Nonuniform Variational Network: Deep Learning for Accelerated Nonuniform MR Image Reconstruction

Jo Schlemper†1, Seyed Sadegh Mohseni Salehi†1, Prantik Kundu[1],
Carole Lazarus[1], Hadrien Dyvorne[1], and Michal Sofka[1]

Hyperfine Research, CT, USA

1 Introduction

Slow acquisitions in Magnetic resonance imaging (MRI) result in reduced patient comfort as well as degraded image quality, where the latter is largely due to patient motion and a long-term accumulation of system imperfections. The system imperfections are even more profound in low-field MRI systems that have lower SNR and are more susceptible to noise interference. In a typical MR imaging technique, k-space is acquired at Nyquist sampling rate and the image is obtained by applying an inverse Fourier transform. However, more efficient 2D or 3D sampling patterns may be designed to speed up MR acquisition time [3, 1, 4, 5]. Recently, deep learning based approaches for accelerated MR image reconstruction have gained popularity due to their promising performances, often exceeding the quality of the CS approaches [2, 8, 6, 9]. In this work, we present a convolutional neural network (CNN) architecture based on the generalization of variational network [2] for non-Cartesian cases, termed *nonuniform variational network* (NVN). Similar to variational networks, the proposed method is based on the *unrolling* of iterative nonlinear reconstruction used in CS, however, we generalize the regularization functional as well as adapting the data fidelity term for nonuniform case. The extensive evaluation reveals that the proposed algorithm is superior over existing deep learning approaches for nonuniform data. Our extensive evaluation shows that the proposed method outperforms existing state-of-the-art deep learning methods, hence offering a method that is widely applicable to different imaging protocols for both research and clinical deployments.

2 Methods

Let $\boldsymbol{x} \in \mathbb{C}^N$ denote a complex-valued MR image to be reconstructed, represented as a vector with $N = N_x N_y$ where N_x and N_y are width and height of the image. Let $\boldsymbol{y} \in \mathbb{C}^M$ $(M << N)$ represent the undersampled k-space measurements. Our problem is to reconstruct $\boldsymbol{x}$ from $\boldsymbol{y}$, formulated as an unconstrained optimization $\underset{\boldsymbol{x}}{\operatorname{argmin}} \frac{\lambda}{2}\|\boldsymbol{A}\boldsymbol{x} - \boldsymbol{y}\|_2^2 + \mathcal{R}(\boldsymbol{x})$, where $\boldsymbol{A}$ is a nonuniform Fourier sampling operator, $\mathcal{R}$ expresses regularization terms on $\boldsymbol{x}$ and λ is a hyper-parameter often associated to the noise level. We propose a new deep learning algorithm to approximate the solution to this optimization problem. Firstly, we consider a gradient descent algorithm which provides a locally optimal solution:

$$\boldsymbol{x}_0 = f_{\text{init}}(\boldsymbol{A}, \boldsymbol{y}) \tag{1}$$

$$\boldsymbol{x}_i = \boldsymbol{x}_{i-1} - \alpha_i \nabla_{\boldsymbol{x}} f(\boldsymbol{x})|_{\boldsymbol{x}=\boldsymbol{x}_{i-1}}, \qquad \nabla_{\boldsymbol{x}} f(\boldsymbol{x}) = \lambda \boldsymbol{A}^H(\boldsymbol{A}\boldsymbol{x} - \boldsymbol{y}) + \nabla_{\boldsymbol{x}} \mathcal{R}(\boldsymbol{x}) \tag{2}$$

where f_{init} is an initializer, α_i is a step size and ∇f is the gradient of the objective function.

Common choices of the initializer are adjoint $f_{\text{init}}(\boldsymbol{A}, \boldsymbol{y}) = \boldsymbol{A}^H\boldsymbol{y}$ and gridding reconstruction $f_{\text{init}}(\boldsymbol{A}, \boldsymbol{y}) = \boldsymbol{A}^H\boldsymbol{W}\boldsymbol{y}$. The idea of variational network (VN) formalism is to first unroll the sequential updates into a feed-forward model, and approximate the gradient term $\nabla\mathcal{R}$ by a series of trainable convolution layers and non-linearities. Such generalization yields an end-to-end trainable network with N_{it} blocks:

$$\boldsymbol{x}_0 = f_{\text{init-cnn}}(\boldsymbol{A}, \boldsymbol{y}|\theta_0) \tag{3}$$

$$\boldsymbol{x}_i = \boldsymbol{x}_{i-1} - \lambda_i \underbrace{\boldsymbol{A}^H(\boldsymbol{A}\boldsymbol{x}_{i-1} - \boldsymbol{y})}_{\text{DC-}i} - \underbrace{f_{\text{cnn}}(\boldsymbol{x}_{i-1}|\theta_i)}_{\text{CNN-}i} \tag{4}$$

