TRANSFORMING GRIDS TO SHELLS AND VICE VERSA: AN EVALUATION OF INTERPOLATION METHODS IN DIFFUSION MRI Q- AND B-SPACE

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Purpose: Diffusion MRI (dMRI) can characterize microscopic diffusion properties of tissue by acquiring multiple images with different diffusion-encoding gradient directions and/or strengths, with each image corresponding to a point in q-space or 'b-space'. A broad variety of methods have been proposed to analyze the diffusion signal (e.g., diffusion tensor imaging (DTI), multi-compartment models, spherical deconvolution (SD), diffusion spectrum imaging (DSI) and q-ball imaging (QBI)), all varying in their preferred or required sampling of q-space [1]. DSI, for example, requires q-space to be sampled on a Cartesian grid, whereas (conventional) DTI and SD approaches typically require the acquisitions to be made on a shell in q-space. To be able to compare different analysis techniques while keeping the scan time within a reasonable range, it is convenient to use a particular acquisition strategy (e.g., Cartesian, single-shell, or multi-shell) and interpolate the required encoding scheme from this set of data, as is done in hybrid diffusion imaging (HYDI) [2]. Furthermore, q-space interpolation methods can also be beneficial for detecting and correcting outliers [3], amongst others. However, there is no consensus in the literature on whether signal interpolation should be done in q- or b-space and on which interpolation method to use (i.e., nearest neighbor, linear, cubic, or model-based using e.g. CHARMED or DKI [1-4]). This 'ad hoc' signal interpolation may strongly influence the numerical accuracy of the computations and, subsequently, the metrics derived from the signal [1]. In this work, we evaluated the difference in interpolated values for different interpolation techniques in both q-space and b-space.

Methods: Interpolation methods: The following interpolation methods were compared: nearest neighbor and linear interpolation in both q- and b-space, cubic interpolation in q-space when data is sampled on a Cartesian grid, and DKI-based interpolation in b-space. For the latter approach, the DKI model was fitted using iteratively weighted linear least squares [5]. For interpolation from a grid, interpolation using a look-up table approach was used (*interpn* in Matlab); for interpolation from other configurations, we used interpolation based on Delaunay triangulation [6] (*griddatan* in Matlab). Simulations: *q- and b-space sampling:* A framework was developed to construct (multi-) shell and Cartesian sampling patterns in either q- or b-space, using the relation $b=(2\pi)^2(\Delta-\delta/3)q^2$ to convert between spaces. Δ and δ were chosen to be 51.6 and 32.8 ms respectively, allowing for a maximum b-value of 12000 s/mm^2 on a clinical system (3T, g_{max} = 61.9 mT/m). *Diffusion signal modeling:* The Zeppelin Bingham CSF (ZeppBingCSF) compartment model [7,8] was implemented to simulate the diffusion signal at any given point in q- and b-space. This model provided the best fit to a rich in vivo dataset [7].

Results: Simulations: Fig. 1 shows three interpolation situations: (a) From Cartesian grid in q-space with an odd amount of points along the axis to an even grid (Cart2Cart); (b) from multi-shell to Cartesian in q-space (Multish2Cart); and (c) from a Cartesian grid in q-space to single shell (Cart2Singlesh). The graphs represent the root mean square error (RMSE) over all interpolated points (in the same space as interpolation is done). The difference between interpolation in q- and b-space is the most prominent for nearest neighbor interpolation in Cart2Cart and linear interpolation in Multish2Cart. In Cart2Cart, cubic interpolation is significantly better than linear. Calculating the interpolated values based on a DKI fit provided the smallest RMSE for all configurations, independent of SNR.

