Deep subspace learning for efficient reconstruction of spatiotemporal imaging data

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Motivation
Model-based deep learning approaches, such as unrolled neural networks¹ have demonstrated state-of-the-art performance for efficiently solving inverse problems. However, the memory costs of training unrolled neural networks remains high, especially when the targeted data is high-dimensional. This often requires trade-offs in network depth to reduce model size, or spatiotemporal resolution to reduce data size.

To this end, we propose DL-Subspace: a novel unrolled neural network architecture which reduces memory usage by solving for low-dimensional, compact representations of spatiotemporal imaging data. DL-Subspace is applied to reconstruction of accelerated dynamic magnetic resonance imaging (MRI) data, demonstrating up to 4X higher memory efficiency and 4X faster inference speeds while maintaining similar image quality metrics as state-of-the-art unrolled networks.

Methods
- **Subspace Model**: Dynamic MRI data can be represented as a product of two matrices containing spatial and temporal basis functions (L, R).
- **Inspired by Arvinte et al.**: The compact, low-rank representation can be solved for directly using a model-based alternating minimization algorithm:
  
  \[
  \min_{X,Y} F(X,Y) = \frac{1}{2} \| H(Y) - L(X) \|^2 + \lambda_1 \| \Phi(Y) \|^2 + \lambda_2 \| \Psi(X) \|^2
  \]

- **Bi-linear Regularized Least Squares Objective**: Minimize:
  
  \[
  \min_{X,Y} \| H(Y) - L(X) \|^2 + \lambda_1 \| \Phi(Y) \|^2 + \lambda_2 \| \Psi(X) \|^2
  \]

- **DL-Subspace Update Rule**: Update rules for X and Y:
  
  \[
  X_{i+1} = \arg \min_{X} \| H(Y_i) - L(X) \|^2 + \lambda_1 \| \Phi(Y_i) \|^2 + \lambda_2 \| \Psi(X) \|^2
  \]

- **Validation Loss (PSNR)**: PSNR is used to evaluate the reconstruction quality.

Results

**Results Table**

<table>
<thead>
<tr>
<th>Method</th>
<th>Unrolls</th>
<th>CG Unrolls</th>
<th>Learner Parameters</th>
<th>Sub-Network Architecture</th>
<th>Kernel Size</th>
<th># Input Features</th>
<th># Hidden Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>DL-ESPIRiT</td>
<td>10</td>
<td>NOX</td>
<td>8.5 million</td>
<td>2D-Time ResNet-5</td>
<td>3 x 3 x 3</td>
<td>7</td>
<td>12</td>
</tr>
<tr>
<td>MoDL</td>
<td>10</td>
<td>NOX</td>
<td>8.5 million</td>
<td>2D-Time ResNet-5</td>
<td>3 x 3 x 3</td>
<td>2</td>
<td>84</td>
</tr>
<tr>
<td>DL-Subspace</td>
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<td>NOX</td>
<td>8.6 million</td>
<td>1D ResNet-5</td>
<td>3 x 1</td>
<td>24</td>
<td>128</td>
</tr>
</tbody>
</table>

- **DL-Subspace** is compared against MoDL² and DL-ESPIRiT³ unrolled networks.
- **All three networks are trained using a supervised L1 loss on multi-slice cardiac MRI data acquired from 21 healthy volunteers (17/3/1 split) + 1 pediatric patient for testing**.

**Fig. 2**: Memory usage (GB) and inference speed (sec/slice) for DL-Subspace with varying block size and number of basis functions. For reference, memory usage of DL-ESPIRiT and MoDL is 1.8 GB. Average inference speed for DL-ESPIRiT and MoDL are 2.5 and 2.8 sec/slice respectively.

**Fig. 3**: Effect of number of basis functions (K) on image reconstruction quality in validation set.

**Fig. 4**: Reconstruction quality evaluated with respect to PSNR and SSIM for all three networks across a range of simulated scan time acceleration rates.

**Fig. 5**: Reconstructions of a retrospectively accelerated dataset from healthy volunteer. No significant difference is observed between DL-ESPIRiT, MoDL, and DL-Subspace images.

**Fig. 6**: Reconstructions of a prospectively accelerated dataset from pediatric patient. DL-Subspace reconstruction depicts slightly better image quality due to enhanced denoising imposed by low-rank prior (blue arrow).

Conclusion
A novel DL-Subspace reconstruction framework is proposed, which uses a subspace model to curb memory requirements of training unrolled neural networks for spatiotemporal image reconstruction. Further validation is necessary to determine efficacy across a larger patient cohort.

References


