

# Accelerated Magnetic Resonance Imaging by Adversarial Neural Network

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**Abstract.** A main challenge in Magnetic Resonance Imaging (MRI) for clinical applications is speeding up scan time. Beyond the improvement of patient experience and the reduction of operational costs, faster scans are essential for time-sensitive imaging, where target movement is unavoidable, yet must be significantly lessened, e.g., fetal MRI, cardiac cine, and lungs imaging. Moreover, short scan time can enhance temporal resolution in dynamic scans, such as functional MRI or dynamic contrast enhanced MRI. Current imaging methods facilitate MRI acquisition at the price of lower spatial resolution and costly hardware solutions. We introduce a practical, software-only framework, based on deep learning, for accelerating MRI scan time allows maintaining good quality imaging. This is accomplished by partial MRI sampling, while using an adversarial neural network to estimate the missing samples. The interplay between the generator and the discriminator networks enables the introduction of an adversarial cost in addition to a fidelity loss used for optimizing the peak signal-to-noise ratio (PSNR). Promising image reconstruction results are obtained for 1.5T MRI where only 52% of the original data are used.

## 1 Introduction

Magnetic Resonance Imaging (MRI) is a non-ionizing imaging modality, and is therefore widely used in diagnostic medicine and biomedical research. The physical principles of MRI are based on a strong magnetic field and pulses of radio frequency (RF) electromagnetic radiation. Images are produced when hydrogen atoms, which are prevalent in living organisms, emit the absorbed RF energy that is then received by antennas in close proximity to the anatomy being examined. Spatial localization of the detected MRI signals is obtained by varying the magnetic field gradients. The discretized RF output is presented in a Fourier space (called K-space), where the x-axis refers to the frequency and the y-axis to the phase. An inverse fast Fourier transform (IFFT) of the K-space is then used for generating anatomically meaningful MRI scans. Figure 1 presents K-space traversal patterns used in conventional imaging. Each row of the k-space is acquired after one RF excitation pulse. The number of rows multiplied by the number of slices (z-axis) determines the total scan time.

The duration of standard single structural MRI acquisition is approximately 5 minutes. Usually, several scans of different modalities or a sequence of scans

are acquired such that the overall scan time is much longer. Lengthy imaging process reduces patient comfort and is more vulnerable to motion artifacts. In cases where motion is inevitable, e.g., fetal MRI, cardiac cine, and lungs imaging, scan time must be significantly shortened, otherwise the produced images might be useless. Moreover, in dynamic MRI sequences, acquisition must be brief such that the temporal resolution of the sequence would allow capturing significant temporal changes, e.g., instantaneous increment of the contrast-enhanced material concentration in DCE-MRI or differences in hemodynamic response expressed in fMRI [10].

A straight forward reduction of the scan time can be obtained by sampling fewer slices, thus reducing the spatial resolution in the z-axis. Spatial distances between adjacent slices of fetal MRI or fMRI, for example, are often as high as 0.5 centimeters. Therefore, a significant portion of the potential input is not conveyed through imaging. On the other hand, under-sampling in the x-y domain leads to aliasing, as predicted by the Nyquist sampling theorem.

Numerous research groups as well as leading MRI scanner manufacturers make significant efforts to accelerate the MRI acquisition process. Hardware solutions allow parallel imaging by using multiple coils [17] to sample k-space data. There exist two major approaches [3] that are currently implemented in commercial MRI machines. Both reconstruct an image from the under-sampled k-space data provided by each of the coils. The sensitivity encoder (SENSE) transforms the partial k-spaces into images, then merges the resulting aliased images into one coherent image [14]. The GeneRalized Autocalibrating Partial Parallel Acquisition (GRAPPA) techniques [7] operate on signal data within the complex frequency domain before the IFFT.

