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Joint estimation of coil sensitivities and image content using a deep image prior

Guanxiong Luo[1], Xiaoqing Wang[1], Volkert Roeloffs[1], Zhengguo Tan[1], and Martin Uecker[1,2]
[1]Institute for Diagnostic and Interventional Radiology, University Medical Center Göttingen, Germany, Göttingen, Germany, [2]Campus Institute Data Science (CIDAS), University of Göttingen, Germany, Göttingen, Germany

Synopsis

Parallel imaging for reduction of scanning time is now routinely used in clinical practice. The spatial information from the coils' profiles are exploited for encoding. The nonlinear inversion reconstruction is a calibrationless parallel imaging technique, which jointly estimate coil sensitivities and image content. In this work, we demonstrate how to combine such a calibrationless parallel imaging technique with an advanced neural network based image prior for efficient MR imaging.

Introduction

Model-based reconstruction with regularization terms on the image is flexible and efficient in improving the reconstruction quality when k-space data is highly undersampled. Recently, several deep learning based reconstruction methods have been proposed for MRI acceleration. However, most of them rely on specific sampling patterns and precomputed coil sensitivities for supervised training, limiting their flexibility in applications. In this work, we present an approach to jointly estimate the coil sensitivities and image regularized by an image prior [2] that is sampling pattern independent. Furthermore, we validated the proposed method with radial k-space data acquired for a human brain.

Theory

Parallel MR imaging can be formulated as a nonlinear inverse problem as follow

$$F(\rho, c) := (\mathcal{F}_S(\rho \cdot c_1), \cdots, \mathcal{F}_S(\rho \cdot c_N)) = y,$$

where $\mathcal{F}_S$ is an undersampled Fourier transform operator and the corresponding k-space data is $y = (y_1, \cdots, y_N)^T$, ρ denotes the spin density and $c = (c_1, \cdots, c_N)^T$ denotes coil sensitivities. Proposed in the nonlinear inverse reconstruction (nlinv) [1], this problem can be solved with the Iteratively Regularized Gauss Newton Method (IRGNM) by estimating $\delta m := (\delta\rho, \delta c)$ in each step k for given $m^k := (\rho^k, c^k)$ with the following minimization problem

$$\min_{\delta x} \frac{1}{2}\|F'(m^k)\delta m + F(m^k) - \boldsymbol{y}\|_2^2 + \frac{\alpha_k}{2}\mathcal{W}(\boldsymbol{c} + \delta c) + \beta_k R(\rho^k + \delta\rho), \quad (1)$$

where $\mathcal{W}(c) = \|Wc\|^2 = \|w \cdot \mathcal{F}c\|$ is a penalty on the high Fourier coefficients of the coil sensitivities and $R(\rho)$ is a regularization term on ρ. The α_k and β_k decay based on reduction factor over iteration steps. In this work, the neural network based log-likelihood prior was investigated [2], formulated with following joint distribution

$$\log P(\hat{\Theta}, \boldsymbol{x}) = \log p(\boldsymbol{x}; \mathrm{NET}(\hat{\Theta}, \boldsymbol{x})) = \log p(x^{(1)}) \prod_{i=2}^{n^2} p(x^{(i)} \mid x^{(1)}, \ldots, x^{(i-1)}),$$

where the neural network $\mathrm{NET}(\hat{\Theta}, \boldsymbol{x})$ outputs the distribution parameters of the mixture of logistic distribution which was used to model images. For each step, the fast iterative gradient descent method (FISTA) [3] is used to minimize Eq (1). The proximal operation on $\log P(\hat{\Theta}, \boldsymbol{x})$ was approximated using gradient updates. The gradient of $\log P(\hat{\Theta}, \boldsymbol{x})$ is computed via backpropagation.

Methods

To obtain a generic image prior for the nonlinear inversion reconstruction, we trained the PixelCNN++ with aliased-free brain images. Then, the computation graph of the neural network and the trained model were exported with TensorFlow. The inference using the trained model was implemented via TensorFlow C API within BART toolbox's framework. The optimization algorithm was then based on existing functionality in BART. For validation, T2*-weighted data (TE=16ms, TR=770ms, 3T) from a human brain was acquired with a GRE sequence. The image matrix was 256×256 and the resolution was 1mm×1mm. We acquired 160 radial k-space spokes using golden angle radial trajectory (2.5-fold acceleration). The gradient delay of radial trajectories was estimated with RING [4]. The number of channels was compressed to eight. At last, we reconstructed images from a different number of spokes (50, 70, 160) and made comparisons of different regularization terms that includes ℓ_2, ℓ_1-wavelet and learned log-likelihood.

