

MULTICHANNEL DIFFUSION MR IMAGE RECONSTRUCTION: HOW TO REDUCE ELEVATED NOISE FLOOR AND IMPROVE FIBER ORIENTATION ESTIMATION

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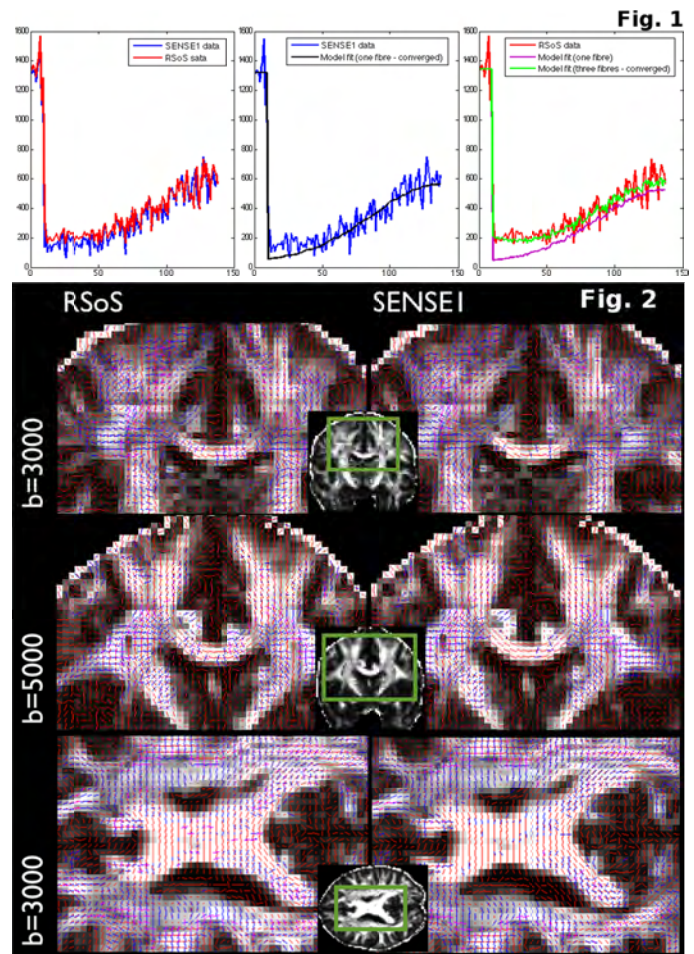
Introduction: Signal intensity in magnitude MR images follows a Rician distribution when single-channel receiver coils are employed [1]. For multi-channel coil acquisitions, noise properties change, and the observed noise levels depend on the image reconstruction method that is used to combine information from the different coils [2]. For the commonly used square-root sum-of-squares (RSoS) reconstruction, the noise follows a non-central-chi distribution [3], whereas for the alternative adaptive reconstruction (AR) [4], a Rician distribution is expected. Additionally, if unknown correlations between coils exist, noise properties become more complex. Such correlations are introduced when using GRAPPA to correct for under-sampled acquisitions, or when using multiband (MB)-GRAPPA for slice un-aliasing [5-8]. For instance, when RSoS reconstruction is performed with GRAPPA for under-sampled acquisitions, the noise follows an *effective* non-stationary non-central-chi distribution with different degrees of freedom and spatial variance than the ones obtained with independent coils [9]. For all these reasons, it is far from obvious to parametrically describe the noise in modern, multi-channel MRI. This is particularly problematic for diffusion-weighted (DW) MRI, where any artificial elevation of the noise floor limits the ability to properly quantify the signal attenuation [10]. This ultimately limits the spatial resolution and maximum diffusion weighting (b -value) that one can reliably use, because of indistinguishable signal attenuations. A non-central-chi distribution will indeed cause an *elevated* noise floor, which may result in higher DWI signal than expected for diffusion gradients aligned with white matter fibers. As shown in [11], such an effect has a significant impact on the estimation of fiber orientation performed either through model-free or model-based approaches. Thus, tractography results may become biased by the image reconstruction method. In the white matter, the phenomenon is particularly evident in regions of high anisotropy, along the dominant fiber direction, where signal attenuation is maximal [11]. In this work, we propose to use a multi-channel SENSE1 reconstruction of GRAPPA un-aliased data, which exhibits Rician noise properties. We compare the performance of the RSoS and SENSE1 reconstruction methods for fiber orientation estimation across different b -values and demonstrate the advantages of the SENSE1 approach.