The compressed sensing (CS) technique [4] allows efficient acquisition and reconstruction of a signal with fewer samples than the Nyquist-Shannon sampling theorem requires, if the signal has sparse representation in a known transform domain. Using CS for MRI reconstruction by sampling a small subset of the k-space grid had been proposed in [9]. The underlying assumption is that the undersampling is random, such that the zero-filled Fourier reconstruction exhibits incoherent artifacts that behave similarly to additive random noise. This, however, would require specified pulse programming.

Recently machine learning techniques based on manifold learning [18,1] and dictionary learning [16,2] were suggested for MRI reconstruction. MRI reconstruction using convolutional neural networks (CNN) was introduced in [19]. The network learns the mapping between zero-filled and fully-sampled MR images. In [12], residual network was proposed for MRI super-resolution. Their model is able to receive multiple inputs acquired from different viewing planes for better image reconstruction. Both works address the reconstruction problems in the image domain rather than the k-space domain. The proposed framework utilizes recent advances in deep learning, while similarly to the CS methods addresses MRI reconstruction directly from the k-space. Specifically, we use generative adversarial networks (GAN) [6,15,13]. GANs are based on the inter-play between two networks: a generator and a discriminator. The generator is ca-

pable of learning the distribution over a data-base, and sample realizations of this distribution. The discriminator is trained to distinguish between ‘generated’ samples and real ones. This powerful combination has been used for generating Computed Tomography (CT)-like images from MRIs [11]. Here, the generator is used for reconstruction of the entire k-space grid from under-sampled data. Its loss is a combination of an adversarial loss, based on the discriminator output and a fidelity loss with respect to the fully sampled MRI. Promising results are obtained for brain MRI reconstruction using only 52% of the data.

The paper is organized as follows. Section 2 presents some theoretical foundation and our method. Section 3 describes the experimental results. Conclusions and future directions are describes in section 4.

## 2 Method

### 2.1 K-space

Let  $\mathbf{u}$  denote the desired signal, a 2D MR image, obtained by the IFFT of the complex k-space signal  $s_0$ . Let  $M_F$  denote a full sampling mask such that the reconstructed MR image is:

$$\mathbf{u} = F^H M_F \odot s_0 \quad (1)$$

where  $H$  is the Hermitian transpose operation,  $\odot$  denotes element-wise multiplication, and  $F^H$  is an orthonormal 2D IFFT operator, such that  $F^H F = I$ . While sampling part of the k-space, using  $M_p$  as a sampling mask, the reconstructed MR image suffers from artifacts and aliasing. An example of the under-sampling (52%) artifacts is shown in Figure 1.

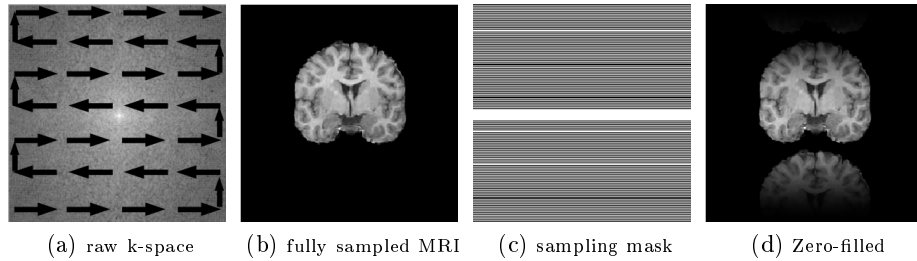


Fig. 1: Under-sampling artifacts: the arrows illustrate the sampling methodology

### 2.2 Objective

Let  $s_p = M_p \odot s_0$  denote the under-sampled k-space. Given a sampling mask and a model  $f$ , defined by the set of parameters  $\Theta$ , our goal is to estimate the missing k-space samples such that:

$$\Theta = \arg \min_{\Theta} L(F^H f(s_p; \Theta), \mathbf{u}) \quad (2)$$

where  $L(\cdot)$  is the loss function. While choosing the loss to be L2 norm is reasonable for natural images, for the k-space, which has different spatial features, this may not be enough. As mentioned in [13], L2 minimization provides a blurry solution. Averaging the high frequency details in the k-space domain results in very poor reconstruction. In order to address this problem, we used the adversarial loss, based on GAN.

