ICCV23 PARIS

HyperCoil-Recon: A Hypernetwork-based Adaptive Coil Configuration Task Switching Network for MRI Reconstruction

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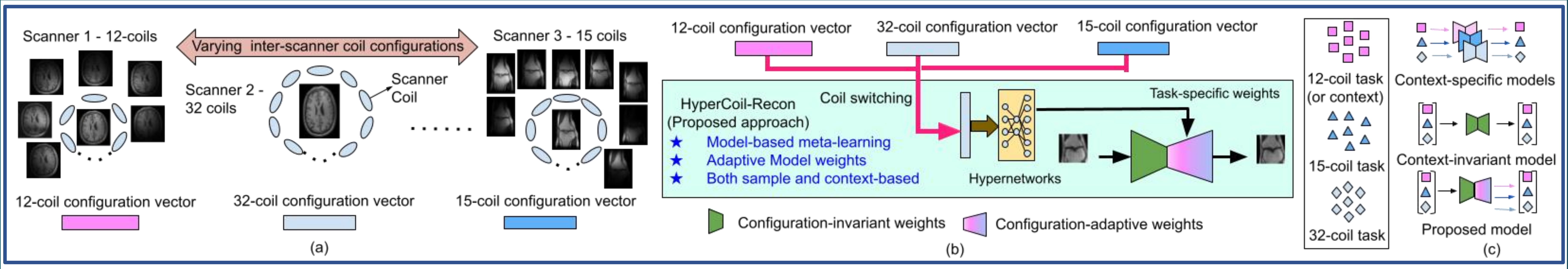


Fig 1: (a) Dynamically varying inter-scanner coil configurations with varying number of coils and their sensitivity maps. (b) Hypernetwork-based coil-configuration task switching model for adaptive MRI reconstruction. (c) Coil Configuration Task-specific models (CCTSM) need training for every coil configuration, while the Task Invariant Model (CCTIM) or joint training has single shared weight set, HyperCoil-Recon infers task-adaptive weights for the reconstruction network, enabling generalization to several unseen contexts without retraining.

Motivation and Clinical Relevance

Parallel imaging, a fast MRI technique, involves dynamic coil configurations i.e. varying sensitivities and number of the coils. 1) Current deep learning (DL)-based image reconstruction models have to be trained for each configuration, posing a barrier to clinical translation, given the lack of computational resources and machine learning expertise for clinicians to train models at deployment, and 2) joint training on diverse configurations learns a single weight set that might underfit to deviated configurations. The purpose of this work is to develop a single DL model for adaptive coil-configuration-based multi-coil MRI reconstruction.

Methods

We propose, HyperCoil-Recon, a hypernetwork-based coil configuration task-switching reconstruction network. that encodes varying configurations of the numbers of coils in a multi-tasking perspective, posing each configuration as a task. The hypernetworks infer and embed task-specific weights into the reconstruction network, 1) effectively utilizing the contextual knowledge of common and varying image features among the various fields-of-view of the coils, and 2) enabling generality to unseen configurations at test time.

