Coil-Agnostic Attention-Based Network for Parallel MRI Reconstruction

Jingshuai Liu[1(✉)], Chen Qin[2], and Mehrdad Yaghoobi[1]

[1] IDCOM, School of Engineering, University of Edinburgh, Edinburgh, UK
{J.Liu, m.yaghoobi-vaighan}@ed.ac.uk
[2] Department of Electrical and Electronic Engineering, Imperial College London, London, UK

1 Experiments

1.1 Multi-Coil Reconstruction Comparisons

Implementations. We compare our method with other deep learning approaches: VS-Net [1], ISTA-Net+ [6], DeepCascade [3, 2], DC-CNN [4], FastMRI U-net [5, 2], and Joint-ICNet [2] on the FastMRI knee database [5]. It is worth noting that DeepCascade and U-net were also used as competing approaches in Joint-ICNet [2]. The comparison results are presented in Suppl. Fig. 1, and Fig. 2. It shows that the proposed framework produces superior results to other comparison methods. It can better preserve textual and structural features, which leads to more faithful and visually appealing reconstructions. The quantitative results demonstrate that our method consistently outperforms other approaches in terms of all evaluation metrics.

1.2 Ablation Studies on Data Consistency Blocks

Implementations. We compare the proposed model with three variants to elucidate how the proposed DACB and RSS-based pipeline benefit the reconstruction performance. The first variant, dubbed (E)-CSM, has 2-channel inputs and outputs representing complex values. It is extended to be (E)-CSM-a and (E)-CSM-b by progressively adopting the single-channel magnitudes as output and input. The visual results are presented Suppl. Fig. 4. We observed that the data type has considerable effects on the reconstruction results and DACB further contributes a performance gain. In Suppl. Fig. 4, we found that (E)-CSM suffers from strong artifacts caused by improper sensitivity estimation, see Suppl. Fig. 3. The proposed model can alleviate the artifacts and yield clean reconstructions without estimating the sensitivity maps.

Map Estimation Artifacts (ME-Arti). We demonstrate how the artifacts in Suppl. Fig. 4 are caused. We display a sensitivity map and the combined image in Suppl. Fig. 3, where the irregular shapes coincide with the artifacts in the reconstruction using (E)-CSM. It shows the impact of inaccurate sensitivity estimation and demonstrates the efficacy of the proposed method.

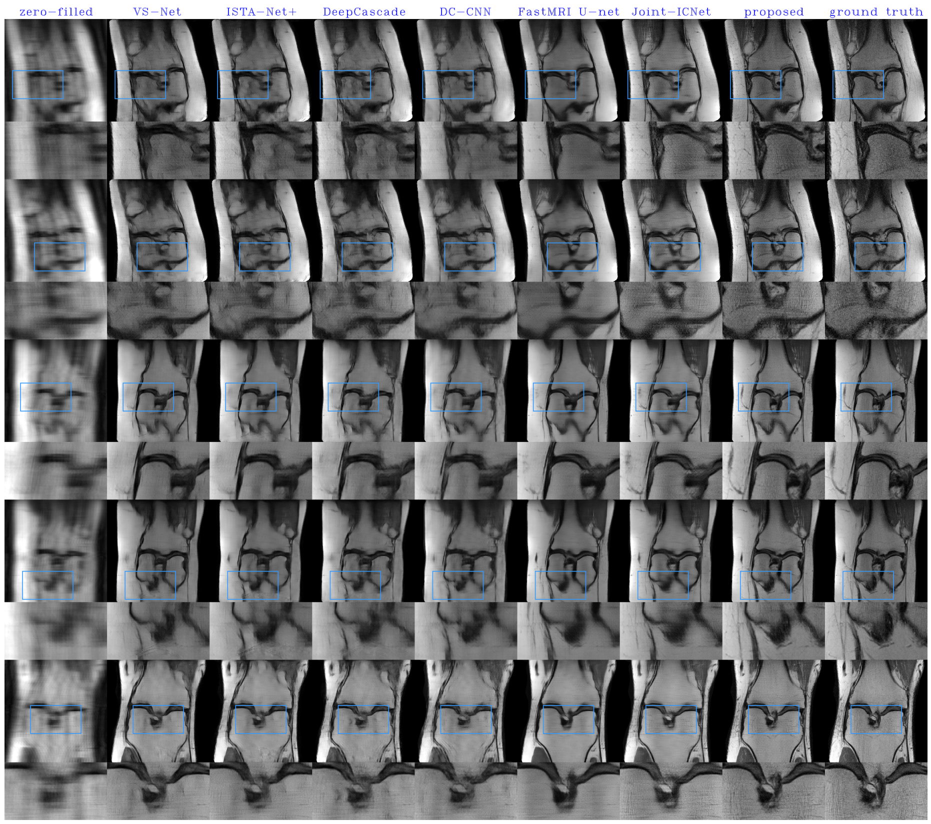

Fig. 1. Comparison results of 8× accelerated MRI reconstruction. First) zero-filled, second) VS-Net [1], third) ISTA-Net+ [6], fourth) DeepCascade [3, 2], fifth) DC-CNN [4], sixth) FastMRI U-net [5, 2], seventh) Joint-ICNet [2], penultimate) proposed, and last) ground truth.

