Using data-driven image priors for image reconstruction with BART

Guanxiong Luo[1] Moritz Blumenthal [1] Martin Uecker [1,2]

[1]Institute for Diagnostic and Interventional Radiology, University Medical Center Göttingen
[2]Campus Institute Data Science (CIDAS), University of Göttingen

Synopsis

Trained neural networks can be incorporated into established MRI reconstruction routines within the BART toolbox. Here, as a proof of concept, we demonstrate training of the prior and implementation of reconstruction pipelines.

Introduction

Advanced reconstruction algorithms based on deep learning have recently drawn a lot of interest as they tend to outperform state-of-the-art methods. BART [1] is a versatile framework for image reconstruction. In this work, we demonstrate how neural networks trained and tested with TensorFlow [5] can be integrated into BART. As an example, we discuss non-Cartesian parallel imaging using the SENSE model regularized by a log-likelihood image prior. The image prior is based on an autoregressive generative network pixel-cnn++ [4]. Furthermore, we validated the reconstruction pipeline using radial brain scans.

Theory

Iterative parallel imaging reconstruction is commonly formulated as the following minimization problem

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \|\mathcal{A}\boldsymbol{x} - \boldsymbol{y}\|_2^2 + \lambda R(\boldsymbol{x}), \tag{1}$$

where the first term ensures data consistency between the acquired k-space data $\boldsymbol{y}$ and the desired image $\boldsymbol{x}$, $\mathcal{A}$ is the forward operator and the regularization term $R(\boldsymbol{x})$ imposes prior knowledge about images in form of total variation [2], sparsity [3], or a learned log likelihood [4]. The learned log-likelihood prior is formulated as follow:

$$\log P(\hat{\Theta}, \boldsymbol{x}) = \log p(\boldsymbol{x}; \texttt{NET}(\hat{\Theta}, \boldsymbol{x})),$$

where the neural network $\texttt{NET}(\hat{\Theta}, \boldsymbol{x})$ outputs the distribution parameters of the mixture of logistic distributions, which was previously used to model images [4].

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Training of prior

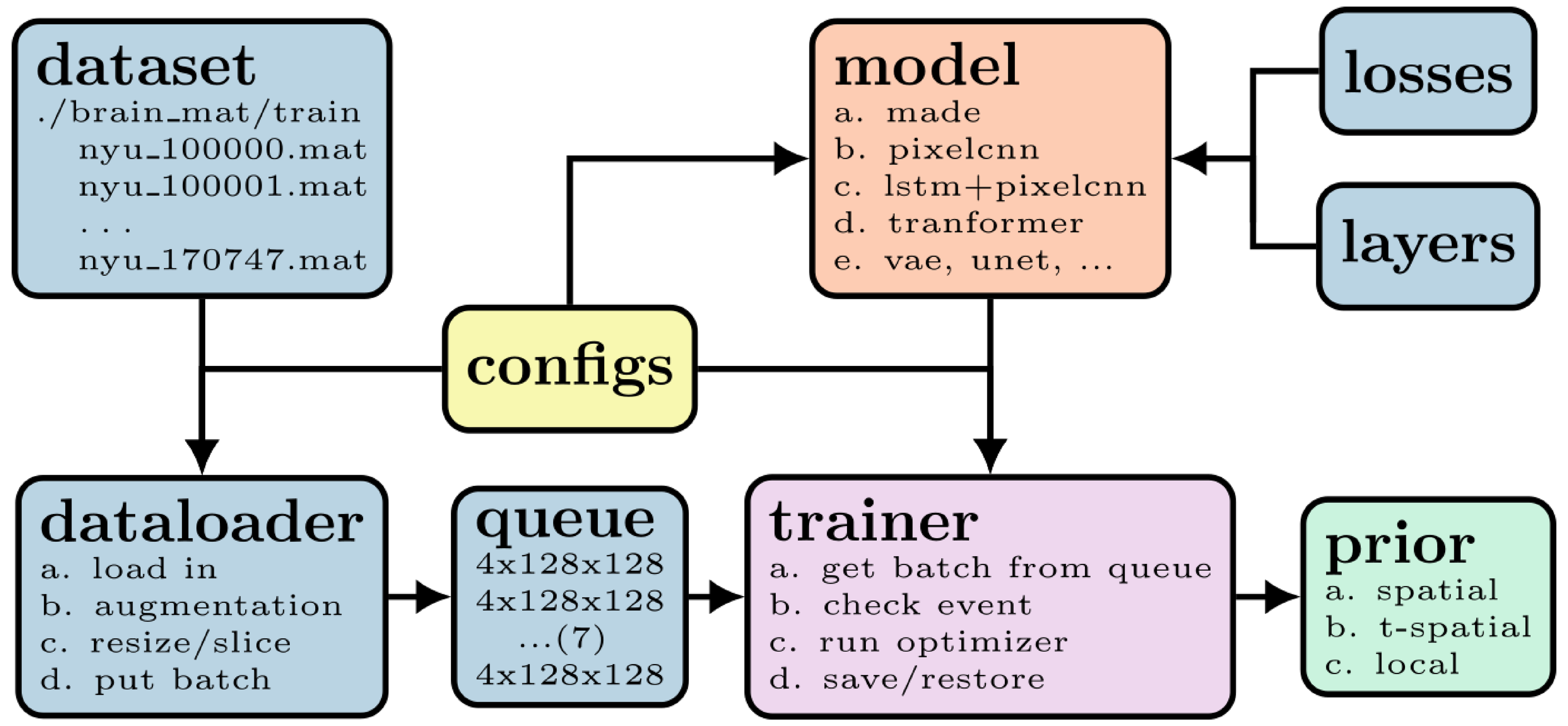

Figure 1. Flow chart of the training program

- Implemented with TensorFlow
- Interruptible training
- Utilities to save configurations of network and training
- Create plug-and-play prior for BART