We trained our model using the adversarial strategy, as described in [6,15]. This method is based on a generator  $G$ , which takes noise  $z$  with uniform distribution  $p_u(z)$  as input and generates samples from the data distribution. A discriminator  $D$  is trained to distinguish between “real” examples from the data and generated (“fake”) examples from  $G$ . During the training process, we optimize  $G$  to maximize the discriminator’s probability of error. Simultaneously,  $D$  is getting better and provides more accurate predictions.

Let  $s_0$  denote a “real” k-space sample from the distribution  $p_r(s_0)$ . The following optimization process can be described by two-players min-max game:

$$\min_G \max_D \mathbb{E}_{s_0 \sim p_r(s_0)} \log [D(x)] + \mathbb{E}_{z \sim p_u(z)} \log [1 - D(G(z))] \quad (3)$$

In equilibrium, the generator  $G$  is able to generate samples that look like the real data. In our case,  $G$  estimates the missing k-space samples from a linear combination of the sampled data and a uniform noise with distribution  $p_u(z)$ . An L2 fidelity constraint is added to the adversarial loss of the generator, as follows:

$$L_G = \alpha \cdot \mathbb{E}_{z \sim p_u(z)} \log [1 - D(F^{-1}(\hat{s}_0))] + \beta \cdot \|(1 - M_p) \odot (\hat{s}_0 - s_0)\|_2^2 \quad (4)$$

where  $\hat{s}_0$  is the estimated k-space and  $\alpha = 1$ ,  $\beta = 0.8$  are hyperparameters tuned by a cross-validation process. The discriminator’s input is the reconstructed MR image, i.e., after IFFT. By that, we are integrating the reconstruction phase in our optimization.

### 2.3 Network Architecture

The generator input is a two-channel image representing the real and the imaginary parts of the partially sampled k-space image,  $s_p$ . Each missing sample is initialized by uniform i.i.d. noise. The pixel  $(i, j)$  in the generator input image is:

$$G_{in}(i, j) = s_{p_{i,j}} + (1 - M_p)_{i,j} z_{i,j} \quad (5)$$

Due to the combination of the adversarial and the fidelity loss,  $G$  produces reasonable k-space samples from a given samples and noise distribution  $p_u(z)$ . In order to use the sampled data,  $s_p$ , and estimate only the missing samples we used a residual network [8] as used in [12], such that:

$$\hat{s}_0 = s_p + (1 - M_p) \odot G_{out} \quad (6)$$

where  $G_{out}$  is the generator output. Figure 2 describes our framework:

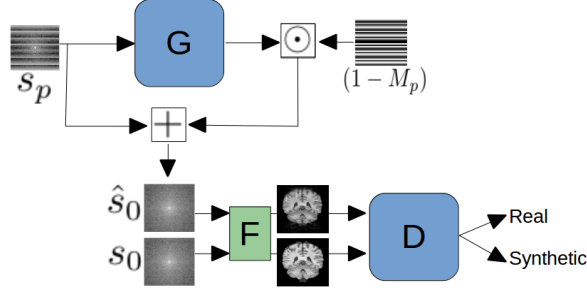


Fig. 2: Framework architecture:  $G$  and  $D$  are the generator and discriminator networks, respectively.  $F$  is a 2D IFFT operator.

A common architecture is used for the discriminator, composed of convolutional layers, batch normalization, and leaky-ReLU as suggested in [15]. For the generator, we compose a dedicated architecture based on multi-channel input for representing the real and imaginary components. Both architectures are shown in Figure 3. The training methodology is doing  $k_g$  generator update steps for each discriminator single step.

