white matter to tractography



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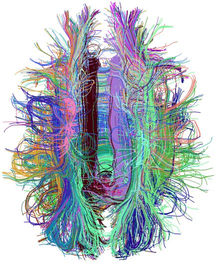

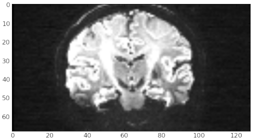
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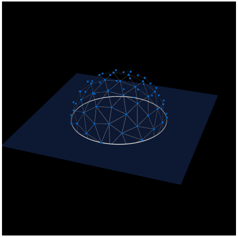
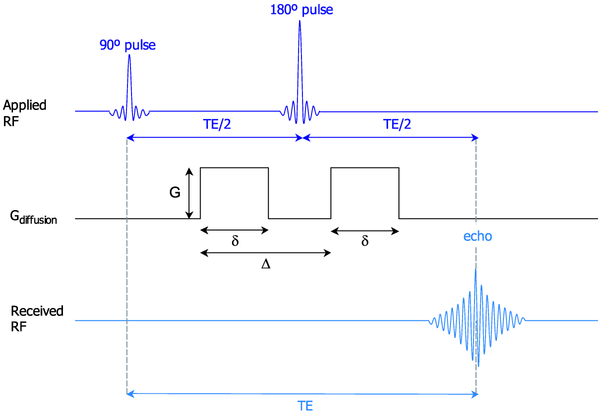


Diffusion MR scanner sequence

- This is the classical Pulsed Gradient Spin Echo (PGSE) sequence of Stejskal and Tanner (1965). More refined sequences are typically used nowadays though the underlying principles are the same.

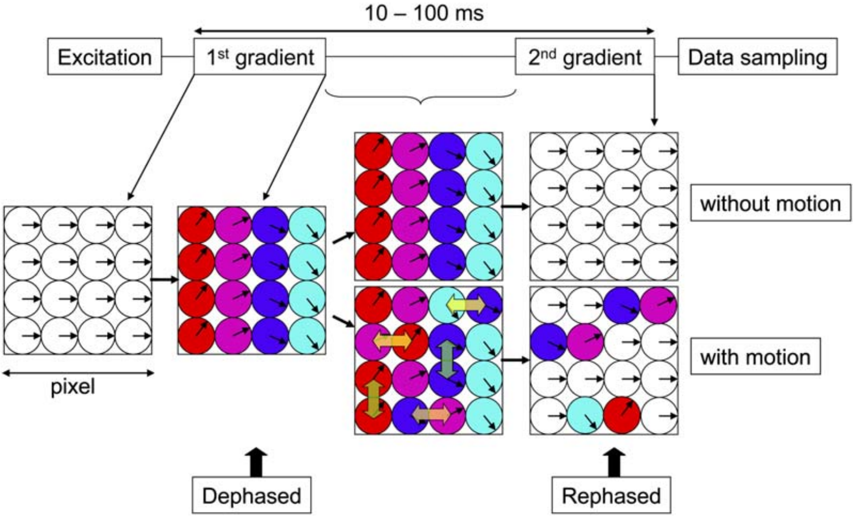


Diffusion MR physics

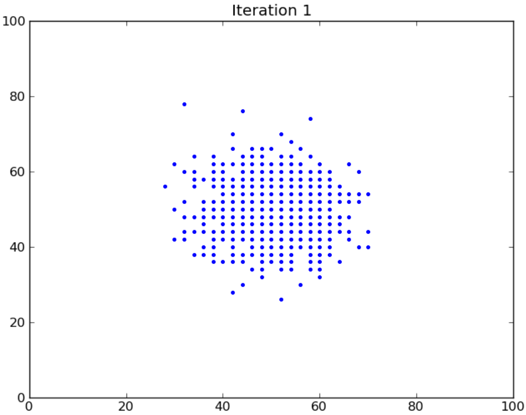
- Protons in water molecules receive gradient pulses **G** of width δ, separated by time Δ.
- The spins precess during this period. The rate of precession is proportional to the local magnetic gradient. A proton spin will experience a phase shift proportional to its molecular diffusion displacement in the direction **G**.
- The refocusing pulse will elicit a signal at each location which is attenuated by the amount of diffusion displacement in the direction **G**.

Schematic (Mori)

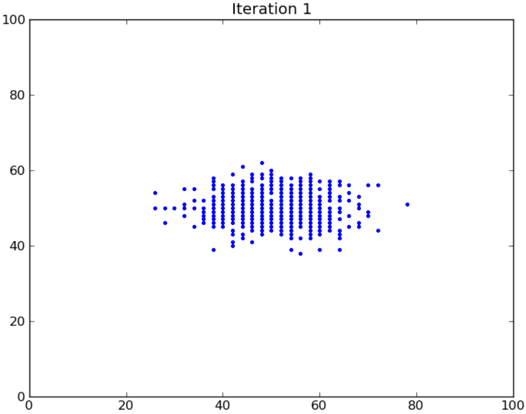
- Diffusion gradient is in left-right direction
- Displacement in this direction is not completely refocused