Methods: Diffusion-weighted images were acquired on a 3T Siemens Connectom Skyra with an SC72 gradient set capable of up to 100 mT/m, but currently operating with a maximum of 84 mT/m [12]. Whole brain DWI were acquired with a 32 channel coil using a multiband EPI sequence with simultaneous multi-slice excitation [5,6] and a mono-polar based diffusion scheme. Image parameters were: $2.2 \times 2.2 \times 2.2$ mm³ voxels (54 slices), TR/TE: 2.2s/84msec, and slice acceleration MB=3 (with a slice shift of 1/3 FOV_{PE} [7,8]) and in-plane acceleration GRAPPA=2. Nine $b=0$ s/mm² and 128 DW volumes at $b=3000$ s/mm² were acquired for a total acquisition time of ~5.25 min. A similar dataset was acquired at $b=5000$ s/mm². The signal from the individual channels was de-correlated based on the covariance matrix of a noise-only acquisition. Sensitivity profiles were estimated from an acquisition with matched parameters, but no diffusion weighting. We obtained magnitude images from the same k -space dataset using *a*) RSoS ($\sum_{ch} |I_{ch}|^2$) and *b*) SENSE1 ($|\sum_{ch} C_{ch} I_{ch}|$) where I_{ch} is the image from the individual channel and C_{ch} is the estimated sensitivity profile. Fiber orientations were estimated from both reconstructions using the ball and stick model [13], under a Rician noise model assumption.

Results and Discussion: The elevated noise floor in the RSoS signal has been shown to cause massive over-fitting (in terms of the number of detected fiber orientations), particularly in very anisotropic voxels [11]. This is illustrated in Figure 1, where the

signal from a voxel of the corpus callosum body is plotted vs. diffusion gradient number (sorted by increasing angle with the principal fiber orientation). The first nine values come from the b_0 images. It can be seen that a one-fiber model correctly predicts the SENSE1 signal, as expected in this part of the brain (Fig. 1, center). However, such a model fails at predicting the RSoS signal, and a three-fiber model is needed (Fig. 1, right). Notice the oscillations of the three-fiber model fit, indicating over-fitting. Figure 2 demonstrates how SENSE1 reconstruction improves the estimation of fiber orientations by minimizing the number of spurious orientations resolved in the corpus callosum, compared to RSoS. At the same time, sensitivity in detecting fiber crossings in the centrum semiovale is retained. The benefits remain regardless of the b -value. We should point out that we illustrate results when fiber orientations are estimated via a model-based approach. However, the improvements are not model-specific. In [11] it has been illustrated that both model-based [13] and model-free [14] approaches suffer from the elevated noise floor of the RSoS. A reduction of the elevated noise floor and of artifacts in orientation estimation can be achieved by AR [11]. However, experiments have shown that AR does not behave as expected for diffusion data. It should be noted that the primary motivation in AR is to suppress artifact or noise for clinical reading instead of retaining signal fidelity for quantification, although these two competing goals can be traded off in implementation.

References: [1] Gudbjartsson and Patz, Magn. Res. Med. 34:910-914, 1995 [2] Dietrich *et al*, Magn. Res. Imag. 26:754-762, 2008 [3] Constantinides *et al*, Magn. Res. Med. 38:852-857, 1997 [4] Walsh *et al*, Magn. Res. Med. 43:682-690, 2000 [5] Moeller *et al*, Magn. Res. Med. 2010 63(5):1144-53 [6] Feinberg *et al*, PLoS One 2010 5(12):e15710 [7] Xu *et al*, ISMRM 2012 [8] Setsompop *et al*, Magn. Res. Med. 2011 in press [9] Aja-Fernandez *et al*, Magn. Res. Med. 65:1195-1206, 2011 [10] Jones *et al*, Magn. Res. Med. 52:979-993, 2004 [11] Sotiropoulos *et al*, OHBM:595, 2011 [12] Kimmling, ISMRM 2012 [13] Behrens *et al*, NeuroImage 34:144-155, 2007 [14] Aganj *et al*, Magn Res Med 64: 554-566, 2010



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