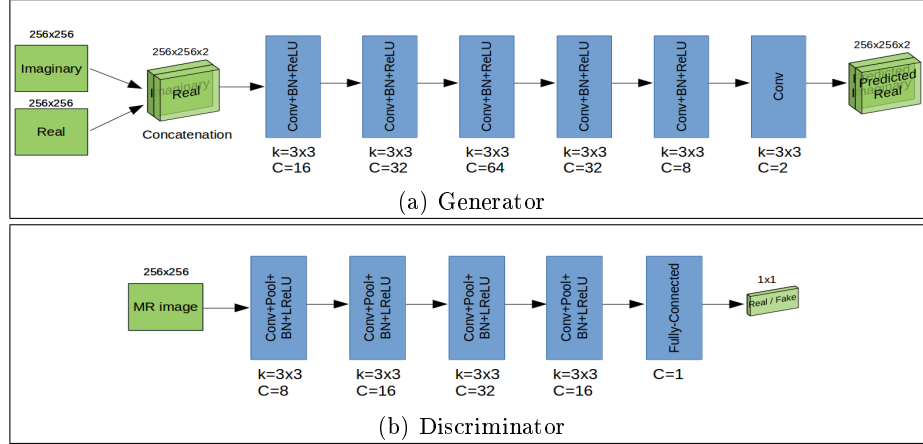


Fig. 3: Networks architecture. The generator input is a two-channel signal, real and imaginary. For each layer,  $k$  is the kernel size and  $C$  is the number of output channels.

### 3 Experimental Results

The training data consists of 55 3D brain MRI (T1) scans of different patients, acquired by 1.5T MR machine with resolution of  $256 \times 256$  pixels. We used  $3k$  2D slices for training and  $1.2k$  for testing. In order to create k-space images for training, inverse orthonormal 2D FFT is applied to the fully-sampled MR images. We sample the k-space images along the phase axis using Cartesian binary mask, while keeping 5% from the centered phases, which is the area that contains 95% of the energy (see Figure 1). Data augmentation is created by random offsets

of the proposed mask and image flipping. This leads us to reconstruction of the MR image from only 52% of the original k-space data.

The generator is composed of 5 blocks of CONV-BatchNorm-ReLU, with output channels 16, 32, 64, 32, 8, respectively. The last layer is CONV with two outputs channels (for real and imaginary parts). The discriminator is composed of 4 blocks of CONV-Pool-BatchNorm-LReLU with output channels 8, 16, 32, 16 and one fully-connected layer. All CONV layers kernel size is  $3 \times 3$ . All weights was initialized by Xavier [5]. We used Adam solver with fixed learning rate of 0.0005 and set  $k_g$  to 20.

We compare the proposed method to reconstruction results obtained by using a conventional compressed sensing method CS-MRI [9] and Zero-filling. In addition, we trained a generator (G) using only L2 loss (CNN-L2). The same sampling mask was used for all cases. Visual comparison is shown in Figure 4. MRIs reconstructed by using the suggested adversarial loss have stronger contrast and no significant aliasing or artifacts. Quantitative evaluation using PSNR values is presented in Table 1. Note that the proposed method outperforms the other methods.

PSNR	Mean	std
Zero-filled	30.48	0.13
CS-MRI	36.78	0.4
CNN-L2	37.12	0.82
<b>Proposed</b>	<b>37.95</b>	0.6

Table 1: Error in PSNR

## 4 Conclusions

We proposed a software-only framework, using GANs for accelerating MRI acquisition. Specifically, high-quality MRI reconstruction using only 52% of the original k-space data is demonstrated. The key idea is based on utilizing an adversarial loss in addition to L2 loss. It is worth mentioning that the proposed sampling mask is currently implemented in commercial MRI machines with no need for additional hardware or dedicated pulse programming. Future work will concentrate on generation of MRI in the presence of pathologies.

