Compressed Sensing MRI with Joint Image-Level and Patch-Level Priors

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**Introduction**

**Problem:** MRI is a promising medical imaging technique but it is limited in slow imaging speed. To overcome this disadvantage, compressed sensing (CS) theory is used to accelerate MR imaging by capturing fewer k-space data for reconstruction.

**Contributions:** We develop a novel compressed sensing magnetic resonance imaging algorithm with joint image and patch priors, and our contributions are below:
1. Joint image-level and patch-level priors are adopted to make use of image global and local sparse nature for promoting MR image structures and suppressing artifacts or noise. Total variation (TV) is efficiently adopted for global sparse prior, and expected patch log likelihood (EPLL) is effectively used for local sparse prior.
2. An efficient optimization scheme is proposed to address the proposed cost function by iteratively alternating 11 norm approximation, latent patch reconstruction, and ideal image reconstruction.

**Proposed Method**

**Model Construction:**

\[ L(x) = \arg \min_x \frac{\lambda}{2} \left\| F_x x - y \right\|_2^2 + \nu \left\| x \right\|_{TV} - \text{EPLL}_p(x) \]

1. \( \left\| F_x x - y \right\|_2^2 \) is data fidelity which uses the L2 norm to ensure the consistency of the reconstruction and the measured data.
2. \( \left\| x \right\|_{TV} \) denotes anisotropic TV adopted to represent image global sparse prior, which employs 11 norm to enforce piece-wise continuous on image gradient.
3. \( \text{EPLL}_p(x) = \sum_j \log(p(R_j)) \) is EPLL which denotes image local sparse prior and employs a finite Gaussian mixture model (GMM) over the pixels of image patches since many image priors can be seen as special cases of GMM.

**Optimization Algorithm:**

We reformulate our objective function by bringing in an auxiliary variable to approximate TV, and introducing a set of auxiliary variables to approach EPLL, and we divide it into three subproblems which can be iteratively addressed until convergence.
1. Update for 11 Norm Approximation.
2. Update for Latent Patch Reconstruction.

**Experiments**

Table 1: PSNR/SSIM of different reconstruction methods on real-valued shoulder with different sampling percentage.

<table>
<thead>
<tr>
<th>Mask</th>
<th>Sampling ratio</th>
<th>SparseMRI</th>
<th>DLMRI</th>
<th>PBDW</th>
<th>RecPF</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cartesian</td>
<td>10</td>
<td>26.34 / 0.824</td>
<td>28.52 / 0.846</td>
<td>27.81 / 0.839</td>
<td>29.35 / 0.863</td>
<td>30.21 / 0.895</td>
</tr>
<tr>
<td>Random</td>
<td>10</td>
<td>27.08 / 0.816</td>
<td>29.09 / 0.841</td>
<td>31.55 / 0.881</td>
<td>33.52 / 0.909</td>
<td>34.53 / 0.924</td>
</tr>
<tr>
<td>Random</td>
<td>20</td>
<td>25.69 / 0.896</td>
<td>27.09 / 0.908</td>
<td>34.87 / 0.955</td>
<td>37.29 / 0.995</td>
<td>38.69 / 0.974</td>
</tr>
<tr>
<td>Random</td>
<td>30</td>
<td>45.76 / 0.979</td>
<td>42.73 / 0.976</td>
<td>43.30 / 0.976</td>
<td>43.50 / 0.976</td>
<td>43.41 / 0.985</td>
</tr>
<tr>
<td>Radial</td>
<td>10</td>
<td>31.96 / 0.858</td>
<td>31.81 / 0.873</td>
<td>32.82 / 0.875</td>
<td>33.02 / 0.897</td>
<td>32.25 / 0.875</td>
</tr>
<tr>
<td>Radial</td>
<td>20</td>
<td>35.60 / 0.910</td>
<td>37.20 / 0.924</td>
<td>37.70 / 0.974</td>
<td>37.91 / 0.936</td>
<td>38.53 / 0.941</td>
</tr>
<tr>
<td>Radial</td>
<td>30</td>
<td>38.66 / 0.944</td>
<td>38.37 / 0.942</td>
<td>38.78 / 0.949</td>
<td>40.02 / 0.954</td>
<td>42.41 / 0.968</td>
</tr>
<tr>
<td>Radial</td>
<td>40</td>
<td>41.18 / 0.964</td>
<td>35.65 / 0.955</td>
<td>39.07 / 0.965</td>
<td>42.03 / 0.968</td>
<td>43.67 / 0.987</td>
</tr>
<tr>
<td>Radial</td>
<td>50</td>
<td>43.00 / 0.974</td>
<td>35.05 / 0.964</td>
<td>39.31 / 0.969</td>
<td>43.65 / 0.977</td>
<td>45.65 / 0.978</td>
</tr>
</tbody>
</table>

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Fig. 1: MRI reconstruction using undersampling k-space data.

Fig. 2: Real-valued shoulder reconstructions and their absolute errors with 25% radial undersampling. (a) DLMRI(38.37/0.942), (b) PBDW(38.78/0.949), (c) RecPF(40.02/0.954), (d) Proposed (42.41/0.968).

Fig. 3: Complex-valued brain reconstructions and their absolute errors with 50% random undersampling. (a) DLMRI(28.67/0.671), (b) PBDW(34.85/0.922), (c) RecPF(36.29/0.961), (d) Proposed (38.09/0.989).