1.3 Robustness to Coil Configurations

We randomly permute the coil orders in inference to demonstrate the robustness of the proposed pipeline to coil configurations. We compare it with Joint-ICNet and DC-CNN which take multi-coil images as input respectively to the sensitivity estimation network and the reconstruction model. The results are presented in Suppl. Fig. 5. The performance of both Joint-ICNet and DC-CNN can be severely affected by coil permutation, showing that they can be susceptible to machine configuration discrepancies. The proposed method leverages the permutation-invariance of the linear aggregation operation and the RSS operator, and shows a strong invulnerability and generalization capacity.

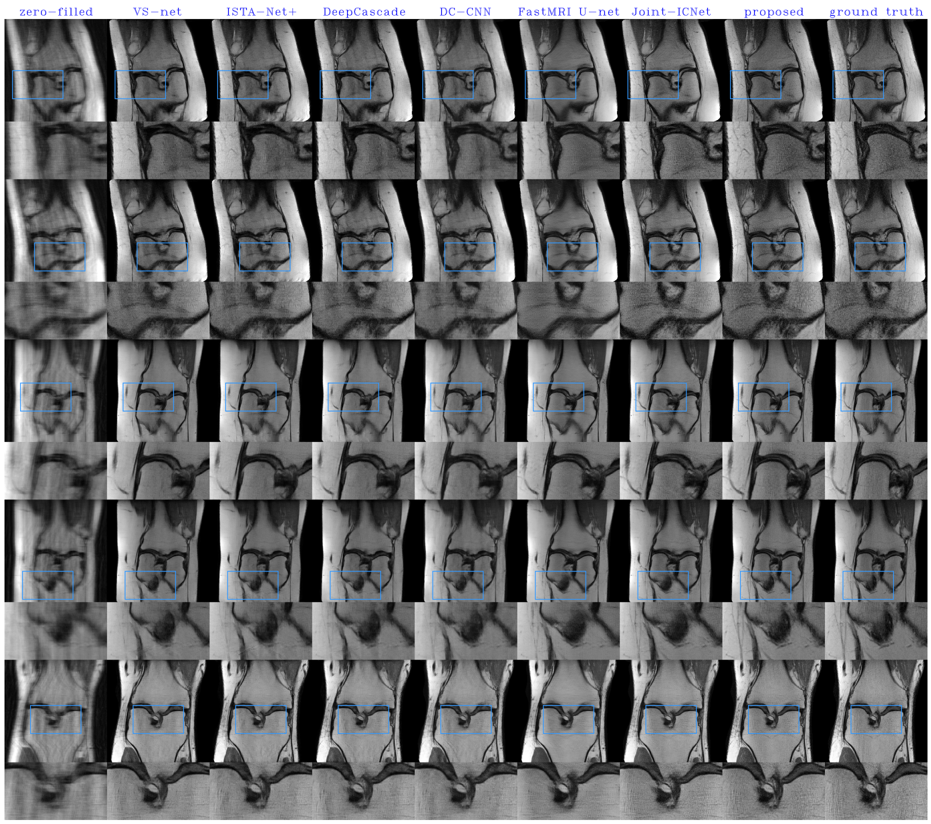

Fig. 2. Comparison results of 4× accelerated MRI reconstruction. First) zero-filled, second) VS-Net [1], third) ISTA-Net+ [6], fourth) DeepCascade [3, 2], fifth) DC-CNN [4], sixth) FastMRI U-net [5, 2], seventh) Joint-ICNet [2], penultimate) proposed, and last) ground truth.

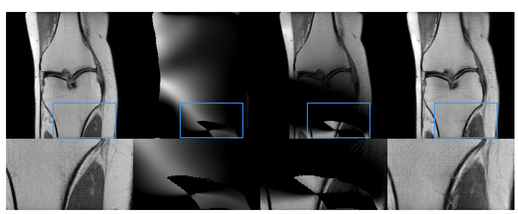

Fig. 3. Map estimation artifacts. First) RSS of fully sampled signal, second) positive component of the imaginary part of a sensitivity map, third) positive component of the imaginary part of the combined image, and last) reconstruction using (E)-CSM.