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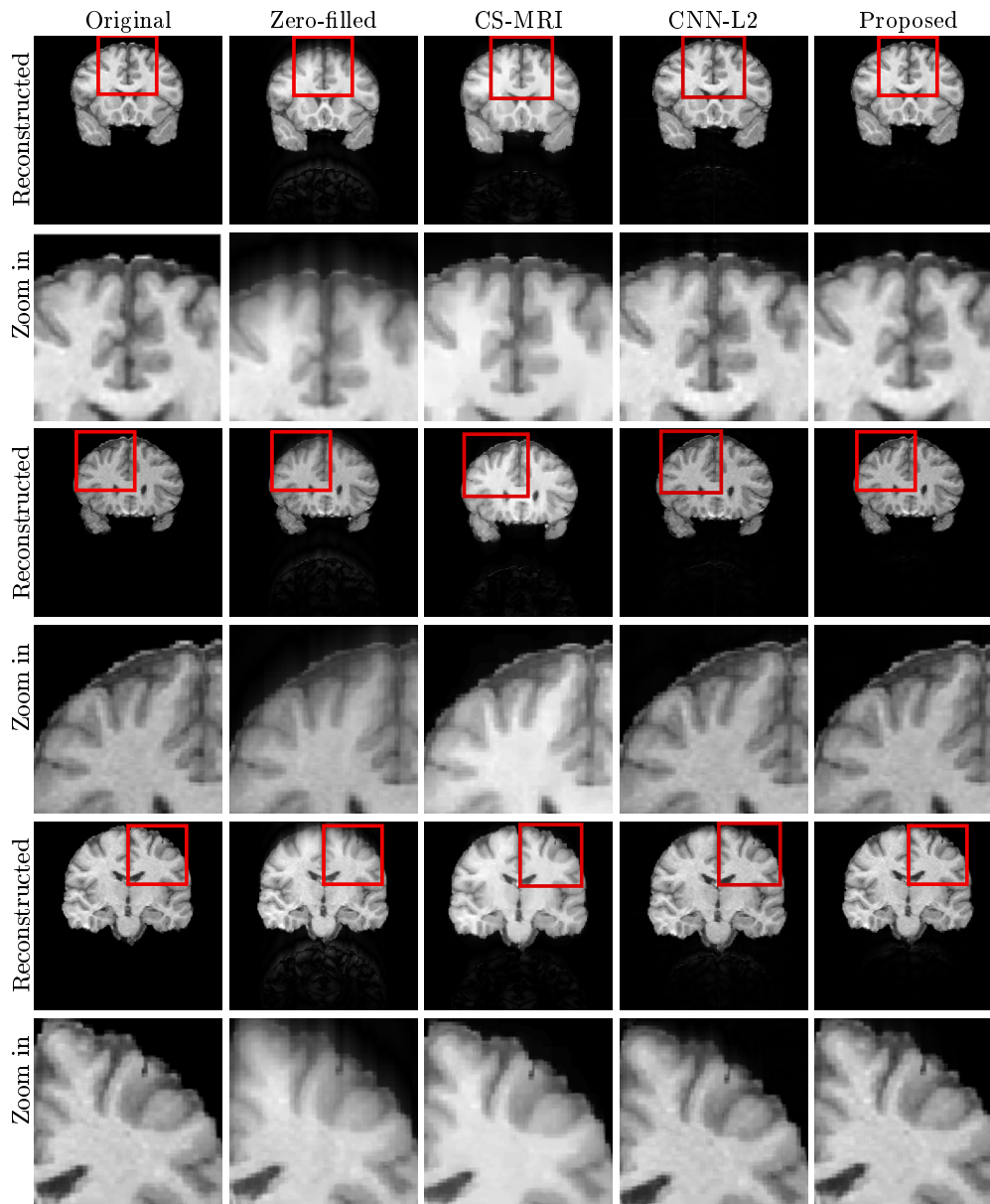


Fig. 4: Examples of reconstructed MR images from under-sampled k-space.