Improved Model-based Learning with Data Augmentation for Quantitative Susceptibility Mapping (QSM)

Juan Liu[1]

[1]Department of Biomedical engineering, Yale University, CT, USA

Introduction

Quantitative susceptibility mapping (QSM) requires solving a challenging ill-posed field-to-source inversion problem. Recently, deep learning techniques[1,2,3,4,5] have been proposed and demonstrated impressive performance. Due to the inherent non-existent ground-truth QSM references, these techniques used either COSMOS maps or synthetic data for network training. The model-based learning uQSM without the need of QSM labels fails to perform well. Here, we proposed uQSM+ to (1) apply model-based learning for QSM, (2) use field perturbation to improve network robustness.

Method

✓Use field perturbation to introduce regularization in model-based learning for QSM

✓Loss function: data consistency loss + total variation loss + consistency regularization loss

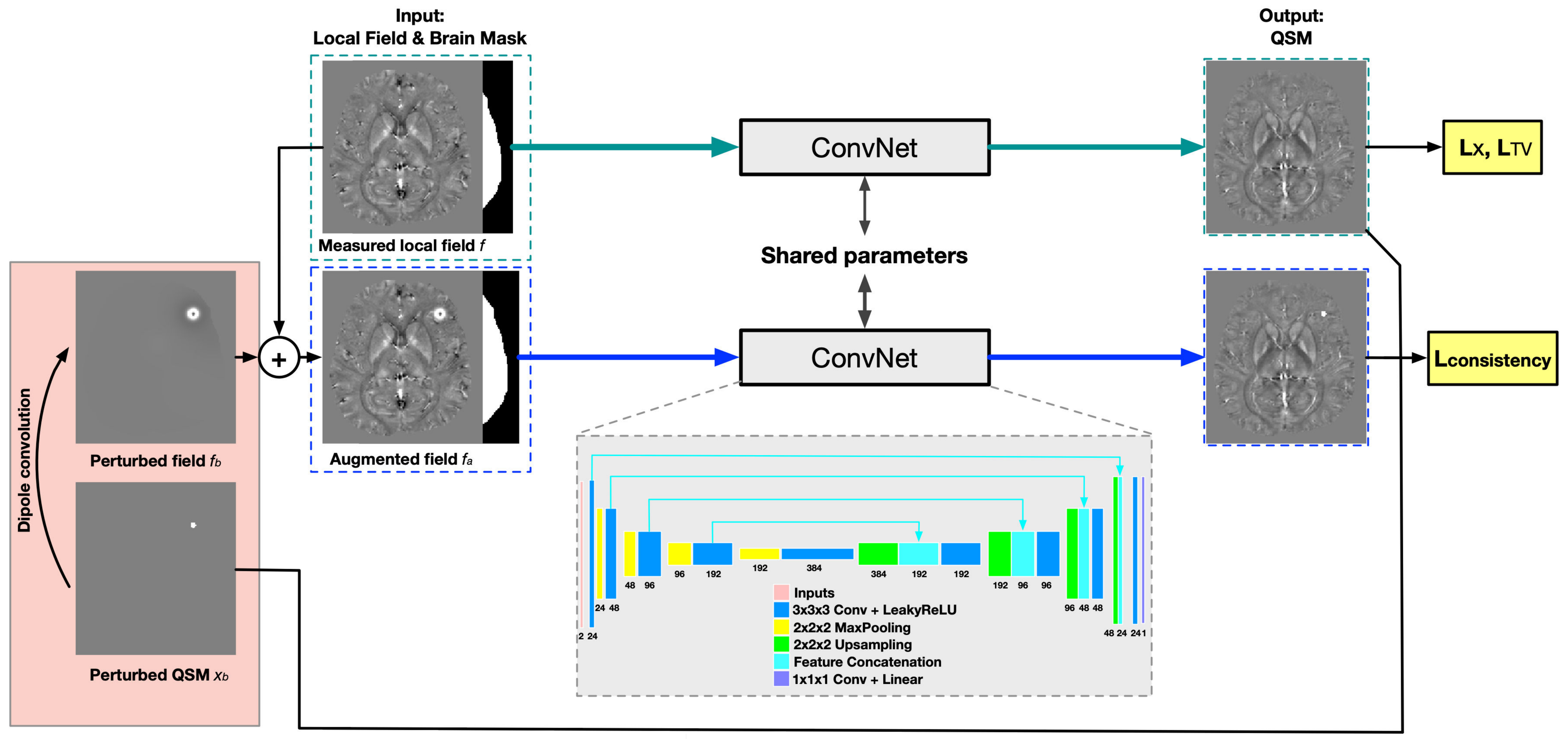

Figure 1. Network architecture

Data

✓9 multi-orientation datasets acquired with 5 head orientations and a 3D single-echo GRE scan with isotropic voxel size 1.0x1.0x1.0mm^3.

