

Accelerated Multi-shot EPI through Machine Learning and Joint Reconstruction

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Target audience: MR physicists focusing on data acquisition and reconstruction for fast imaging.

Purpose: Multi-shot echo planar imaging (msEPI) allows high-resolution acquisition with reduced distortion, but combining shots is prohibitively difficult because of shot-to-shot physiological phase variations, particularly in gradient-echo EPI with long TE. These variations can be mitigated using navigators, albeit at the cost of imaging efficiency and in many cases, significant remaining artifacts. Navigator-free approaches employ parallel imaging to reconstruct each shot, from which phase variations are estimated [1,2]. This imposes a limit on the achievable distortion reduction since parallel imaging typically breaks down beyond R>4 acceleration in PE axis. We propose NEATR (Network Estimated Artifacts for Tempered Reconstruction) for navigator-free msEPI, and synergistically combine machine learning (ML) and MR physics-based reconstruction. Our Residual CNN provides minimally aliased images of each shot despite R=6-fold acceleration, which allows estimation of shot-to-shot phase variations. The images are further refined through our Joint Reconstruction which utilizes the estimated phase as additional sensitivity variation as well as k-space data from all shots. This way NEATR fully harnesses sensitivity encoding and all the acquired data, while avoiding black-box application of ML. Python code/data are available: <http://bit.ly/2qtW551>

Acquisition: Four volunteers were scanned with spin-and-gradient-echo (SAGE [3]) msEPI with 2-shots at R=3 (FOV= 220x220x149 mm, mtx= 142x142x48, TEs= 27/74/122/169 ms, TR= 12.6sec). Each shot was reconstructed using GRAPPA [4], and coil-combined with ESPIRiT sensitivities [5]. Magnitudes of the 2-shots were averaged to obtain clean reference data.

Reconstruction: Each of the 2-shots were retrospectively undersampled by R=6-fold, and the second shot was shifted by $\Delta k_y=3$ to provide complementary coverage. Each shot was then reconstructed with SENSE [6] at R=6,

and their magnitudes were averaged for improved SNR [Fig1a]. This provided corrupted input data for ML.

Residual CNN [Fig1b]: was employed to learn the mapping between the SENSE-R6 reconstructed data and the error in the SENSE reconstruction. SAGE data from three volunteers were used for training, and the fourth subject was reserved for testing. U-Net architecture [7,8] with 5 levels, ℓ_1 loss, leaky ReLU activation and 64 filters at the highest level was trained on all echoes to enable multi-contrast processing. The training set was augmented 16-fold with scaling, flips and rotations.

Joint Reconstruction: To further clean up artifacts, we fix the U-Net magnitude result m_{unet} and solve for the phase of t^{th} shot ϕ_t using wavelet (Ψ) regularized reconstruction [9]: $\min_{\phi_t} 1/2 \|\mathbf{F}_t \mathbf{C} e^{i\phi_t} m_{unet} - d_t\|_2^2 + \alpha \|\Psi \phi_t\|_1$ [Fig1c]. Here \mathbf{F}_t is Fourier transform for shot t , \mathbf{C} are the coil sensitivities, and d_t are the shot k-space data. Once shot phases are estimated, we jointly solve for the magnitude m_j using data from all shots:

$$\min_{m_j} \sum_t \left\| \begin{bmatrix} \mathbf{F}_t \mathbf{C} e^{i\phi_t} \\ \mathbf{F}_{-t} \mathbf{C}^* e^{-i\phi_t} \end{bmatrix} m_j - \begin{bmatrix} d_t \\ d_{-t}^* \end{bmatrix} \right\|_2^2 + \beta \|m_j\|_2^2$$

[Fig1d]. Here, the virtual coil k-space data d_{-t}^* and the corresponding conjugate sensitivities $\mathbf{C}^* e^{-i\phi_t}$ ensure that m_j is real-valued.

Results [Fig2]: SENSE-R6 suffered from artifacts and noise amplification (11.3% RMSE), which were largely mitigated by U-Net (7.9%) but some aliasing artifacts were still visible (yellow arrow). Joint Reconstruction provided further improvement in image quality and artifact reduction (6.9% error). $\alpha = 0.3$ and $\beta = 0.01$ were chosen to minimize RMSE.

Discussion: NEATR synergistically combined ML with MR-physics to prevent black-box application of U-Net, and generates the final image with a more conventional physics reconstruction to keep ML in check. In return, ML enabled R=6-fold acceleration, which would not be possible with sensitivity encoding alone. Overall, NEATR reduced RMSE by 1.6-fold over SENSE to enable ultra-fast, low distortion and artifact- and navigator-free scans.

References: [1] N Chen, NIMG'13; [2] Z Zhang, NIMG'15; [3] H Schmiedeskamp, MRM'12; [4] MA Griswold, MRM'02; [5] M Uecker, MRM'14; [6] KP Pruessmann, MRM'99; [7] O Ronneberger, MICCAI'15; [8] KH Jin, IEEE TIP'17; [9] F Ong, MRM'17.