Discussion and Conclusion: In this preliminary study we have shown the influence of the q-space interpolation method on the error of the interpolated values for different configurations in simulations. There are differences between interpolation in q-space or b-space for some configurations due to the different relative spacing of the points. The strong performance of the DKI-based interpolation may be explained by the fact that this method uses all acquired points to inform us on the points to be interpolated, whereas the nearest neighbor, linear, and cubic interpolation are mostly determined by the surrounding points in q- or b-space. In future work we will focus on the evaluation on real data

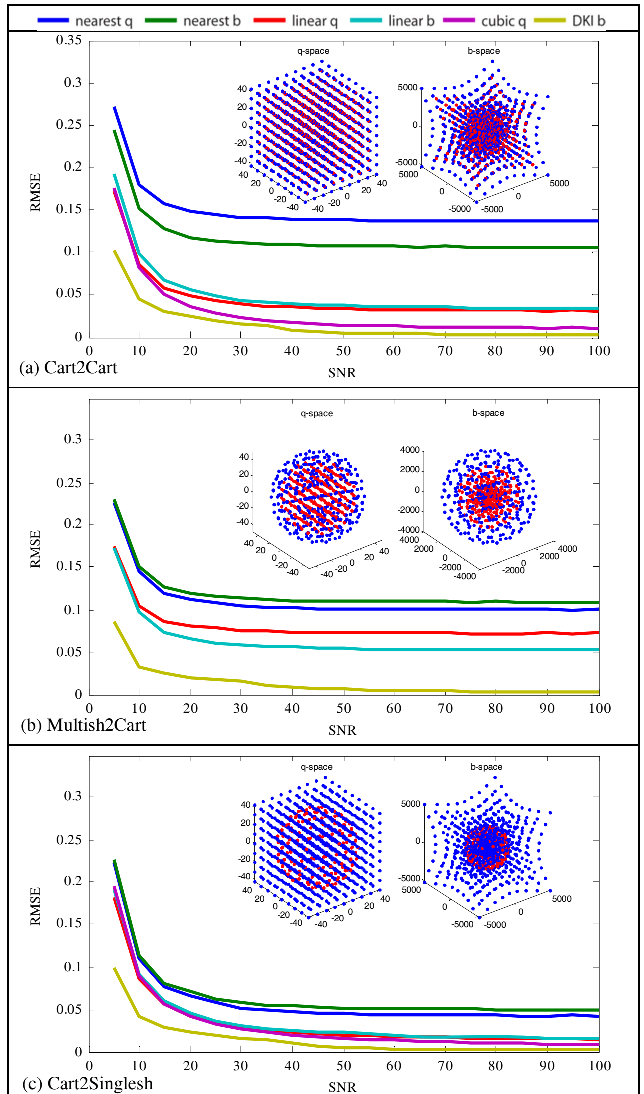

Fig. 1: RMSE of the interpolated values as function of SNR, averaged over 10 noise iterations, for different interpolation methods. The inset displays the original dataset in blue and the interpolated points in red for (a) Cartesian in q-space ($q_{max}=0.043\,\mu m^{-1}$ along axis, 9×9×9 grid) to moved Cartesian ($q_{max}=0.038\,\mu m^{-1}$ along axis, 8×8×8 grid), (b) Multiple shell ($b=[500,1000,2000,3000,4000]s/mm^2$ with [12,42,42,92,162] directions on the sphere) to Cartesian in q-space ($q_{max}=0.043\,\mu m^{-1}$, 9×9×9 grid), and (c) Cartesian in q-space ($q_{max}=0.043\,\mu m^{-1}$ along axis, 9×9×9 grid) to single shell ($b=2500\,s/mm^2$, 162 directions on the sphere).

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References

1. Assemlal et al, Medical Image Analysis 15: 369 - 396, 2011; 2. Wu et al, NeuroImage 36: 617–629, 2007; 3. Sharman et al, JMRI 33:1491–1502 2011; 4. Assaf et al, NeuroImage 27: 48 – 58, 2005; 5. Veraart et al, NeuroImage 81: 335-46, 2011; 6. Watson, *Contouring: A guide to the analysis and display of spatial data*, Pergamon, 1994; 7. Ferizi et al, MICCAI 2013 Volume 8149, 2013, pp 74-81; 8. Panagiotaki et al, NeuroImage 59 2241–2254, 2012;