MR Image Synthesis

# pGAN & cGAN

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## Image Synthesis in Multi-Contrast MRI With Conditional Generative Adversarial Networks

Salman UH. Dar, *Student Member, IEEE*, Mahmut Yurt, Levent Karacan, Aykut Erdem, Erkut Erdem, and Tolga Çukur, *Senior Member, IEEE*

***Abstract*— Acquiring images of the same anatomy with multiple different contrasts increases the diversity of diagnostic information available in an MR exam. Yet, the scan time limitations may prohibit the acquisition of certain contrasts, and some contrasts may be corrupted by noise and artifacts. In such cases, the ability to synthesize unacquired or corrupted contrasts can improve diagnostic utility. For multi-contrast synthesis, the current methods learn a nonlinear intensity transformation between the source and target images, either via nonlinear regression or deterministic neural networks. These methods can, in turn, suffer from the loss of structural details in synthesized images. Here, in this paper, we propose a new approach for multi-contrast MRI synthesis based on conditional generative adversarial networks. The proposed approach preserves intermediate-to-high frequency details via an adversarial loss, and it offers enhanced synthesis performance via pixel-wise and perceptual losses for registered multi-contrast images and a cycle-consistency loss for unregistered images. Information from neighboring cross-sections are utilized to further improve synthesis quality. Demonstrations on $T_1$ - and $T_2$- weighted images from healthy subjects and patients clearly indicate the superior performance of the proposed approach compared to the previous state-of-the-art methods. Our synthesis of the multi-contrast MRI exams without the need for prolonged or repeated examinations.**

***Index Terms*— Generative adversarial network, image synthesis, multi-contrast MRI, pixel-wise loss, cycle-consistency loss.**

### I. Introduction

MAGNETIC resonance imaging (MRI) is pervasively used in clinical applications due to the diversity of contrasts it can capture in soft tissues. Tailored MRI pulse sequences enable the generation of distinct contrasts while imaging the same anatomy. For instance, $T_1$-weighted brain images clearly delineate gray and white matter tissues, whereas $T_2$-weighted images delineate fluid from cortical tissue. In turn, multi-contrast images acquired in the same subject increase the diagnostic information available in clinical and research studies. However, it may not be possible to collect a full array of contrasts given considerations related to the cost of prolonged exams and uncooperative patients, particularly in pediatric and elderly populations [1]. In such cases, acquisition of contrasts with relatively shorter scan times might be preferred. Even then a subset of the acquired

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## Background & Goal

### Background

- Due to scan time limitations, obtaining specific contrasts may be challenging

### Goal

- Conditional GAN models for synthesizing images of distinct contrasts from a single modality
- Using correlated information across neighboring cross sections within a volume

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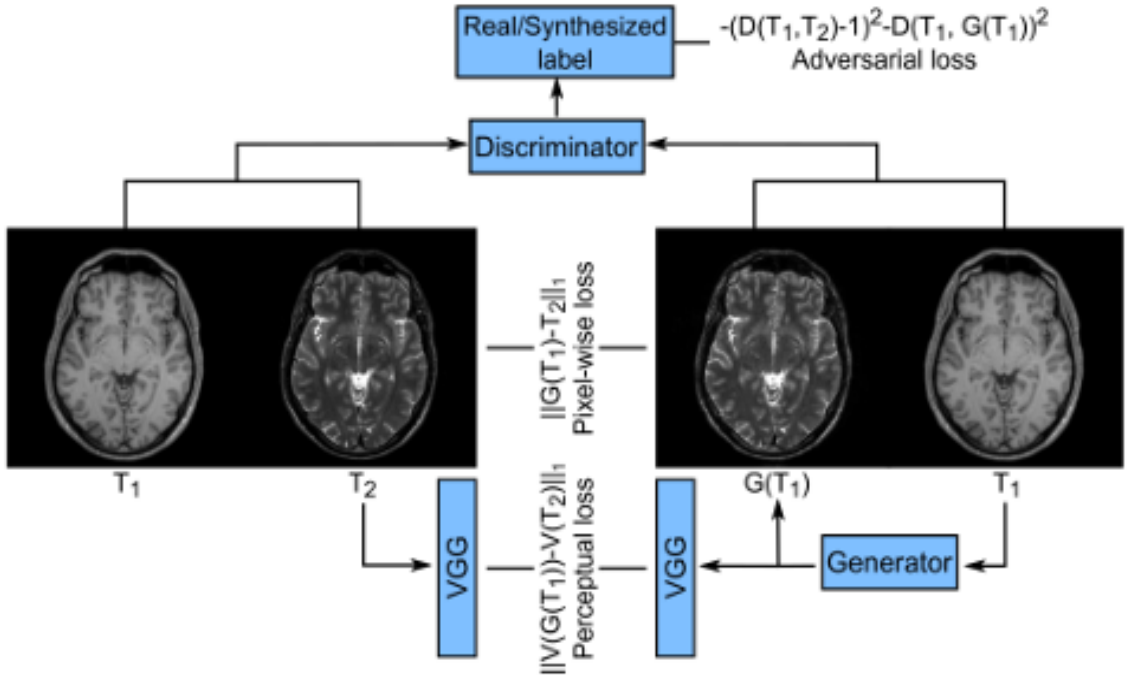
## Network architecture & Loss functions

