1982

Wave-Encoded Model-Based Deep Learning with Joint Reconstruction and Segmentation

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Figures

Figure 1. a. the proposed network architecture for joint MRI reconstruction and segmentation with model-based deep learning and U-net. **b.** the reconstruction scheme using model-based deep learning for cartesian and wave-encodings.

Synopsis

We propose a wave-encoded model-based deep learning (wave-MoDL) strategy for simultaneous image reconstruction and segmentation. We use CNN-based regularizers in both k- and image-space to employ features in both domains and successfully incorporated wave-encoding strategy into MoDL reconstruction. Wave-MoDL enables R_yxR_z=4x4-fold accelerated 3D imaging using a 32-channel array while reducing NRMSE by 1.45-fold compared to wave-CAIPI. Further, we jointly train wave-MoDL and a U-net for simultaneous reconstruction and segmentation to get additional gain.

Introduction

Recently developed model-based deep learning (MoDL) improves image reconstruction by incorporating a convolutional neural network (CNN) into parallel imaging forward model to help denoise and unalias undersampled data[1]. Wave-controlled aliasing in parallel imaging (wave-CAIPI) employs extra sinusoidal gradient modulations during the readout to harness coil sensitivity variations in all three-dimensions and achieve higher accelerations[2,3]. Wave-encoding strategy was successfully combined with the variational network to provide high-quality images at high acceleration[4,5]. In this abstract, we propose wave-encoded (wave-) MoDL and train it jointly with a U-net for simultaneous image reconstruction and segmentation. We incorporated wave trajectory into MoDL reconstruction to better utilize sensitivity encoding. CNNs in both k- and image-space were used to improve the reconstruction by employing features in both domains[6]. Further, we take advantage of multi-task learning for joint reconstruction and segmentation, where recent studies reported that training multiple tasks improves the performance of each task[7,8].

Methods

Figure 1a shows the proposed network architecture for joint reconstruction and segmentation with wave-MoDL and U-net. Both mean square error (MSE) and categorical cross entropy (CCE) losses were used to train the network. Figure 1b shows the cartesian- and proposed wave-encodings in the MoDL network. The reconstruction of standard wave-CAIPI is described as follows,

$$x = \underset{x}{\mathrm{argmin}} \ \| WF_yPF_xCx - b\|_2^2$$

$$= \underset{x}{\mathrm{argmin}} \ \| A(x) - b\|_2^2$$

where x is the reconstructed image, W is the subsampling mask, P is the wave point spread function in the k_x-y-z hybrid domain, C is the coil sensitivity map, and b is the subsampled image, respectively. We used two denoising networks in k- and image-space for wave-MoDL as follows[6].

$$x = \underset{x}{\mathrm{argmin}} \ \| A(x) - b \|_2^2 + \lambda_1 \| N_k(x) \|_2^2 + \lambda_2 \| N_i(x)\|_2^2$$

Figure 2. MoDL reconstruction at R_y=4. MoDL (i), (k), and (ki) represent MoDL with CNN regularizers in the image-space, k-space, and both k- and image-space, respectively.

where N_k and N_i represents residual CNN networks in the k- and image-space, respectively. We used the alternating minimization-based solution as described in (1,6), by which the network is unrolled as shown in Figure 1a.

To train the network, we used the Calgary-Campinas public dataset[9] and the Human connectome project (HCP) dataset. These datasets include 12-channel GRE images for 67 subjects at 1mm-iso resolution, and 32-channel MPRAGE images for 50 subjects at 0.8mm-iso resolution, respectively. 70%, 15%, and 15% of the subjects in each dataset were used for training, validating, and testing the network, respectively. BART and FREESURFER were used to estimate coil-sensitivity maps and
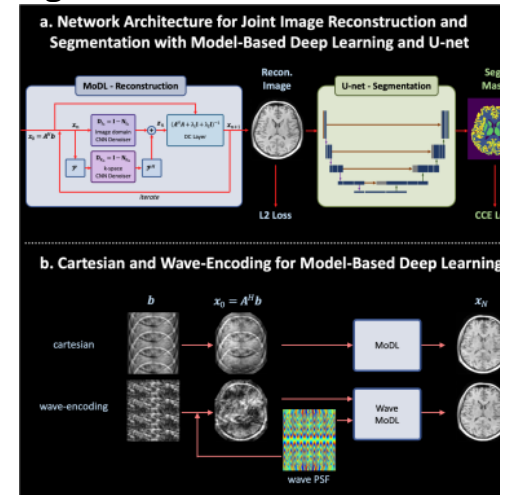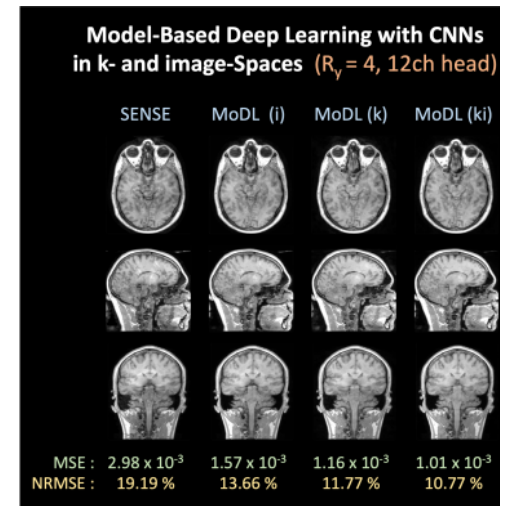
ground-truth segmentation labels[10,11]. We aimed to identify four classes, cortical gray matter (GM CTX), subcortical gray matter (GM SUB), white matter (WM), and background (BG). Quadro RTX 5000 was used to train the network. We applied 8-cycle cosine and sine wave-encoding with a maximum gradient strength of 8mT/m, at 200Hz/pixel bandwidth. Example data and code can be found at 'https://anonymous.4open.science/r/96c9ea60-69b6-4931-8e6a-72a1094626ee'

