Comparison of different compressed sensing denoising strategies for DSI acquisition for several diffusion mixing times

Miguel Molina-Romero[1,2], Jonathan I. Sperl[2], Tim Sprenger[1,2], Pedro A. Gómez[1,2], Xin Liu[1,2], Ek T. Tan[3], Christopher J. Hardy[3], Luca Marinelli[3], Bjoern Menze[1], Derek K. Jones[4], and Marion I. Menzel[2]

[1]Technical University Munich, Garching, BY, Germany, [2]GE Global Research, Garching, BY, Germany, [3]GE Global Research, Niskayuna, NY, United States, [4]Cardiff University Brain Research Imaging Centre (CUBRIC), Cardiff University, Cardiff, Wales, United Kingdom

Introduction – Varying the diffusion mixing time (Δ) in a Stejskal-Tanner experiment [1] allows one to obtain information about the tissue microstructure organization [2][3][4]. These types of experiments require either high-gradient-field scanners, scanning times on the order of days, or prior knowledge of the fiber orientation direction. Nevertheless, these problems can be solved while keeping the number of measurements under 120 with fixed maximum gradient strength as shown by [5] and [6]. On the other hand, sampling the full q-space allows one to work with no model constraints in the propagator space and potentially might reveal further tissue information. However, a full DSI acquisition for a given set of more than one diffusion mixing time is clinically not feasible in terms of measuring time, since only one mixing acquisition time takes about 50 minutes (511 directions and 48 slices). Therefore, we need a technique that allows combining DSI acquisition and different diffusion mixing times while the measuring time is reduced or kept constant, as we increase the number of acquisitions in the mixing time direction. In this abstract, we expand the compressed sensing method presented in [7] to the diffusion mixing time (Δ) and study five different denoising algorithms for the compressed sensing problem.

Methods – Synthetic diffusion data are generated using Camino [8] for three different substrates: free diffusion, parallel cylinders with fixed diameter (3 μm), and parallel cylinders with a gamma radii distribution (0.6μm mean), for SNR levels of 5 dB, 10 dB, 15 dB, 20 dB, 25 dB and no noise, and for the last two substrates, permeability between compartments is set to zero. The acquisition scheme collects data in a single direction of q-space (from 1 to 100 m^{-1} in 2 m^{-1} steps) orthogonal to the orientation of the cylinder, and for a set of mixing times (from 5 to 150 ms in 5 ms steps), the diffusion gradient width is constant and equal to 4 ms, and TE is 180 ms for every shot. The data are undersampled in the q-Δ domain, for 3 acceleration factors (R=2.02, 3.8 and 7.3), with a randomly uniform distributed binary matrix.

The compressed sensing algorithm proposed here consists of an adaptation of an iterative shrinkable/thresholding algorithm (ISTA) [9]. In this case, the transformation of the mixing time domain has no direct physical interpretation, unlike q-space has over the propagator domain (r-space) through a Fourier Transform (FT), and thus we should consider different transforms. Here, we compare four transform domains: Laplace Transform (LT), Fourier Transform, Cosine Transform (CT), Wavelet Transform (WT); and one denoising method in the propagator domain: Total Variation (TV). The full compressed sensing algorithm works as follows: the subsampled q-space data are zero filled and transformed (FT) to the r-space for each mixing time. Data in r-space are transformed (LT, FT, CT and WT) in the mixing time direction and denoised with a SURE threshold[10][11], or denoised directly in r-space for the TV case. These transformations are then inverted back to the q-space where part of the reconstructed data is replaced with measured data. This process is repeated for a given number of iterations (5000). Convergence is boosted by a Nesterov updating scheme [12] when possible.