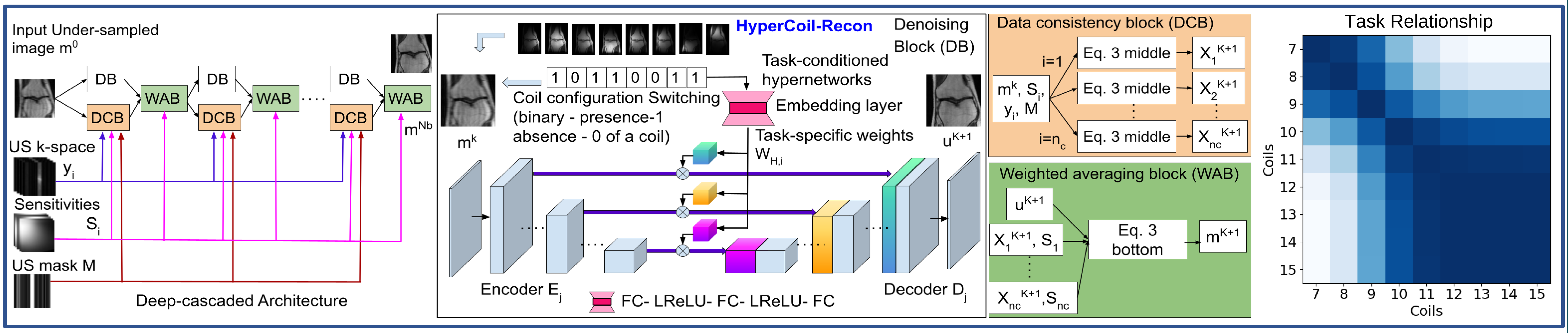


Fig 2: (Left) Deep Cascaded HyperCoil-Recon Architecture with the hypernetworks and the reconstruction network blocks, data consistency, and weighted-average blocks. The hypernetwork has three fully connected layers and two Leaky ReLU non-linear layers. (Right) Matrix plot showing the inter-task relationship. Tasks with neighboring coil configurations exhibit more similarity, while far-apart configurations exhibit lesser similarity.

Table - 01: (Left) Quantitative comparison of HyperCoil-Recon with other multi-coil MRI reconstruction methods on large-scale clinical data. The column pairs are the evaluation results of the 7-9-11 model (trained on 7, 9 &11 coils) on the 12-coil unseen task (same dataset), the 7-9-11 model on the 32-coil unseen task (unseen dataset), and the 15-28-31 model (trained on 15, 28 & 31 coils) on the 32-coil task (reference for column 2) (Right) SSIM Plots showing generality to unseen coil contexts 8, 9, 11, 13 –15 coils combining 7, 10, &12 coils.

Method	12-coil testing on 7-9-11 model (seen dataset & unseen coils)		32-coil testing on 7-9-11 model (unseen dataset and coils)		32-coil on 15-28-31 model (seen dataset & unseen coils)	
	5x	10x	5x	10x	5x	10x
	PSNR / SSIM	PSNR / SSIM	PSNR / SSIM	PSNR / SSIM	PSNR / SSIM	PSNR / SSIM
ZF	25.20 / 0.726	23.70 / 0.632	26.40 / 0.780	25.50 / 0.745	26.40 / 0.780	25.50 / 0.745
VS-Net	27.61 / 0.862	26.08 / 0.802	19.03 / 0.707	18.61 / 0.671	31.04 / 0.921	29.39 / 0.869
VarNet	26.06 / 0.839	24.57 / 0.789	19.19 / 0.673	17.85 / 0.615	28.99 / 0.885	27.49 / 0.828
RecurrentVarNet	29.17 / 0.908	27.46 / 0.855	18.81 / 0.707	18.50 / 0.675	31.83 / 0.925	30.82 / 0.893
KIKI-Net	31.13 / 0.911	29.24 / 0.865	23.25 / 0.853	22.50 / 0.815	32.44 / 0.943	30.53 / 0.896
DC-Unet	31.42 / 0.914	29.14 / 0.865	23.13 / 0.859	22.90 / 0.824	33.92 / 0.948	31.72 / 0.908
SWin	31.42 / 0.914	29.14 / 0.865	23.13 / 0.859	22.90 / 0.824	33.92 / 0.948	31.72 / 0.908
EnchantedNet	31.29 / 0.912	29.00 / 0.861	26.63 / 0.887	26.47 / 0.846	33.29 / 0.937	30.75 / 0.889
HyperCoil-Recon	**33.54 / 0.928**	**30.39 / 0.878**	**31.15 / 0.924**	**29.55 / 0.882**	**36.13 / 0.955**	**32.52 / 0.910**