pGAN




### Adversarial loss

- Conditional GANs can be employed that receive t he source image as an additional input

### pGAN loss

- In a scenario where the source and target images are regi stered, pGAN uses pixel-wise loss & perceptual loss

### Cross section

- leveraged correlated information across neighboring cro ss-sections by conditioning the networks

$$L_{condGAN-k}(D,G) = -E_{\mathbf{x}_k,y}[(D(\mathbf{x}_k,y)-1)^2] - E_{\mathbf{x}_k}[D(\mathbf{x}_k,G(\mathbf{x}_k))^2],$$

$$L_{L1-k}(G) = E_{\mathbf{x}_k,y}[\|y - G(\mathbf{x}_k)\|_1],$$

$$L_{Perc-k}(G) = E_{\mathbf{x}_k,y}[\|V(y) - V(G(\mathbf{x}_k))\|_1],$$

Eq 1. pGAN Loss

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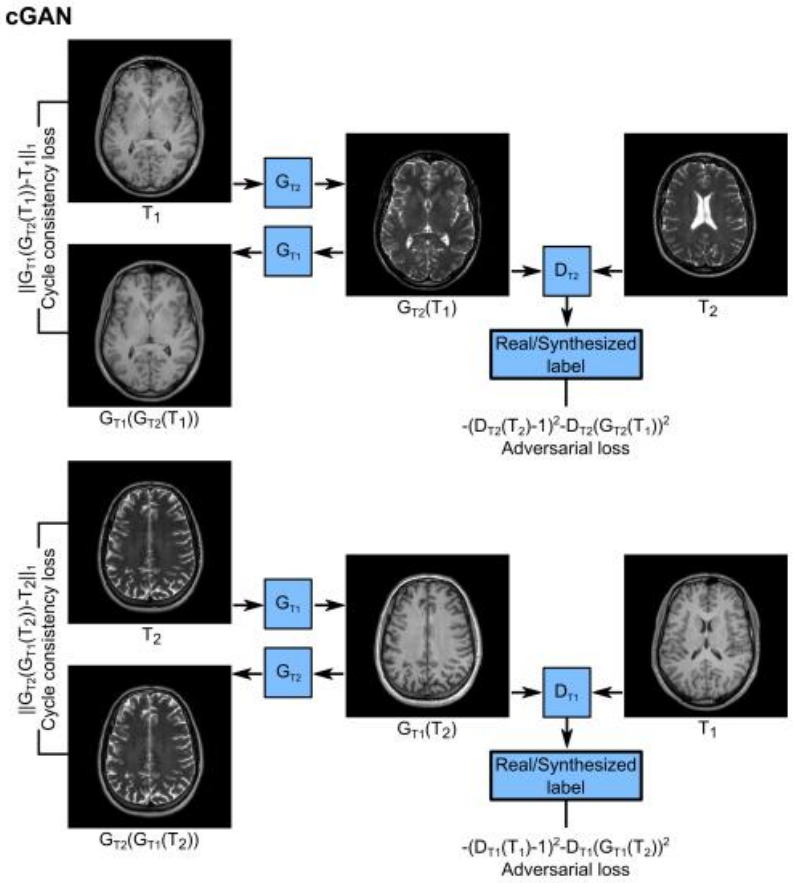
## Network architecture & Loss functions




