

Combining MR Physics and Machine Learning to Tackle Intractable Problems

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Synopsis

We are combining Machine Learning (ML) with MR-physics based image reconstruction to tackle intractable problems. We address open problems that are either too stochastic to be modeled (e.g. shot-to-shot phase variations in multi-shot EPI due to physiological noise), or that admit a computationally prohibitive model (e.g. motion correction with simultaneous estimation of motion parameters and image content). Using ML to jumpstart physics-based non-convex reconstructions dramatically improve their efficiency and helps avoid local minima. In return, MR-physics reconstruction keeps ML in check, and avoids using it as a blackbox. Such synergistic combination also provides >2x reduction in RMSE over conventional reconstruction.

Introduction

We are proposing to use ML to solve difficult problems in MR. These problems are either impossible to model (e.g. physiological/thermal noise), or there is a model (e.g. motion) whose solution is computationally infeasible. Rather than treating ML as a blackbox, we are using it to jumpstart MR-physics based non-convex reconstructions, which would otherwise be computationally prohibitive and stuck at local minima. This allows us to simultaneously harness ML and sensitivity encoding.

With the combination of ML and MR-physics, we are mitigating patient motion, shot-to-shot phase variations that obstruct Multi-Shot EPI (MS-EPI) reconstruction, and noise in high-resolution diffusion acquisition.

Data / Python code: <http://bit.ly/2y1xK65>

Residual Convolutional Neural Networks (CNN)

Rather than estimating the artifact-free image, we learn the mapping between the corrupted image and the artifacts instead. Optimization for residual mapping is easier, allowing deeper networks with improved accuracy. Following [1,2], we employ Residual CNN [Fig1] with a patch-based approach using 51x51 windows, which are averaged during reconstruction. L1-loss and ADAM optimizer [3] were used in Keras running on a Titan-XP GPU.

Motion Correction with Residual CNN and TAMER

To enable efficient motion correction without navigators for RARE/TSE acquisition, we trained a residual network to correct for motion between shots.

Acquisition: in vivo TSE *without* motion, 2mm in-plane resolution, matrix=128x128, TE/TR=98/6100ms at Turbo Factor=4 (32-shots).

Training: motion trajectories measured on 20 Alzheimer's patients were utilized to simulate artifacts. A 27-layer Residual CNN learned the mapping between the corrupted images and simulated motion artifacts.

Reconstruction: The network was applied to an unseen motion [Fig2a, 43.3%RMSE], which substantially reduced artifacts [Fig2b, 25.4%RMSE]. This cleaner image was used to initialize TAMER [4], an MR-physics based reconstruction that simultaneously solves for motion parameters and clean image:

$$\min_{A_t, x} \sum_t \|F_t C A_t x - k_t\|_2^2$$

where A_t is an affine motion transformation for shot t , F_t is the undersampled DFT for this shot, C are coil sensitivities, x is the unknown image and k_t is the k-space of shot t . TAMER solves this difficult non-convex problem by alternating between motion and image estimation, and computation takes several hours. By initializing TAMER with Residual CNN image, we accelerated the computation >30-fold (several minutes), and cleaned up the remaining artifacts [Fig2c, 15.3%RMSE].

Multi-shot Multi-contrast EPI: mitigating physiological noise with Residual CNN and Joint Reconstruction

MS-EPI allows high-resolution acquisition with reduced distortion, but combining shots is prohibitively difficult because of shot-to-shot physiological phase variations [Fig3a]. These variations may be mitigated using navigators, at the cost of imaging efficiency and in many cases, significant remaining artifacts. We obviate the need for navigators that reduce efficiency, and demonstrate spin-and-gradient-echo (SAGE [5]) MS-EPI.

Acquisition: Four volunteers were scanned with SAGE MS-EPI with 3-shots (FOV=220x220x149mm³, mtx=142x142x48, TEs=27/74/122/169/216ms, TR=12.6sec).

Training: Data from three volunteers were used for training a multi-contrast 25-layer network. Sliding-window combination of shots was used as corrupted input, and GRAPPA [6] reconstruction was used as the clean target.

Reconstruction: Sliding-window reconstruction of test subject [Fig3a, 13.2%RMSE] was processed with Residual CNN to mitigate most of the artifacts [Fig3b, 6.4%RMSE]. To further clean up the artifacts, we propose a physics-based Joint Reconstruction. We fix the CNN magnitude image m_{cnn} , and solve for the phase of each shot ϕ_t using phase-regularized reconstruction [7]:

$$\min_{\phi_t} \|F_t C e^{i\phi_t} m_{cnn} - k_t\|_2^2$$

Once we have the phase of each shot, we jointly solve for the magnitude m_{joint} using data from all shots:

$$\min_{m_{joint}} \sum_t \|F_t C e^{i\phi_t} m_{joint} - k_t\|_2^2$$

This further refines the reconstruction **[Fig3c, 5.1%RMSE]**.

Denoising ultra high-resolution gSlider-SMS diffusion acquisition

gSlider-SMS allows high-resolution diffusion imaging using volumetric noise averaging via RF-encoded thick slabs [8]. Despite using cutting-edge Connectome scanner and 64-channel coil [9], achieving submillimeter resolution with high-SNR is encoding-intensive, requiring multiple averages and long scans. We use ML to mitigate thermal noise, thereby improving SNR and reducing scan times.