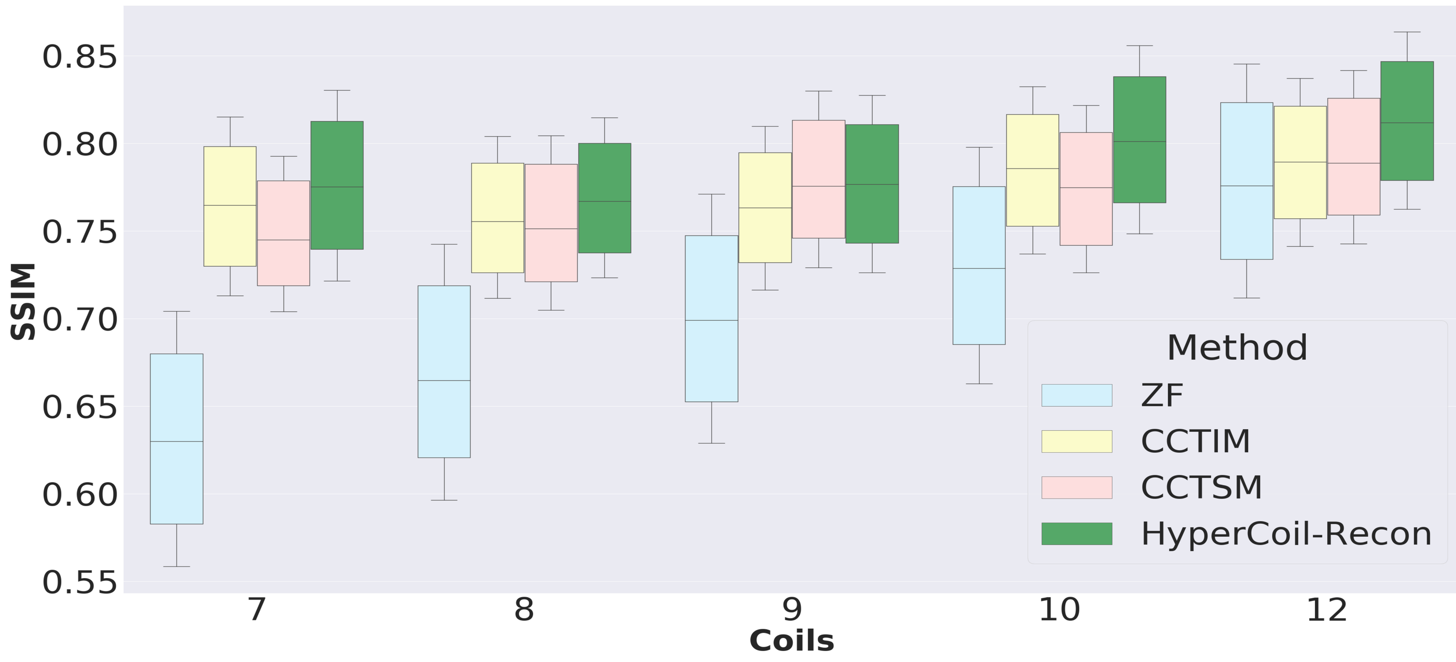
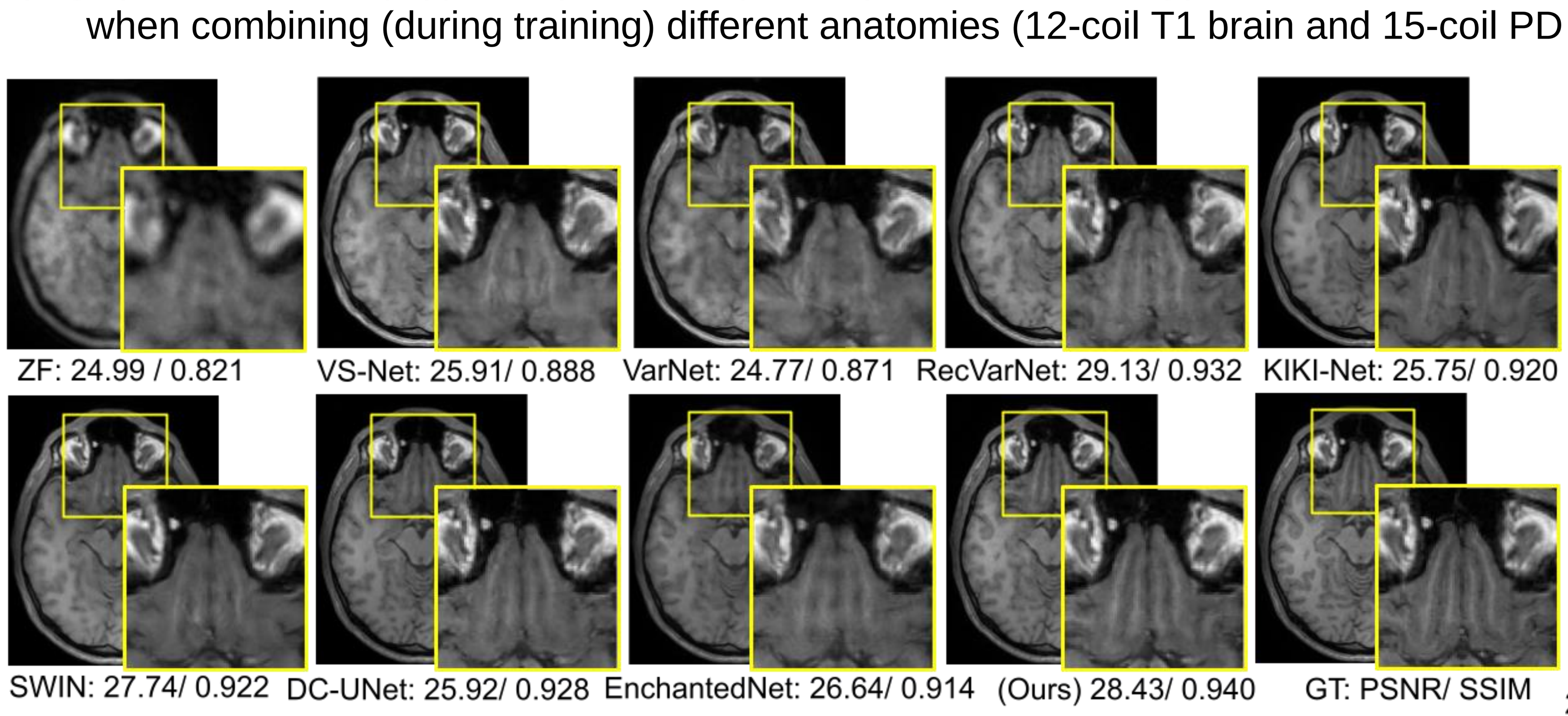