References

1. Duan, J., Schlemper, J., Qin, C., Ouyang, C., Bai, W., Biffi, C., Bello, G., Stat-

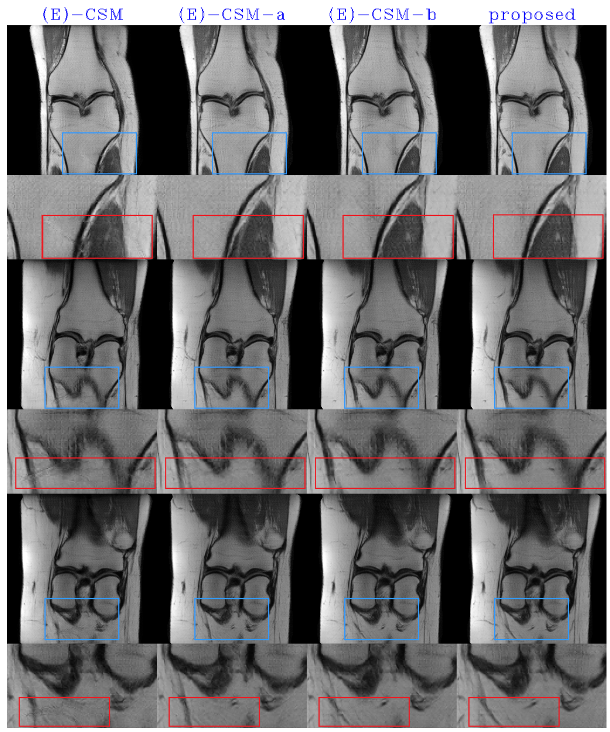

Fig. 4. Ablation results of 8× accelerated MRI reconstruction. First) (E)-CSM, second) (E)-CSM-a, third) (E)-CSM-b, and last) proposed.

ton, B., Regan, D., Rueckert, D.: VS-Net: variable splitting network for accelerated parallel MRI reconstruction. Springer International Publishing pp. 713–722 (2019)
2. Jun, Y., Shin, H., Eo, T., Hwang, D.: Joint deep model-based MR image and coil sensitivity reconstruction network (Joint-ICNet) for fast MRI. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) pp. 5270–5279 (June 2021)
3. Schlemper, J., Caballero, J., Hajnal, J., Price, A., Rueckert, D.: A deep cascade of convolutional neural networks for dynamic MR image reconstruction. IEEE Transactions on Medical Imaging **37**(2), 491–503 (2018). https://doi.org/10.1109/TMI.2017.2760978
4. Schlemper, J., Duan, J., Ouyang, C., Qin, C., Caballero, J., Hajnal, J., Rueckert, D.: Data consistency networks for (calibration-less) accelerated parallel MR image reconstruction. Abstract from ISMRM 27th Annual Meeting and Exhibition (2019)
5. Zbontar, J., Knoll, F., Sriram, A., Muckley, M., Bruno, M., Defazio, A., Parente, M., Geras, K., Katsnelson, J., Chandarana, H., Zhang, Z., Drozdzal, M., Romero, A., Rabbat, M., Vincent, P., Pinkerton, J., Wang, D., Yakubova, N., Owens, E., Zitnick, C., Recht, M., Sodickson, D., Lui, Y.: FastMRI: an open dataset and benchmarks for accelerated MRI. CoRR **abs/1811.08839** (2018)
6. Zhang, J., Ghanem, B.: ISTA-Net: iterative shrinkage-thresholding algorithm inspired deep network for image compressive sensing. IEEE Conference on Computer

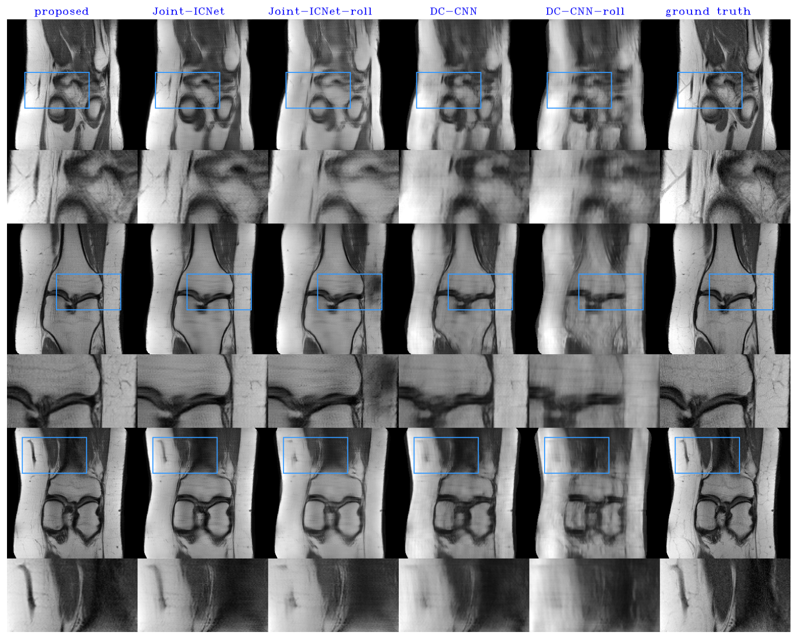

Fig. 5. Comparisons of 8× accelerated MRI reconstruction using random coil permutation. First) proposed None/rolled, second) Joint-ICNet [2], third) Joint-ICNet rolled, fourth) DC-CNN [4], penultimate) DC-CNN rolled, and last) ground truth.

Vision and Pattern Recognition (CVPR) pp. 1828–1837 (2018)