Acquisition: Two volunteers were scanned at 760um isotropic resolution (mtx=290x210x176, TE/TR=82/5000ms) to collect 12-averages of $b=2500\text{s/mm}^2$ data.

Reconstruction: averages were registered using FLIRT [10], and 12-average data were used as the clean target. A 20-layer network was trained on one subject, and applied to another. Compared to single-average data which had 29.9%RMSE **[Fig4]**, CNN result had 17.1% error, similar to having 3-averages of gSlider (15.9%RMSE).

Discussion and Conclusion

We combined ML with MR-physics to provide >2x RMSE reduction over conventional reconstruction, and substantial computation efficiency when modeling is impossible/impractical. This synergistic combination removed the black-box application of ML, and allowed MR-physics to keep ML in check. In return, ML facilitated the solution of non-convex, difficult physics-driven reconstruction problems.

This way, CNN+TAMER now performs rapid motion correction without navigators, and CNN+MS-EPI will allow artifact-free, ultra-fast acquisition with low distortion. CNN+gSlider enjoys ~3-fold increase in SNR, enabling even higher resolution diffusion scans.

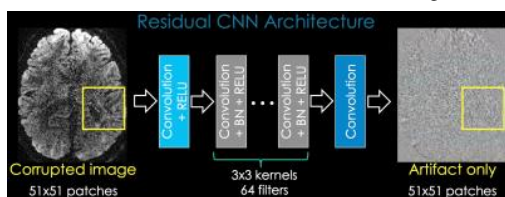
Acknowledgements

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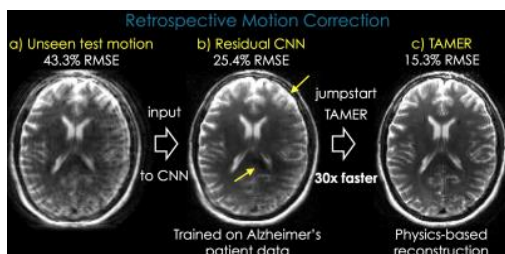
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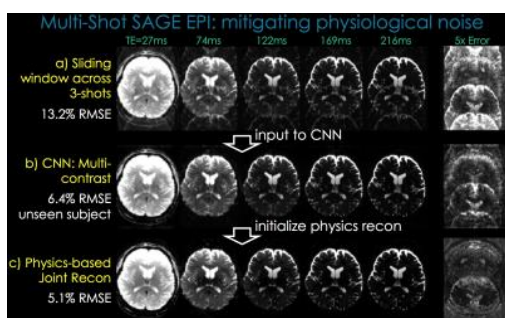
Figures



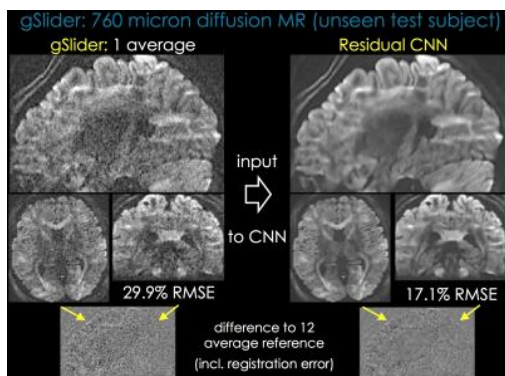
Rather than learning the original mapping between clean and corrupted data, we learn the residual relation between the corrupted and artifact-only images. The Residual CNN architecture is simple, consisting of convolutional layers, batchNormalization (BN, for faster training and improved performance) and RELU nonlinearities. Middle layers employ 3x3 kernels with 64 filters. We follow a patch-based approach where we slide 51x51 windows across the image and average the network outputs in each voxel.



Residual CNN trained on Alzheimer's patient data allows substantial motion artifact reduction when applied to an unseen test motion. There are however minor remaining artifacts (yellow arrows). We use this interim CNN reconstruction to jumpstart MR-physics based TAMER algorithm, which uses the extra degrees of freedom in coil sensitivities to simultaneously estimate motion parameters and the clean image. This non-convex problem is difficult to solve and normally takes hours. With the CNN initialization, the optimization can be performed 30-fold faster, and the remaining artifacts are eliminated.



Sliding window reconstruction across 3-shots of multi-contrast, multi-shot EPI leads to substantial artifacts (13.2%RMSE) due to shot-to-shot physiological phase differences. These are largely mitigated using multi-contrast Residual CNN (6.4%RMSE) for this unseen test dataset. We use the CNN result to initialize our MR-physics based Joint Reconstruction: given the CNN magnitude, we estimate the phase of each shot. With these phase estimates, we then jointly solve for the magnitude image with data from all 3-shots. This leads to further improvement (5.1%RMSE) over the CNN reconstruction.



Residual CNN provides substantial SNR improvement for gSlider-SMS diffusion acquisition at 760um isotropic resolution. Despite exploiting cutting-edge hardware (Connectome scanner and 64-channel custom head-coil) and volumetric noise averaging benefit of gSlider, achieving such high-resolution with high-SNR is very encoding intensive. Residual CNN reconstruction has similar error as 3-averages of gSlider acquisition (17.1% vs 15.9%), indicating a near 3-fold improvement in SNR-efficiency. We note that the structured artifacts (yellow arrows) in both 1-average gSlider and CNN reconstructions are in part due to imperfect registration between individual averages in the 12-average ground truth data.