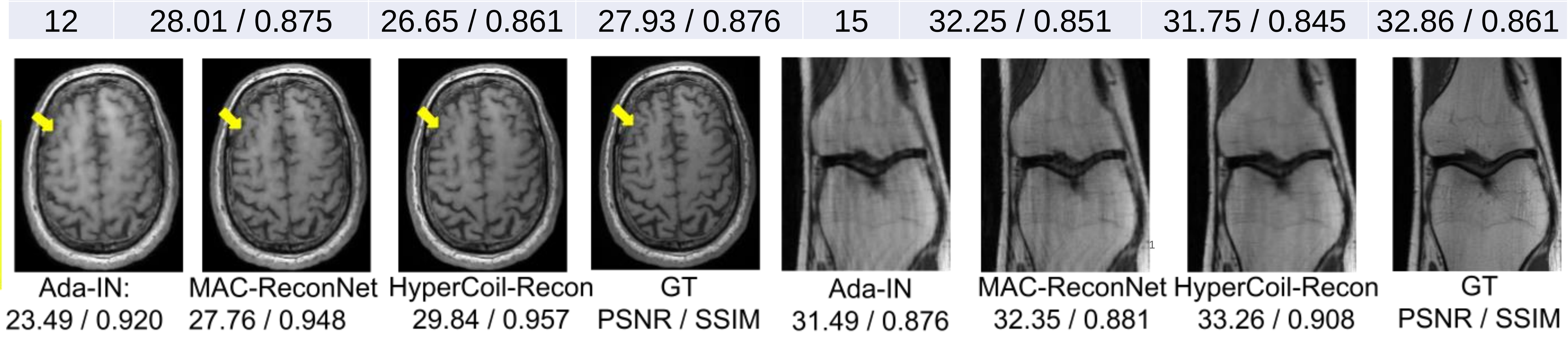