Results

The comparisons of reconstructions using different regularization were shown in Figure 1, including the moderate undersampling (2.5-fold acceleration) and the high undersampling k-space data (5.74-fold/ 8-fold acceleration). The learned log-likelihood prior tends to smooth images and suppress noises but preserves the boundaries between tissues well. One set of coil sensitivities estimated from 50 radial k-space spokes is shown in Figure 2. Figure 3 presents the structural similarity indices of reconstructions from different numbers of radial k-space spokes.

Conclusion and Discussion

We demonstrated how a learned log-likelihood prior trained from aliased-free images can be incorporated into calibration-less parallel imaging compressed sensing reconstruction using nonlinear inversion. One advantage of the proposed method is that the same prior can be used with different sampling patterns. Learning the intrinsic relationship between the pixels from aliased-free images, the log-likelihood prior shows better performance over ℓ_1-wavelet prior.

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References

[1] Uecker M et al., "Image reconstruction by regularized nonlinear inversion—joint estimation of coil sensitivities and image content." Magnetic Resonance in Medicine 60.3 (2008): 674-682.

[2] Luo G et al., "MRI reconstruction using deep Bayesian estimation." Magnetic Resonance in Medicine 84.4 (2020): 2246-2261.

[3] Beck A et al., "A fast iterative shrinkage-thresholding algorithm for linear inverse problems." SIAM journal on imaging sciences 2.1 (2009): 183-202.

[4] Rosenzweig S, Holme HCM, Uecker M. "Simple auto-calibrated gradient delay estimation from few spokes using Radial Intersections (RING)." Magnetic resonance in medicine 81.3 (2019): 1898-1906.

[5] Lustig M et al. "Compressed sensing MRI." IEEE signal processing magazine 25.2 (2008): 72-82.

[6] Uecker M et al., BART Toolbox for Computational Magnetic Resonance Imaging, DOI:10.5281/zenodo.592960

Figures

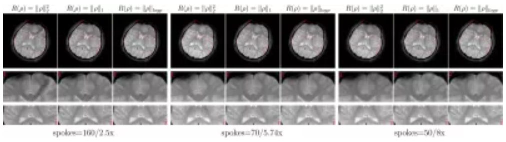

Figure 1. For the case of moderate undersampling, the two reconstructions regularized by log-likelihood and ℓ_1 are very close, and the structural similarity index between them is 0.95. The ℓ_1 reconstruction has blocky artifacts in Region 1 introduced by the wavelet transform, especially for higher undersampling. Overall, the learned log-likelihood outperforms ℓ_1 in noise suppression, especially in Region 2. The reconstructions regularized by the learned log-likelihood also better preserve the boundaries between tissues and have less noise.

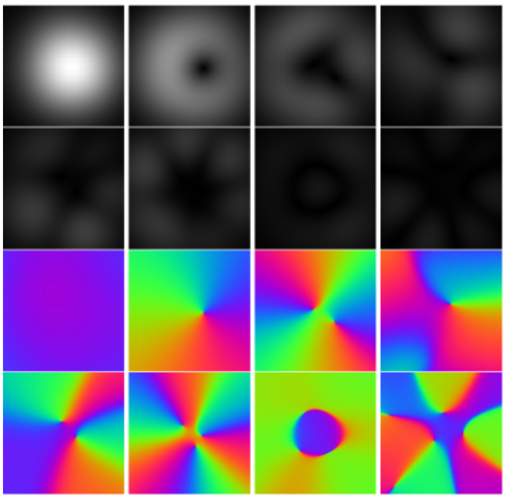

Figure 2. Reconstructed coil sensitivities (grayscale magnitude and color-coded phase) after channel compression.

	spokes=160/2.5x	
	ℓ_1-nlinv	logp-nlinv
spokes=50/8x		
ℓ_1-nlinv	0.8933	0.9128
logp-nlinv	0.9219	0.9407
spokes=70/5.74x		
ℓ_1-nlinv	0.9572	0.9366
logp-nlinv	0.9425	0.9523

Figure 3. Computed SSIMs of ℓ_1-nlinv and logp-nlinv based reconstructions (8x and 5.74x undersampling) with respect to 160 radial spokes.

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