† Co-first authors. Emails: {jschlemper,ssalehi}@hyperfine-research.com

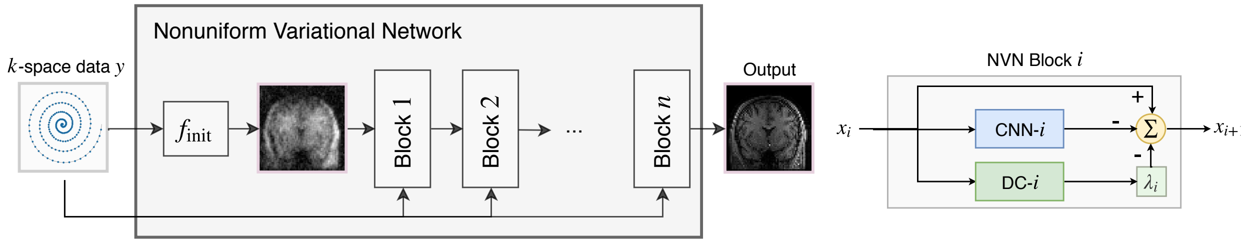

Fig. 1. The architecture of Nonuniform Variational Network.

Table 1. Quantitative result for acceleration factor (R) 2 and 4. For each metric, mean and standard deviation is computed. MSE's are scaled by 10^3. The proposed approaches consistently outperformed the baseline approaches (U-net and k-space U-net) for both acceleration factors.

	$R = 2$			$R = 4$		
Methods	MSE	SSIM	PSNR	MSE	SSIM	PSNR
U-net	0.47 (1.55)	0.96 (0.05)	35.68 (3.67)	0.67 (1.13)	0.94 (0.07)	33.71 (3.23)
U-net (k)	0.77 (0.81)	0.89 (0.10)	33.83 (3.62)	1.31 (7.53)	0.87 (0.11)	31.84 (3.35)
NVN	**0.40 (0.60)**	0.96 (0.06)	36.11 (3.60)	0.66 (1.40)	0.91 (0.12)	34.01 (3.43)

where the learnable parameters are $\{\theta_0, \ldots, \theta_{N_{\text{it}}}, \lambda_1, \ldots, \lambda_{N_{\text{it}}}\}$. Note that the step size α_i is absorbed in the learnable parameters. In this work, a general non-convex regularization functional is approximated by state-of-the-art CNN denoisers [7]. $\boldsymbol{A}$ is expressed as $\boldsymbol{G}\boldsymbol{F}_s\boldsymbol{D}$, where $\boldsymbol{G}$ is implemented as a sparse GPU matrix multiplication, $\boldsymbol{F}_s$ is a FFT, and $\boldsymbol{D}$ is a diagonal matrix. The proposed architecture, termed *nonuniform variational network* (NVN), is shown in Fig. 1, where the data consistency term is shown in *DC-i* block and CNN is shown in *CNN-i* block.

3 Results

We used 640 randomly selected T1-weighted and T2-weighted brain images from Human Connectome Project [1] to evaluate the efficacy of our proposed architecture (600 for training and 40 for testing). We performed the following pre-processing steps: (1) adding phase information to the magnitude data using two-dimensional Fourier bases with randomly sampled low order coefficients; (2) multiplying the images by spatially localized complex coil sensitivity profiles; (3) adding a realistic amount of noise observable for parallel image acquisition; (4) resampling the images to a field of view (FOV) of $180 \times 180 \times 180\text{mm}^3$, with the isotrophic resolution of $1.15 \times 1.15 \times 1.15\text{mm}^3$, resulting in the matrix size 192^3. We generated the sampling trajectory with the target acceleration factor $R \in \{2, 4\}$.

4 Discussion and Conclusion

In this work, we proposed nonuniform variational network (NVN), a nonuniform extension of variational network, which performed the state-of-the-art deep learning models for reconstruction.

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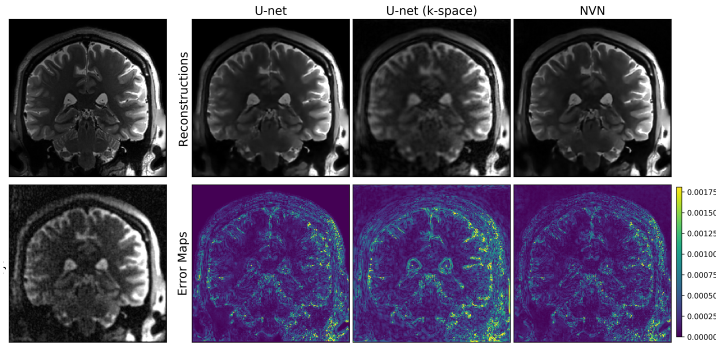

Fig. 2. The reconstructions for 192×192 T2 weighted image, $R = 4$. (top) Reconstructions (bottom) error maps. The reconstructions from NVN resulted in lower error, owing to the data consistency block.

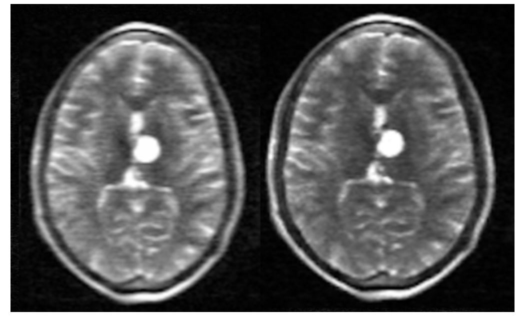

Fig. 3. Linear (left) and NVM (right) reconstruction of low-field MRI acquisition.

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