Fig 3: (Left) Qualitative comparison of the HyperCoil-Recon with other multi-coil MRI reconstruction architectures for the unseen 12-coil task using the 7-9-11 model of the same dataset. (Right): Quantitative (top) and qualitative (bottom) results of the HyperCoil-Recon with other adaptive MRI reconstruction methods - MAC-ReconNet and AdaIn under multi-modal scenario when combining (during training) different anatomies (12-coil T1 brain and 15-coil PD knee), with different contrast and different coil configurations (7, 10 and 12 coils respectively))



Coils	MAC-ReconNet	AdaIn	HyperCoil-Recon	Coils	MAC-ReconNet	AdaIn	HyperCoil-Recon
7	24.95 / 0.815	23.49 / 0.793	26.60 / 0.844	10	30.53 / 0.857	29.44 / 0.835	31.84 / 0.855
8	25.28 / 0.826	23.88 / 0.805	26.85 / 0.852	11	31.17 / 0.860	30.19 / 0.845	32.24 / 0.864
9	25.70 / 0.838	24.23 / 0.817	27.13 / 0.860	12	31.58 / 0.862	30.92 / 0.853	32.56 / 0.867
10	26.37 / 0.852	24.64 / 0.827	27.43 / 0.866	13	31.89 / 0.860	31.39 / 0.855	32.71 / 0.867
11	27.08 / 0.863	25.35 / 0.842	27.71 / 0.872	14	32.18 / 0.857	31.70 / 0.853	32.86 / 0.866
12	28.01 / 0.875	26.65 / 0.861	27.93 / 0.876	15	32.25 / 0.851	31.75 / 0.845	32.86 / 0.861



Experiments

Our experiments include, 1) Generalization to unseen coil configurations when trained on few configurations, 2) Task relationship, 3) Performance Comparison with other multi-coil MRI reconstruction architectures on large-scale clinical datasets, 4) Comparison with other adaptive MRI reconstruction methods for multi-modal acquisition contexts, and 5) An ablative study.

Conclusion

We introduce a simple and unified coil-configuration task-switching CNN in a multi-tasking perspective to infuse the knowledge of dynamic coil configurations in multi-coil MRI reconstruction.

Results

The results reveal that our approach 1) adapts on the fly to various unseen configurations up to 32 coils when trained on lower numbers (i.e. 7 to 11) of randomly varying coils, and to 120 deviated unseen configurations when trained on 18 configurations in a single model, 2) matches the performance of coil configuration-specific models, and 3) outperforms configuration-invariant models with improvement margins of ~ 1 dB / 0.03 and 0.3 dB / 0.02 in PSNR / SSIM for knee and brain data.

References

[1] Sriprabha Ramanarayanan, Balamurali Murugesan, Keerthi Ram, and Mohanasankar Sivaprakasam. MAC-ReconNet: A Multiple Acquisition Context based Convolutional Neural Network for MR Image Reconstruction using Dynamic Weight Prediction. MIDL 2020.

[2] Sriprabha Ramanarayanan, Balamurali Murugesan, Arun Palla, Keerthi Ram, Ramesh Venkatesan, Mohanasankar Sivaprakasam, MCI-HyperNet: A multiple contextual information-based adaptive weight learning network for controllable image reconstruction, Neurocomputing, 2023.

This work was supported by IIT Madras and HTIC.