### Adversarial loss

- Conditional GANs can be employed that receive t he source image as an additional input

### cGAN loss

- In a scenario where the source and target images are unregistered, cGAN uses a cycle consistency loss

$$L_{GAN-k}(D_y, G_y) = -E_{\mathbf{y}_k}[(D_y(\mathbf{y}_k) - 1)^2] \\ -E_{\mathbf{x}_k}[D_y(G_y(\mathbf{x}_k))^2]$$

$$L_{cycle-k}(G_x, G_y) = E_{\mathbf{x}_k}[\|\mathbf{x}_k - G_x(G_y(\mathbf{x}_k))\|_1] \\ +E_{\mathbf{y}_k}[\|\mathbf{y}_k - G_y(G_x(\mathbf{y}_k))\|_1]$$

Eq 2. cGAN Loss

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### Comparison with cross-section

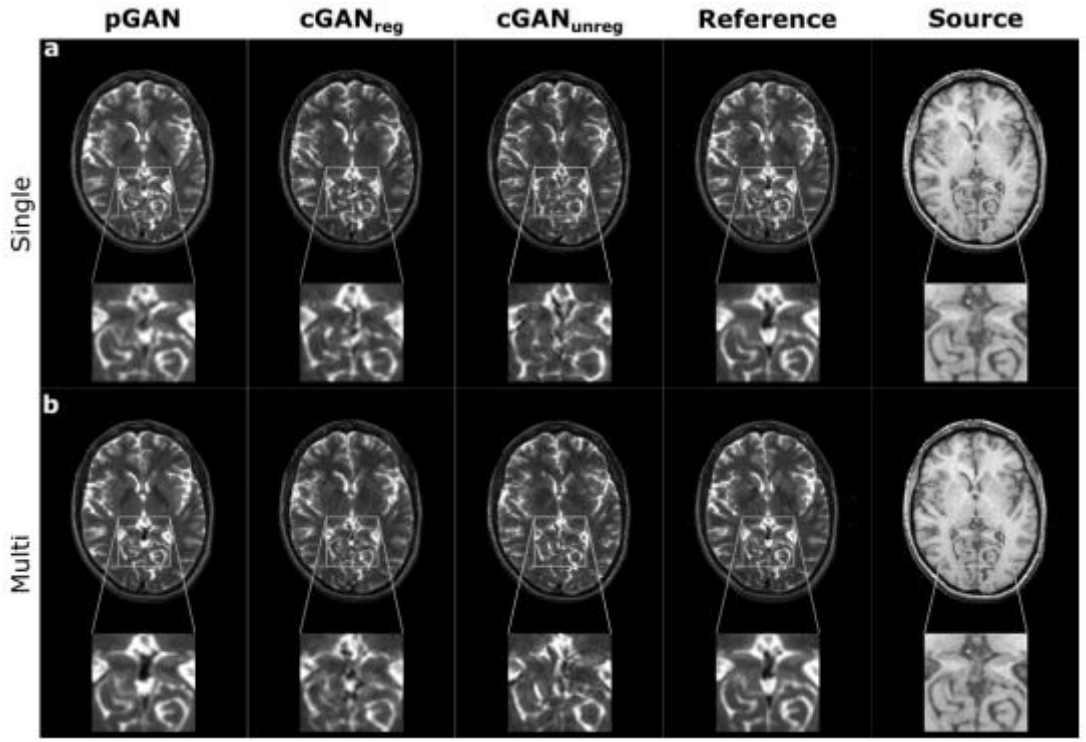


Fig 2. Synthesis results for pGAN/cGAN & Single/Multi cross section models

| | cGAN$_{unreg}$ | | cGAN$_{reg}$ | | pGAN | |
|---|---|---|---|---|---|---|
| | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR |
| $T_1 \rightarrow T_{2\#}$ | 0.829 ±0.017 | 23.66 ±0.632 | 0.895 ±0.014 | 26.56 ±0.432 | **0.920 ±0.014** | **28.79 ±0.580** |
| $T_{1\#} \rightarrow T_2$ | 0.823 ±0.021 | 23.85 ±0.420 | 0.854 ±0.024 | 25.47 ±0.556 | **0.876 ±0.028** | **27.07 ±0.618** |
| $T_2 \rightarrow T_{1\#}$ | 0.826 ±0.015 | 23.20 ±0.503 | 0.892 ±0.017 | 26.53 ±1.169 | **0.912 ±0.017** | **27.81 ±1.424** |
| $T_{2\#} \rightarrow T_1$ | 0.821 ±0.021 | 22.56 ±1.008 | 0.863 ±0.022 | 26.15 ±0.974 | **0.883 ±0.023** | **27.31 ±0.983** |

Table 1. Quality of Synthesis in single cross section models

| | cGAN$_{unreg}$ | | cGAN$_{reg}$ | | pGAN | |
|---|---|---|---|---|---|---|
| | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR |
| $T_1 \rightarrow T_{2\#}$ | 0.829 ±0.016 | 23.65 ±0.650 | 0.895 ±0.014 | 26.62 ±0.489 | **0.926 ±0.014** | **29.34 ±0.592** |
| $T_{1\#} \rightarrow T_2$ | 0.797 ±0.027 | 23.37 ±0.604 | 0.862 ±0.022 | 25.83 ±0.384 | **0.883 ±0.027** | **27.49 ±0.643** |
| $T_2 \rightarrow T_{1\#}$ | 0.824 ±0.015 | 24.00 ±0.628 | 0.900 ±0.017 | 27.04 ±1.238 | **0.920 ±0.016** | **28.16 ±1.303** |
| $T_{2\#} \rightarrow T_1$ | 0.805 ±0.021 | 23.55 ±0.782 | 0.864 ±0.022 | 26.44 ±0.871 | **0.887 ±0.023** | **27.42 ±1.127** |

Table 2. Quality of Synthesis in multi cross section models(k = 3)

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### Comparison with conventional methods

