Semi-supervised Super-resolution GANs for MRI reconstruction

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Abstract

➢ Problem and Motivation

- Reconstructing high-resolution MRIs is time and energy consuming
- Take measurement at a low sampling rate (cheap and fast), improve the reconstruction using GANs (fast and high-quality)
- Limited high-quality MRIs available for training the network
- One application: real-time-MRI-guided neurosurgery

➢ Related Work

- Super-Resolution GAN: apply to general images, paired supervision critical to generator performance
- CycleGAN: semi-supervised but no detail accuracy

➢ Contributions

- Novel patching method stabilizes LSGAN training and boosts generator performance
- Remove the need for pixel-wise loss and pairing between inputs and labels
- Semi-supervised using 1/6 of the training set as labels

Dataset

➢ High-quality MRIs for knees

- Training set: 17 patients
- Test set: 3 patients
- 320 images for each patient
- Resize to 160x256 from 320x512 for faster training: Lanczos resampling

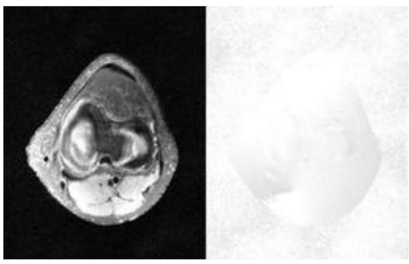
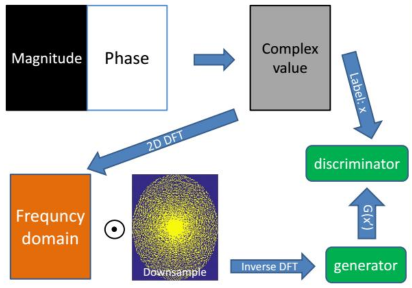


Figure 1: One of the images. Left half is the magnitude and right half is the phase.

Methods



➢ Generator and Discriminator Networks

- Generator: deep residual network; 4 residual blocks followed by 3 convolution layers; 64 3x3 feature maps for each layer. End with a data consistency layer

$$G(\hat{\mathbf{x}}) = \mathcal{F}^{-1}\{mask \odot \mathcal{F}\{\hat{\mathbf{x}}\} + (1 - mask) \odot \mathcal{F}\{\mathbf{x_{-1}}\}\}$$

- Discriminator: 7 convolution layers with batch normalization and no pooling. 4 to 32 and 32 3x3 feature maps

➢ Objective

- Baseline [1]

$$L_D(\theta_d) = \mathbb{E}[(1 - D(\mathbf{x};\theta_d))^2] + \mathbb{E}[(D(G(\tilde{\mathbf{x}};\theta_g);\theta_d))^2]$$

$$L_G(\theta_g) = (1-\lambda)\mathbb{E}[(1 - D(G(\tilde{\mathbf{x}};\theta_g);\theta_d))^2] + \boxed{\lambda\mathbb{E}[\,||\mathbf{x} - G(\tilde{\mathbf{x}};\theta_g)||_1]}\,.$$

- LSGAN [2] with Patching

$$L_D(\theta_d) = \frac{1}{16}\sum_{i=1}^{16}\mathbb{E}[(1 - D(\mathbf{x}_i;\theta_d))^2] + \frac{1}{16}\sum_{i=1}^{16}\mathbb{E}[(D(G(\tilde{\mathbf{x}}_i;\theta_g);\theta_d))^2]$$

$$L_G(\theta_g) = \frac{1}{16}\sum_{i=1}^{16}\mathbb{E}[(1 - D(G(\tilde{\mathbf{x}}_i;\theta_g);\theta_d))^2]$$

- WGAN with Gradient Penalty [3]

$$L_D(\theta_d) = \mathbb{E}[D(G(\tilde{\mathbf{x}};\theta_g);\theta_d)] - \mathbb{E}[D(\mathbf{x};\theta_d)] + \eta\mathbb{E}_{\hat{\mathbf{x}}\sim\mathbf{P}_{\hat{x}}}\left[(||\nabla_{\hat{\mathbf{x}}}D(\hat{\mathbf{x}})||_2 - 1)^2\right]$$

$$L_G(\theta_g) = -\mathbb{E}[D(G(\tilde{\mathbf{x}};\theta_g);\theta_d)]$$

Results

➢ Experiments

On the baseline model:

- Number of mini-batch trained with L1 loss: 0 doesn't work at all, 200 quickly diverges, 3000 diverges slower

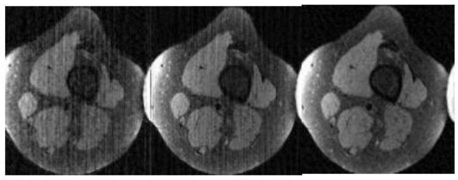


Figure 2. Gene output at test time, trained with all labels. Left to right: baseline with 3000 L1 batches, baseline with 95% L1 loss, LSGAN-Patch

On our models without L1 loss:

- Downsampling ratios: 2, 3, 5
- Decrease number of L1 batches from 2000 to 0, then break pairing
- Number of high-quality images used as labels: 17, 6, 3 patients

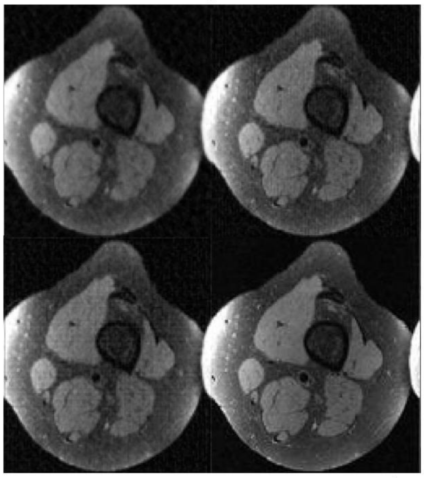


Figure 3. Left to right, top to bottom: input, LSGAN with 1/3 label, WGAN with 1/6 label, ground truth

Model	SNR	SSIM
Baseline w/ 3k L1	14.31	0.58
LSGAN-Patch full label	21.41	0.85
LSGAN-Patch 1/3 label (6 pat.)	19.93	0.81
WGAN full label	21.67	0.86
WGAN 1/6 label (3 pat.)	20.01	0.82

Table 1. Quantitative evaluations

➢ GAN training tricks for LSGAN

- LReLU, SGD and input dropout for disc

➢ Patching variation

- Number of patches
- 4x4 grid vs. random patching

Reference

[1] M. Mardani, E. Gong et al. Deep generative adversarialnetworks for compressed sensing automates MRI.CoRR,abs/ 1706.00051, 2017.
[2] X. Mao, Q. Li, H. Xie, R. Y.K. Lau, Z. Wang, and S. P. Smolley, "Least-squares generative adversarial networks," arXiv:1611.04076v3 [cs.CV], April 2017.
[3] I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, andA. C. Courville. Improved training of wasserstein gans. In Advances in Neural Information Processing Systems, pages5769–5779, 2017.