✓2019 QSM reconstruction challenge stage2.

Results

✓ Improved quantitative metrics score.

	PSNR (dB)	NRMSE (%)	HFEN (%)	SSIM (0-1)
TKD	43.4 ± 0.5	91.4 ± 6.7	72.9 ± 6.6	0.831 ± 0.016
MEDI	41.5 ± 0.6	113.8 ± 7.6	100.4 ± 9.1	**0.902±0.016**
DIP	44.0 ± 0.8	85.5 ± 6.7	65.7 ± 4.5	0.859 ± 0.020
uQSM	45.6±0.4	71.4±5.0	62.8±5.0	0.890 ± 0.015
uQSM+	**46.1±0.5**	**67.2±3.9**	**59.6±3.4**	0.892 ± 0.012
zs-uQSM+	46.0±0.5	67.5±3.8	60.4±4.5	0.887 ± 0.012

Table 1. Quantitative evaluation on multi-orientation datasets

✓ Greatly suppress the streaking artifacts and shading artifacts shown in Fig2 and Fig4

✓ But underestimate the susceptibility values at calcification and vessels, shown in Fig3

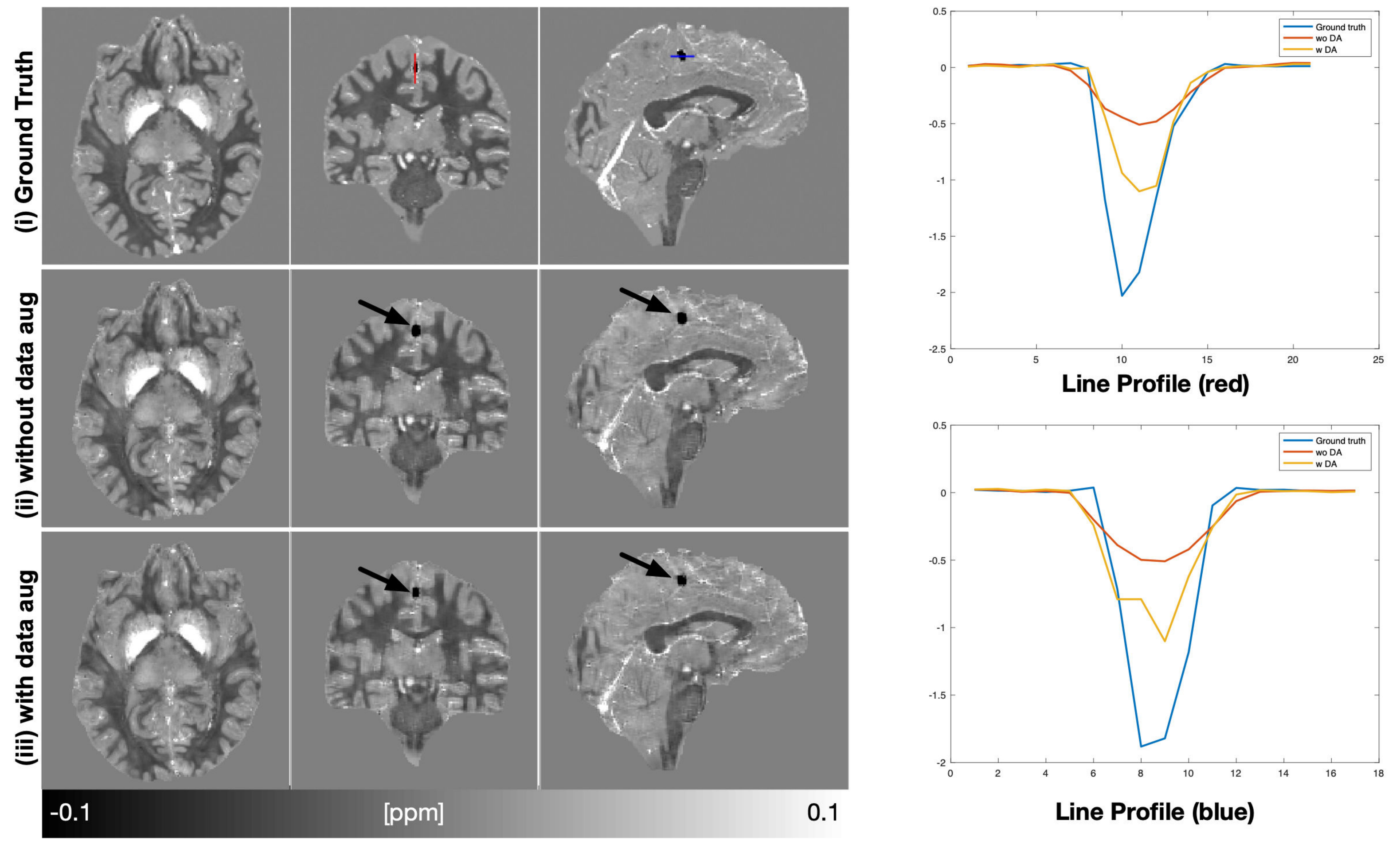

Figure 3. Comparison of QSM applying data augmentation on a 2019 QSM reconstruction challenge dataset

Discussion & Conclusion

We apply input field perturbation to improve model-based learning for QSM. It greatly suppresses the artifacts in the QSM. However, it has the problem that it underestimates the susceptibility values at calcification and vessels which have high susceptibility values and low signal-to-noise.

Acknowledgments

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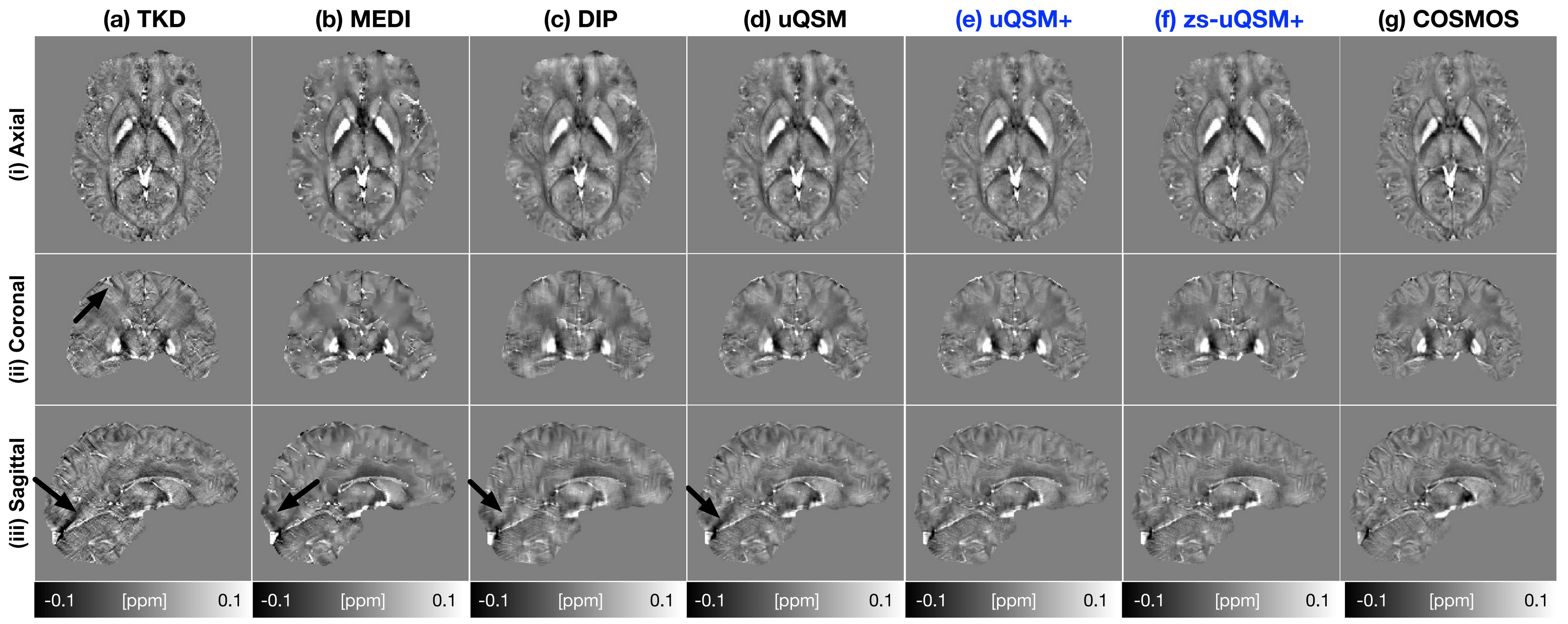

