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

Juan Liu

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 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 without the need of QSM labels fails to perform well. Here, we proposed 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

Data
- 9 multi-orientation datasets acquired with 5 head orientations and a 3D single-echo GRE scan with isotropic voxel size 1.0x1.0x1.0mm³
- 2019 QSM reconstruction challenge stage 2

Results
- Improved quantitative metrics score.

Table 1. Quantitative evaluation on multi-orientation datasets

<table>
<thead>
<tr>
<th>Method</th>
<th>PSNR (dB)</th>
<th>NRMSE (%)</th>
<th>HFEN (%)</th>
<th>SSIM (0-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TKD</td>
<td>44.1 ± 0.5</td>
<td>91.4 ± 0.7</td>
<td>72.9 ± 0.6</td>
<td>0.831 ± 0.016</td>
</tr>
<tr>
<td>MEDI</td>
<td>41.5 ± 0.6</td>
<td>133.8 ± 7.6</td>
<td>100.4 ± 9.1</td>
<td>0.902 ± 0.016</td>
</tr>
<tr>
<td>DIP</td>
<td>44.0 ± 0.8</td>
<td>85.5 ± 6.7</td>
<td>65.7 ± 4.5</td>
<td>0.859 ± 0.020</td>
</tr>
<tr>
<td>uQSM</td>
<td>45.6 ± 0.4</td>
<td>71.4 ± 5.0</td>
<td>62.8 ± 5.0</td>
<td>0.800 ± 0.013</td>
</tr>
<tr>
<td>uQSM+</td>
<td>46.1 ± 0.5</td>
<td>67.2 ± 3.9</td>
<td>59.46 ± 3.4</td>
<td>0.802 ± 0.012</td>
</tr>
<tr>
<td>zs-uQSM+</td>
<td>46.0 ± 0.5</td>
<td>67.5 ± 3.8</td>
<td>60.4 ± 4.5</td>
<td>0.887 ± 0.012</td>
</tr>
</tbody>
</table>

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
We thank Professor Jongho Lee for sharing the multi-orientation QSM datasets.

Reference