Shape matters: isotropic diffusion

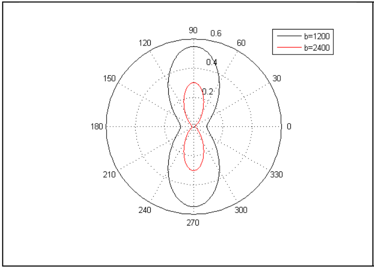


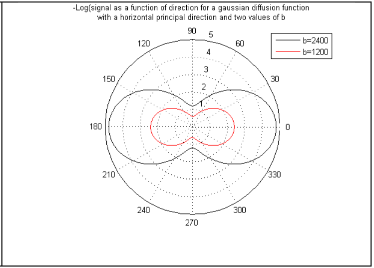
Shape matters: non-isotropic diffusion



Signal dependence on direction

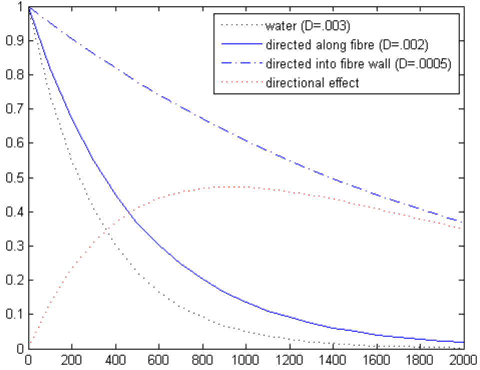
- The distribution of displacements - or diffusion propagator - is an indicator of underlying structures
- Linear fibrous tissue containing water will hinder movement towards the walls of the fibres by comparison with movements along the fibre





signal	-log(signal)

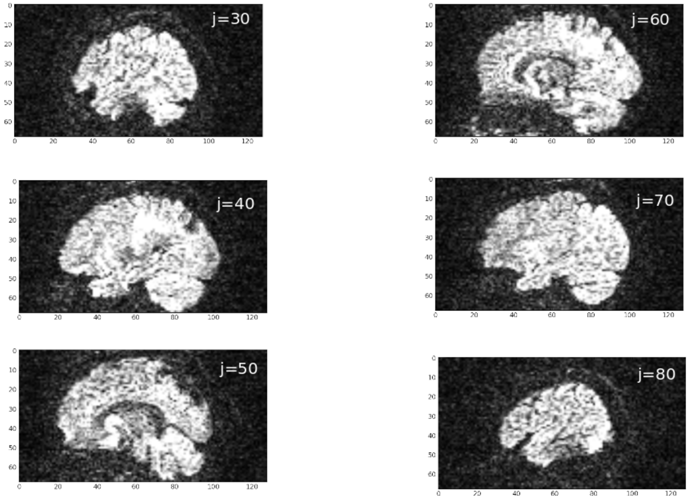
Signal dependence on diffusivity



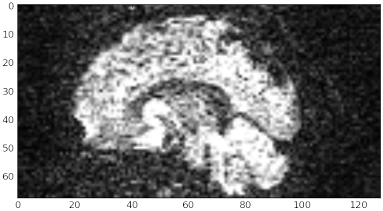
Fourier relationship

- The diffusion MR signal is in essence a Fourier Transform of the diffusion propagator
- In the idealised gaussian, brownian motion case if the propagator is $p(r|r_0)\ \exp(-(r-r_0)^T D(r-r_0))$ then the signal is $S\ \exp(-kG^T D^{-1} G))$ where G is the diffusion gradient and k depends on Δ, δ and other physical constants.
- Directions of maximum diffusivity are directions of minimum signal and vice versa

One volume of data (g=[0,1,0])

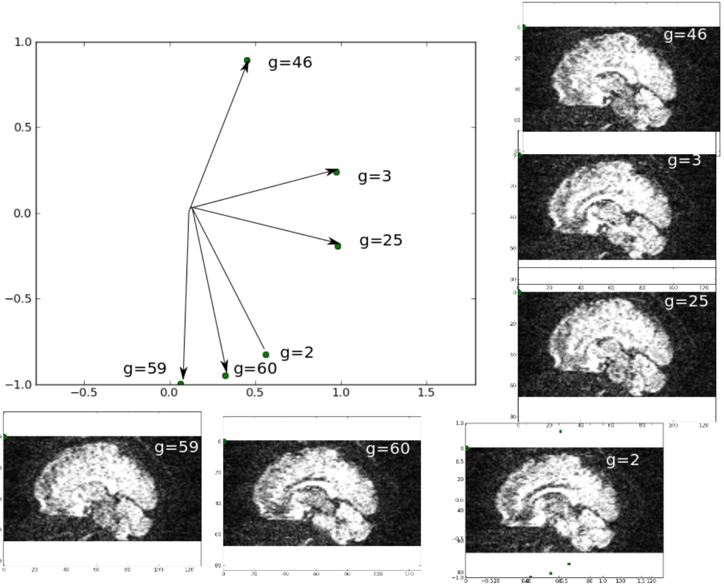


One slice



Slice j=60 Gradient [0,1,0] perpendicular to slice

The same slice for six different (nearly) in-plane gradient directions



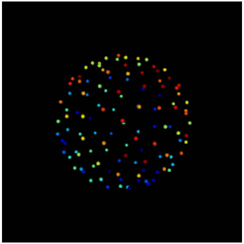
6 dimensional data

- we are thus dealing with 6 (or 3+3) dimensional datasets.
  - 3 dimensions coding the location $\mathbf{r} = [x, y, z]$ in scanner (or subject) space
  - 3 dimensions coding the direction $\mathbf{G}$ $=[u, v, w]$ in gradient-direction-and-strength space
- in order to create pictures like these we need to have
  - a means of charcterising local directional information
  - a means of creating streamlines
  - finite resolution means that there may well be more than one direction in which we want to lead the streamlines