Figure 2. Comparison of QSM results on a multi-orientation QSM data

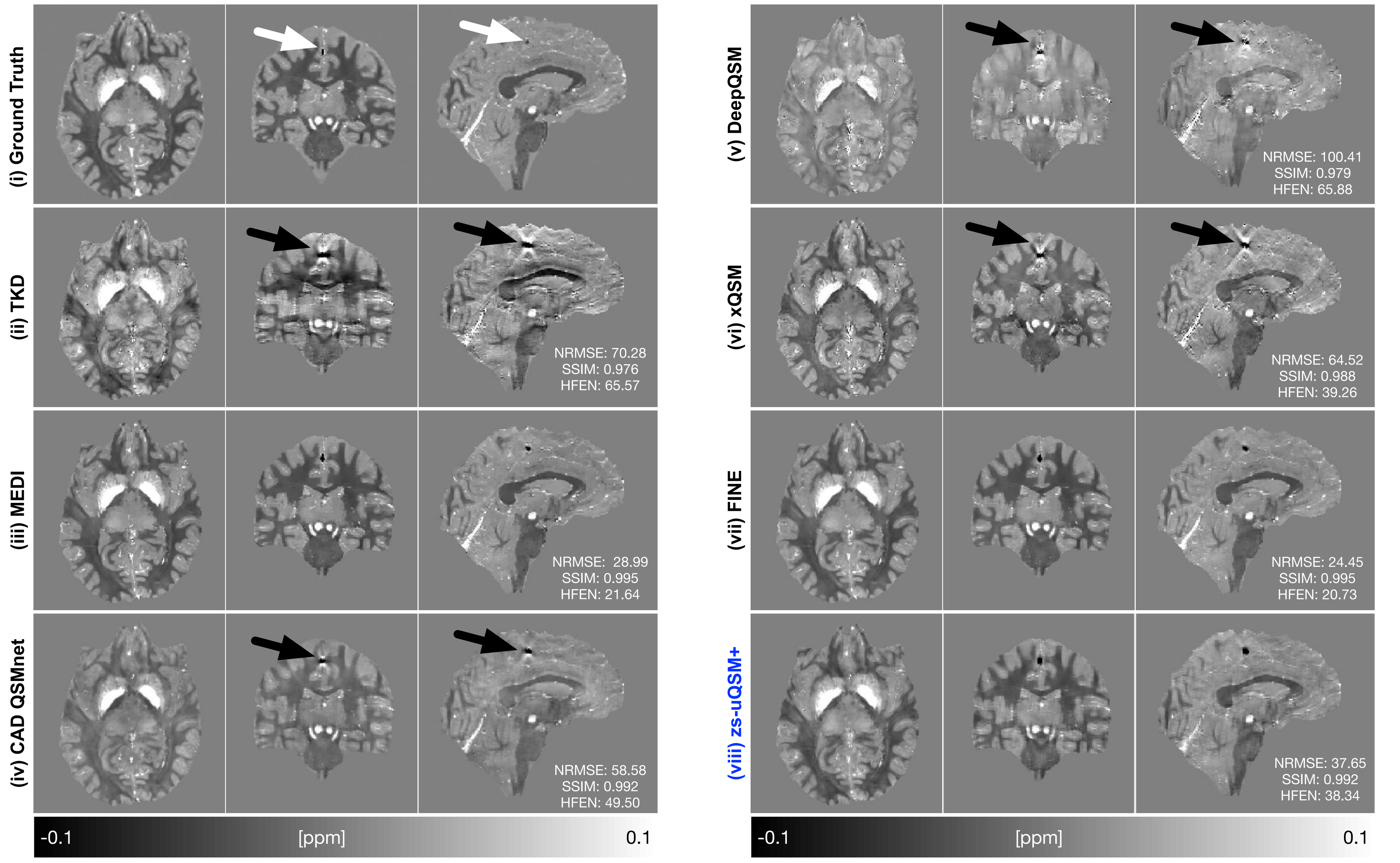

Figure 4. Comparison of QSM on a 2019 QSM reconstruction challenge dataset

Reference

[1] Yoon, Jaeyeon et al. Neuroimage 179 (2018): 199-206.
[2] Bollmann, Steffen, et al. Neuroimage 195 (2019): 373-383.
[3] Chen, Yicheng, et al. NeuroImage 207 (2020): 116389.
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