Results

- Model-based Deep Learning reconstruction with CNNs in k- and image-space

Figure 2 shows MoDL reconstruction at R_y=4 with 12-channel Calgary-Campinas data. MoDL (i), (k), and (ki) represent MoDL with CNN architecture in the image-space, k-space, and both k- and image-space, respectively. For a fair comparison, we used 150K network parameters for all cases; MoDL (i) and (k) have 64 filters in a CNN with 5 layers and MoDL (ki) has 45 filters in each of the two networks with 5 layers. We observed that CNN regularizers in the k-space provide a significant gain for reconstruction. Using two denoisers in the k- and image-space further reduced NRMSE to 10.77%.

- Wave encoded model-based deep learning network (wave-MoDL)

Figure 3 shows the MoDL and wave-MoDL reconstructions at $R_y x R_z$=3x3 on 12-channel Calgary-Campinas data. We used two CNN regularizers in the k- and image-space. SENSE failed to reconstruct clean images due to high acceleration in this 12-channel dataset. MoDL improved the images but still suffered from noise amplification and folding artifacts. Wave-CAIPI significantly improved the images by reducing NRMSE of SENSE by 2.65-fold. Wave-MoDL further improved the reconstruction and reduced NRMSE to 9.66%.

- Joint image reconstruction and segmentation

Figure 4 shows joint reconstruction and segmentation with wave-MoDL and U-net on 12-channel Calgary-Campinas data. Using wave-CAIPI images directly as an input to a pre-trained U-net shows poor performance due to noise amplification in the reconstructed images. Combining separately trained wave-MoDL and U-net shows better segmentation results thanks to improved reconstruction. Joint reconstruction and segmentation provided better results on the segmentation task compared with the combination of the separately trained wave-MoDL and U-net.

- High accelerated wave-MoDL on 32-channel HCP data

We used wave-MoDL to reconstruct $R_y x R_z$=4x4-fold accelerated high-resolution HCP dataset acquired with 32-channel array. SENSE and cartesian-MoDL suffered from noise amplification and artifacts. Wave-CAIPI could significantly improve the results, however lacked SNR at this high under-sampling rate. Wave-MoDL mitigated the noise amplification and reduced NRMSE to 15.71%.

Discussion & Conclusion

We introduced a joint reconstruction and segmentation strategy with wave-MoDL and U-net. Incorporating wave-encoding markedly improved image quality, thus allowing us to push the acceleration to 16-fold on the HCP dataset. Wave-MoDL enabled a 47-second, whole-brain MPRAGE acquisition at 0.8mm-iso resolution with high fidelity.
We separated the 3D data into slice groups and trained on sets of aliasing slices. Though this approach is not able to use the information from adjacent slices, it significantly reduces the memory footprint and facilitates training with high channel count data.

Acknowledgements

References

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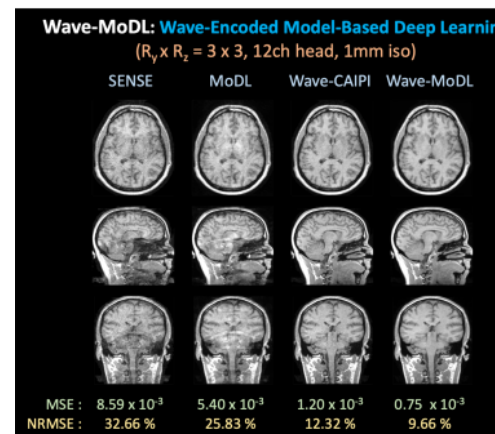

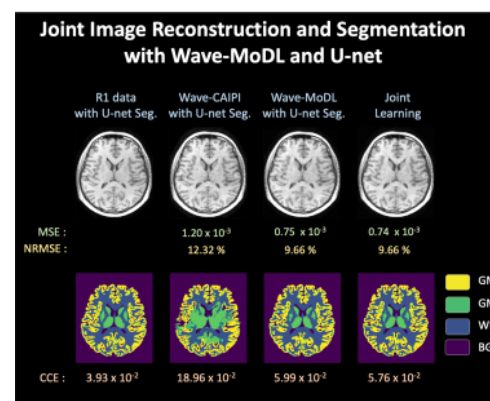**Figure 3.** Reconstructed images using SENSE, MoDL, wave-CAIPI, and wave-MoDL at $R_y x R_z$=3x3.

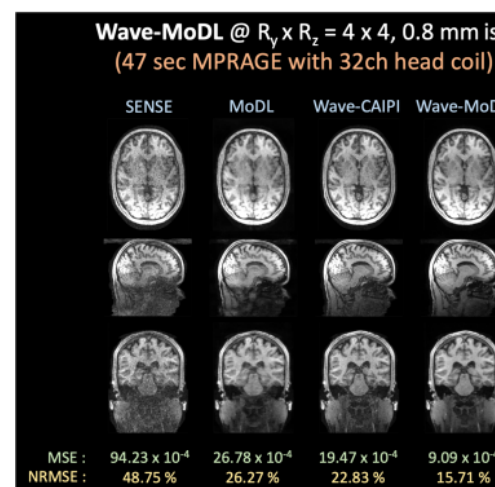**Figure 4.** Joint image reconstruction and segmentation with wave-MoDL and U-net at $R_y x R_z$=3x3.

Figure 5. Reconstructed images using SENSE, MoDL, wave-CAIPI and wave-MoDL at $R_y x R_z$=4x4 on 32-channel HCP data.

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