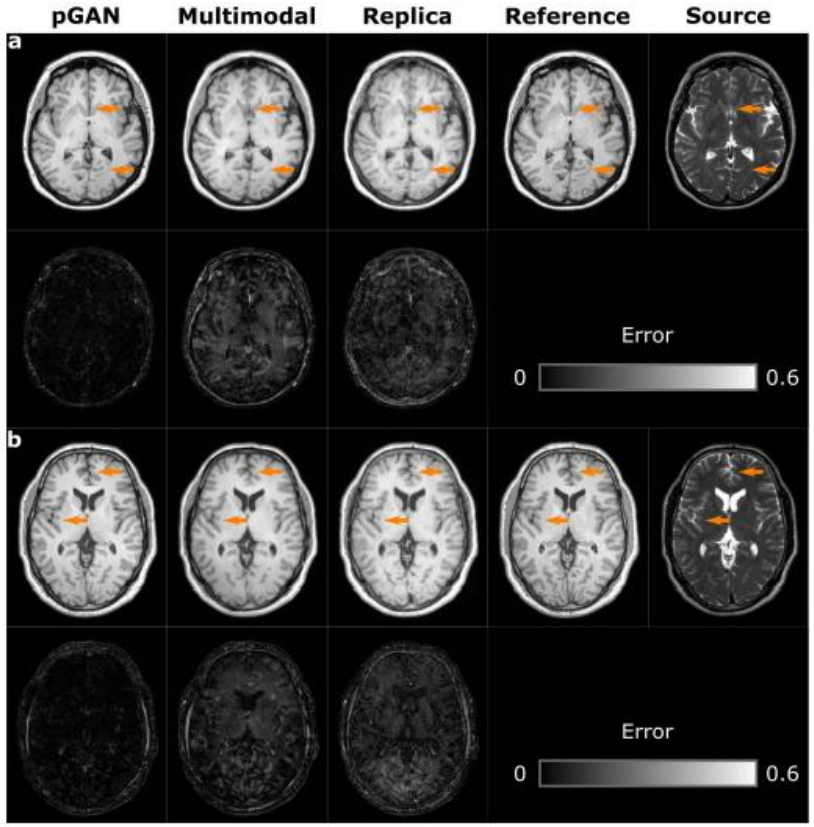


Fig 3. Synthesis results for several models

| | pGAN | | Replica | | Multimodal | |
|---|---|---|---|---|---|---|
| | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR |
| $T_1 \rightarrow T_{2\#}$ | **0.948 ±0.014** | **29.77 ±1.568** | 0.912 ±0.028 | 25.40 ±2.084 | 0.936 ±0.015 | 27.72 ±0.910 |
| $T_{1\#} \rightarrow T_2$ | **0.917 ±0.012** | **27.89 ±0.887** | 0.863 ±0.023 | 24.08 ±1.427 | 0.898 ±0.014 | 26.11 ±0.769 |
| $T_2 \rightarrow T_{1\#}$ | **0.926 ±0.013** | **27.27 ±0.960** | 0.865 ±0.013 | 20.46 ±0.921 | 0.895 ±0.015 | 22.61 ±1.105 |
| $T_{2\#} \rightarrow T_1$ | **0.953 ±0.012** | **29.55 ±1.423** | 0.887 ±0.033 | 21.82 ±1.600 | 0.936 ±0.017 | 25.91 ±1.689 |