Implementation

The integration of the trained prior into the reconstruction follows these steps:

1. Wrapped the exported computation graph into BART's non-linear operator (nlop). The forward pass is called via nlop's forward function.
2. The gradient of $R_{logp}(\boldsymbol{x})$ is called via nlop's adjoint function.
3. The initialization of an exported graph, the restoration of a saved model, and the inference are implemented with TF's C API[5].
4. The dependencies on CUDA and cuDNN for TensorFlow are satisfied with Conda [6].
5. FISTA [7] is used to solve Eq (1).

The option in BART's `pics` is as follow:

```
$ bart pics -R LP:{model}:λ:pct:n <ksp> <coilsen> <out>,
```

where `pct` is the update percentage and the `n` specifies the number of model inferences for every FISTA iteration.

Results

To validate the developed pipeline, images from T_2^*-weighted prospectively undersampled radial k-space data are reconstructed (Figure 2). We set $\lambda = 10, pct = 0.7, n = 1$

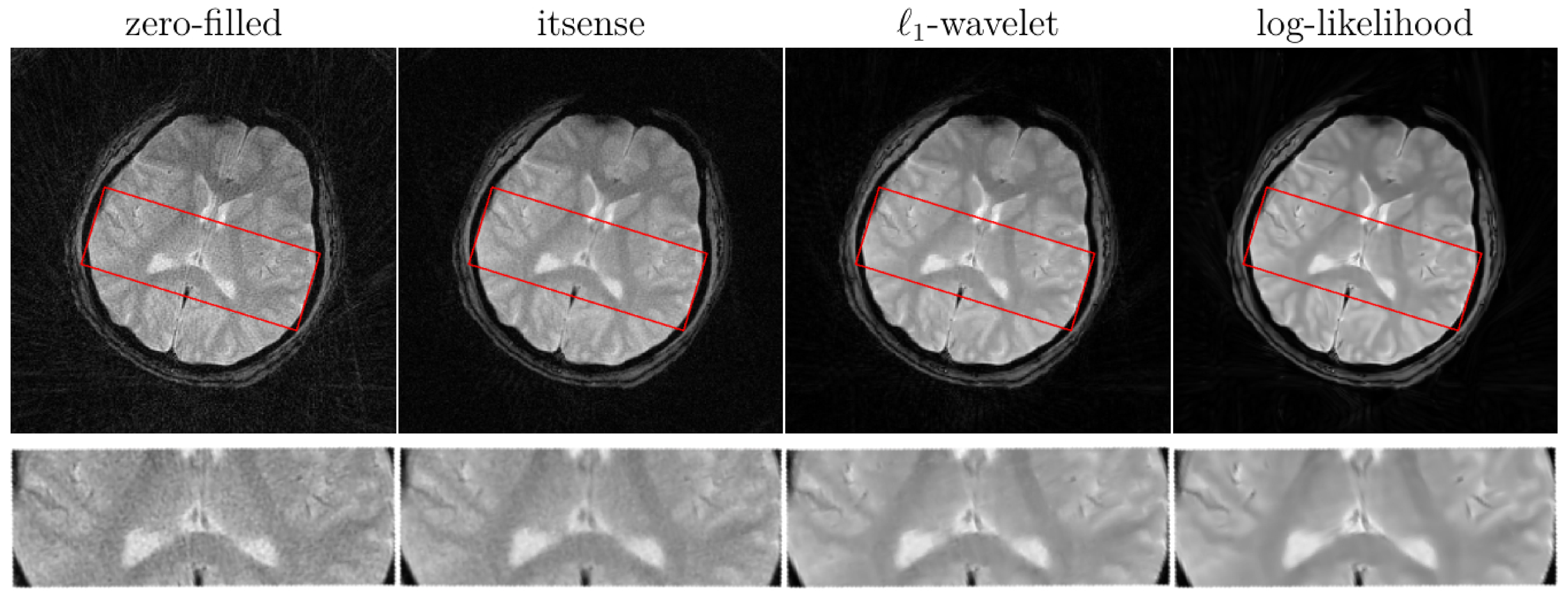

Figure 2. Images are reconstructed from 60 radial k-space spokes via zero-filled, iterative sense, ℓ_1-wavelet, learned log-likelihood (left to right).

Conclusion

The BART toolbox is a flexible framework for the integration of trained neural networks. Based on existing functionalities, a deep image prior could easily be integrated into general reconstruction pipelines.

References

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guanxiong.luo@med.uni-goettingen.de