A deep nonlinear subspace modelling and reconstruction for diffusion-weighted imaging using variational auto-encoder: Latent space decoded reconstruction (LASER)

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TARGET AUDIENCE: Medical imaging specialists and researchers interested in deep-learning based reconstructions

PURPOSE: Improve the noise suppression and image sharpness in diffusion-weighted imaging (DWI) data for high b-values (b $\geq$ 1000 s/mm²)

METHODS: Based on research about usage of auto-encoder (AE) networks in reconstruction of DWI data [1] to improve noise suppression, we here present a combination of the standard reconstruction of multi-shot MRI data multiplexed sensitivity-encoding (MUSE) [2] with the approach first presented in [3] to include the decoder part of an AE in the forward operator. Using a variational auto-encoder (VAE) in training and converting the approach to DWI leads to the voxel-wise reconstruction scheme LAtent Space dEcoded Reconstruction (LASER) (forward operator depicted in Figure 1).

The VAE is first trained with biophysically simulated diffusion signals using the ball-and-stick model [4] and according to the sequence of the data to reconstruct with and without noise of different amounts to reconstruct denoised signals. The decoder is then used in the forward operator to decrease the amount of unknowns in the reconstruction to the size of the latent space of the trained network, resulting in an easier reconstruction problem. The output of the decoder is then scaled by the b0 image for a complex scaling of the diffusion encoded signal and then fed to the typical MUSE forward operator. The reconstruction is additionally regularized by the TV-norm of the latent variable images.

To investigate the performance a multi-shell diffusion tensor imaging (DTI) brain scan was performed, where 114 diffusion directions were acquired, with b = 0 s/mm² measurements interspersed every 10 diffusion directions. The voxel size resolution was 1.0 mm² isotropic with a 3 times in-plane acceleration, a simultaneous multi-slice (SMS) factor of 3 and acquired in 2 shots. The VAE was trained with 4248000 signals (noisy and clean) for this specific acquisition, 3 layers encoding and decoding depth, tanh activation function and 11 latent variables. The training took 4 hours. The LASER method is compared to the results of pure MUSE and locally low rank (LLR) regularized [5] reconstructions.

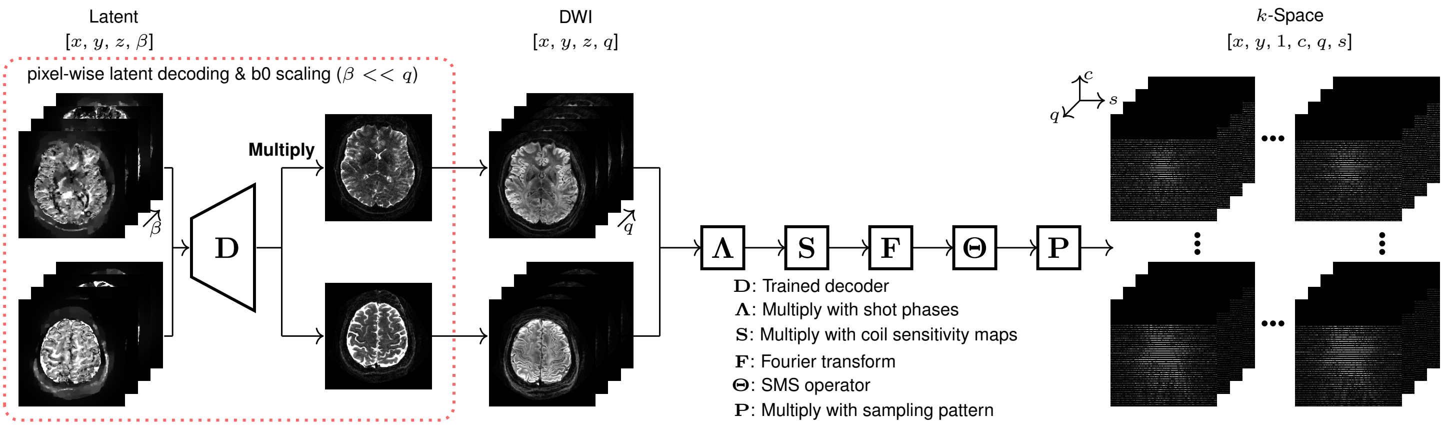

Figure 1: Forward operation of LASER reconstruction

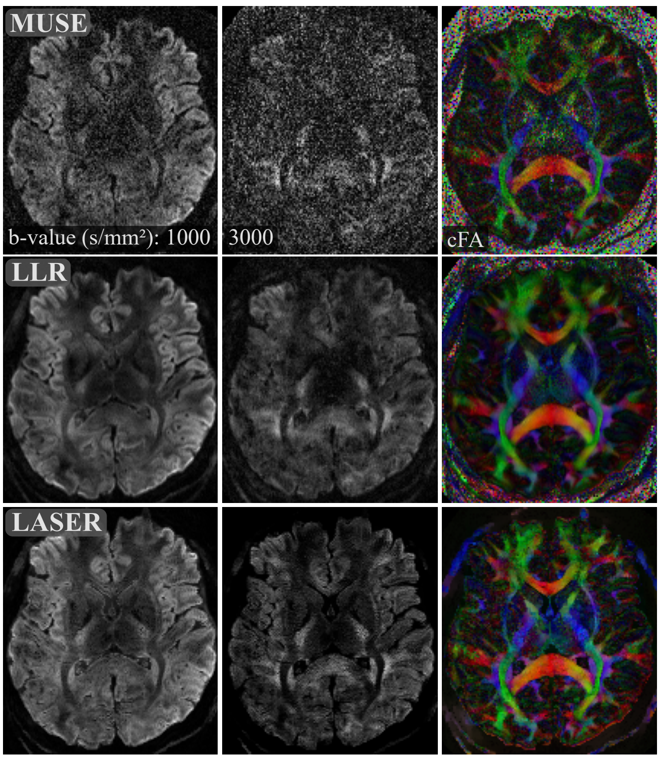

Figure 2: Results of reconstruction for MUSE, LLR and LASER reconstruction. Depicted are diffusion encodings with b-value 1000 and 3000 s/mm² (same applied gradient) and the colored fractional anisotropy (cFA) map

RESULTS: The comparison is done for a specific encoding direction with a b-value of 1000, 3000 s/mm² and the cFA map and shown in Figure 2. LASER and LLR show improved noise suppression compared to MUSE in general, but LASER shows significantly more details and higher resolution for higher b-values compared to LLR and the cFA looks sharper. The proposed method shows more structures in the higher b-value domain compared to the blurred LLR and the noisy MUSE.

DISCUSSION AND CONCLUSION: Further investigation of possible hallucination and artifacts in LASER are necessary. The impact of different diffusion models in the training process should be a topic of research. The method still faces the challenge of b0 artifact propagation in the reconstruction to all diffusion encoding directions, due to the scaling process and needs to be tackled in future research. The improved noise suppression and resolution for higher b-values is achievable with LASER, which could also make higher acceleration possible and should also be a future research topic.

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