Results – Since the data follow an approximately exponential decay in the mixing time direction, the natural transformation would be the Laplace Transform. However, the inverse problem is numerically ill-posed and leads to instability. Thus, the LT must be discarded. Secondly, the FT requires symmetry along the mixing time direction. This implies that negative mixing times would need to be considered as a mathematical abstraction. This has no meaning from a physical perspective, and thus the FT must also be rejected. Finally, CT, WT together with SURE thresholding, and TV are compared for every substrate and for different SNR levels. A comparison of the mean absolute error for the three denoising approaches and the gamma radii distributed cylinders substrate is shown in Figure 1. According to the figure, there is no statistical evidence that any of the proposed denoising algorithms performs better than the others. However, WT and TV appear to be more stable as the acceleration factor is increased. Moreover, WT does not perform as well as the others for infinite SNR and acceleration factors of 2.02 and 3.8, and besides, computationally speaking it is about 30 times slower than TV. In fact, TV is the fastest algorithm, as it is also twice faster than CT. Therefore, TV appears to be the best choice between the three presented algorithms. Similar results are obtained for free diffusion and fixed diameter parallel cylinders substrates.

Discussion and conclusion – In this abstract we study five different denoising algorithms, applied to a compressed sensing method [7], to undersample DSI data acquired for different mixing times. Considering that the typical SNR for a DSI acquisition is between 10 to 25 dB, we can say that TV seems to be the best option for an acceleration factor up to 4. However, we must consider that in this study we are measuring 30 different diffusion mixing times. For this acceleration factor an acquisition time of up to 94 minutes would be necessary. Therefore, at least an acceleration of 8 is required to keep the current scanning time for this amount of mixing times. At any rate, these are preliminary results and must be validated by fitting the reconstructed and original data to a reference model [3] and comparing the results.

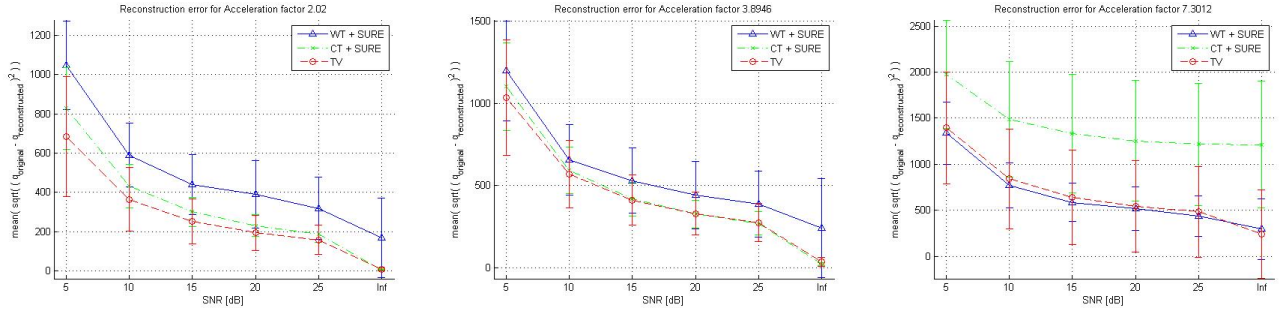

Fig. 1: Comparison of the performance (in terms of mean absolute error) for the denoising algorithms based on WT and CT, with SURE threshold, and TV, for the gamma radii distribution cylinders substrate.

References – [1] E. Stejskal and J. Tanner, *J. Chem. Phys.*, 1965. [2] G. J. Stanisz et al. *Magn. Reson. Med.*, vol. 37, pp. 103–111, 1997. [3] Y. Assaf et al. *Magn. Reson.*, 2008. [4] S. Lasič et al. *Comput. Diffus. MRI Work. MICCA*, vol. 66, no. 2, pp. 356–65, Aug. 2011. [5] D. C. Alexander, *Magn. Reson. Med.*, vol. 60, pp. 439–448, 2008. [6] D. C. Alexander et al. *Neuroimage*, vol. 52, pp. 1374–1389, 2010. [7] M. I. Menzel et al. *Magn. Reson. Med.*, vol. 66, no. 5, pp. 1226–33, Nov. 2011. [8] P. A. Cook et al. ISMRM, 2006, vol. 14, p. 2759. [9] J. I. Sperl et al. ISMRM, 2012, no. x, p. 828. [10] S. Mallat, in *A Wavelet Tour of Signal Processing*, 1999, pp. 20–41. [11] C. M. Stein, *The Annals of Statistics*, vol. 9. pp. 1135–1151, 1981. [12] Y. Nesterov, *Sov. Math. Dokl.*, vol. 27, pp. 372–376, 1983.