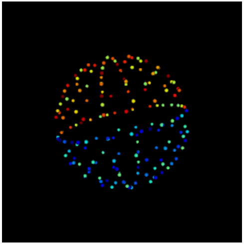
Acquisition and reconstruction

- We need a set of directions and gradient strengths in **q-space**
  - time is important so we may need keep the number down
  - as equally distributed as possible
- The choice may depend on the reconstruction algorithm we will use
  - direct discrete Fourier transform from q-space would predicate a grid of sampling values
  - orientation distribution methods want a 'good' set of directions on the unit sphere
- We need a sphere to represent the directional information in the voxel

Two acquisition spheres



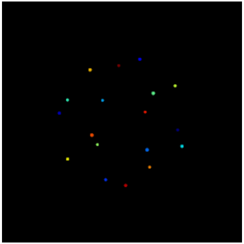
Siemens standard 64 directions



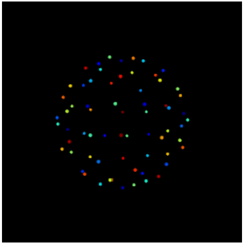
Yeh's 102 direction DSI design

`These plots were created using dipy/scratch/very_scratch/get_vertices`

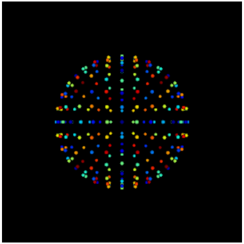
Some reconstruction spheres



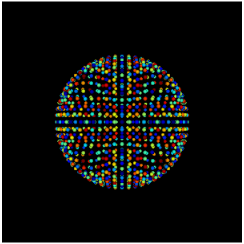
This is an icosahedron F=20, E=30, V=12



Subdividedx2: F=80, E=, V=



Subdividedx3: F=160, E=, V=



Subdividedx4: F=320, E=, V=

These plots were created using dipy/scratch/very_scratch/get_vertices

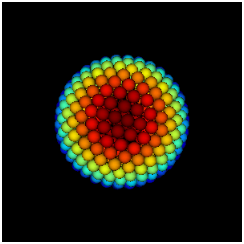
Transfer matrix

- The transfer matrix $\mathbf{T}$ is important in considering how the acquisition paradigm and the reconstruction representation interact with each other
- If $\mathbf{G}$ is the matrix of acquisition directions (MR gradients), and $\mathbf{V}$ is matrix of vertices on the reconstruction sphere

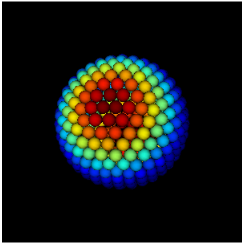
$$\mathbf{T} = \mathbf{G}\mathbf{V}^{\mathbf{T}}$$

- $\mathbf{T}$ is the matrix of cosines of angles between acquisition gradients and reconstruction vertices
  - we are interested in various elementwise transforms of $\mathbf{T}$: $|\mathbf{T}|$, $|\mathbf{T}|^{\mathbf{k}}$, $\mathrm{sinc}(|\mathbf{T}|/\lambda)$ ...

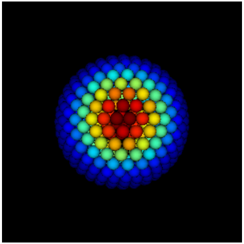
Point spread functions



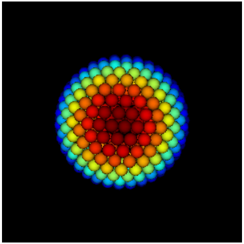
abs



squared



fourth power

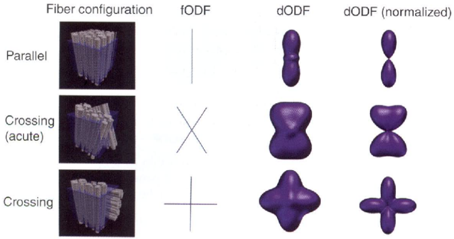


sinc

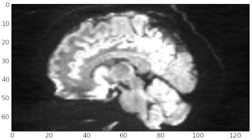
These plots were created using

`dipy/scratch/very_scratch/get_vertices`

Complex matter



The end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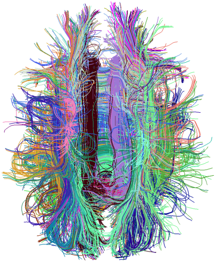

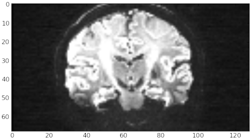
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