Learning-based Cardiac Cine MRI Reconstruction at 7T

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Introduction: MR Imaging with ultra-high magnetic fields can increase the achievable spatial or temporal resolution, thus potentially increasing the depiction of important diagnostic image details, but it is also limited by RF field non-uniformity and tissue heating [1]. In this work, we study the applicability of different Machine Learning-based methods for high resolution image reconstruction of undersampled cardiac cine MR data obtained on a 7T scanner.

Methods: MRI data were acquired on a Magnetom 7T scanner (Siemens, Erlangen, Germany) with a 32-element body array (MRI-tools, Berlin, Germany) driven in 8Tx/32Rx mode in 25 healthy volunteers [2-4]. Subject-specific static phase-only shimming in the heart was performed to compensate for spatial RF field non-uniformities based on subject-specific 3D non-respiration resolved B_1^+ maps [2-3]. ECG triggered high-resolution 2D CINE image datasets were acquired with the subject-specific shim in approximately 25 seconds: FA=50°, TE/TR=2.43/33.53 ms, FOV=$384\times 212\,\text{mm}^2$, resolution $=0.8\times 0.8\times 3\,\text{mm}^3$, GRAPPA=2, 23-49 cardiac phases. The raw data were exported and used to generate the target images. We retrospectively undersampled the k-space data using Gaussian binary masks with different acceleration factors $R = 8, 12$ and reconstructed the images with iterative SENSE [5], a model-based deep learning (MoDL) method [6] using a XT,YT-FFT U-Net [7] as CNN-block, an adaptive dictionary learning and sparse coding approach [8] and a variational network [9]. We split the available data in portions of 19/3/3 for training/validation/testing.

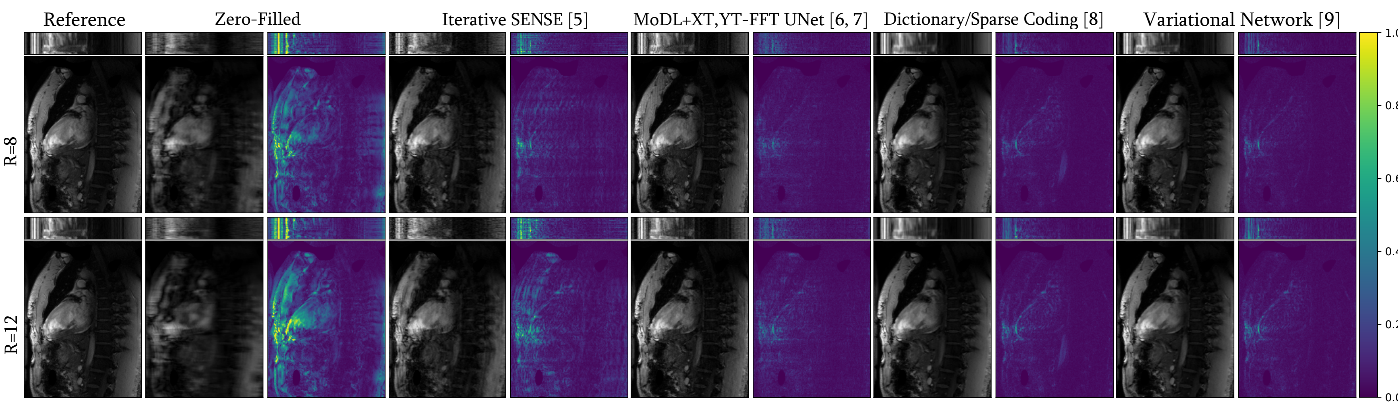

Figure 1. Images reconstructed with the reported methods as well as the corresponding point-wise error images (magnified by factor of two) for two acceleration factors, $R = 8$ and $R = 12$.

Table 1. Quantitative results obtained for the images shown in Figure 1.

	R=8					R=12				
Method	ZF	It. SENSE [5]	[6]+[7]	[8]	[9]	ZF	It. SENSE [5]	[6]+[7]	[8]	[9]
NRMSE	0.54	0.29	0.19	0.15	0.15	0.59	0.39	0.22	0.18	0.19
SSIM	0.78	0.88	0.92	0.94	0.94	0.75	0.83	0.91	0.93	0.92

Results and Discussion: Figure 1 shows a qualitative comparison of the images reconstructed with the different methods for $R = 8$ (first row) and $R = 12$ (second row) and the corresponding point-wise error-images. Table 1 lists the normalized root-mean squared error (NRMSE) and the structural similarity index measure (SSIM) for the images shown in Figure 1. All methods successfully removed undersampling artefacts and noise yielding satisfactory reconstruction results. Thereby, the learning-based methods perform comparably well amongst each other. The dictionary learning/sparse coding method [8] performed slightly better in terms of quantitative values than the NNs-based methods [6,7] and [9], however, being slower by orders of magnitude in terms of reconstruction time (hours vs few seconds).

Conclusion: Our preliminary results demonstrate the potential for the application of ML-based methods for the acceleration of the acquisition of cardiac cine MR data at 7T. Assuming sufficient SNR, the 12-fold acceleration allows for doubling the in-plane resolution of the CINE images while reducing the scan time down to ∼10 seconds.

References:

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