Table 3. Quality of synthesis in IXI dataset

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## Comparison with conventional methods

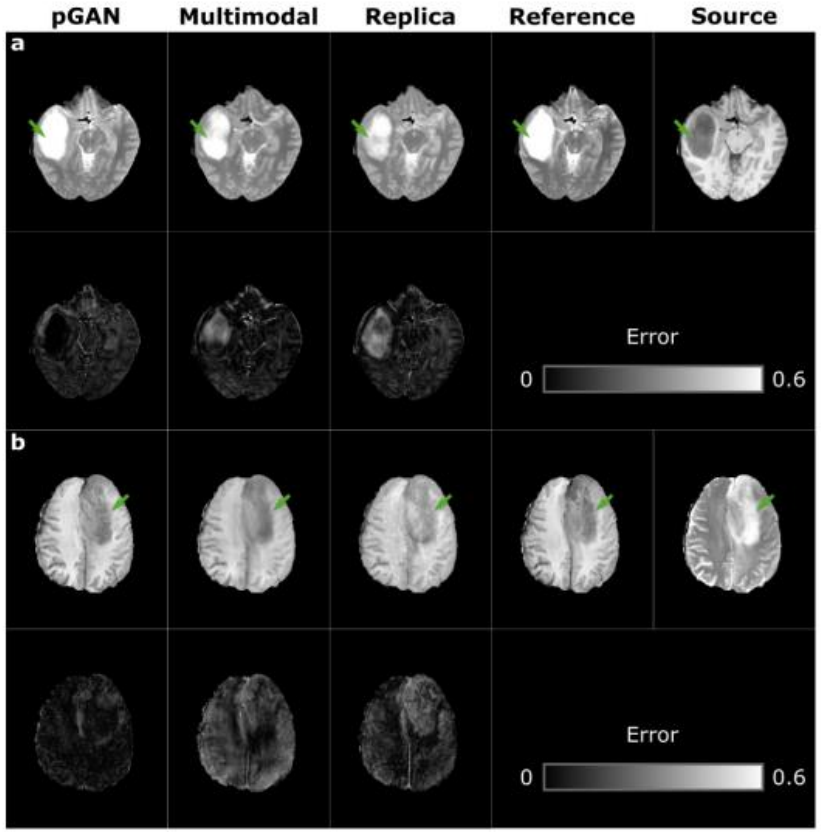


Fig 4. Synthesis results on glioma patients

| | pGAN | | Replica | | Multimodal | |
|---|---|---|---|---|---|---|
| | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR |
| $T_1 \rightarrow T_2$ | **0.946 ±0.009** | **27.19 ±1.456** | 0.924 ±0.014 | 24.64 ±1.615 | 0.939 ±0.011 | 25.09 ±1.013 |
| $T_2 \rightarrow T_1$ | **0.940 ±0.009** | **25.80 ±1.867** | 0.917 ±0.007 | 24.49 ±1.230 | 0.935 ±0.010 | 23.78 ±2.080 |

Table 4. Quality of synthesis in BraTS

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## Implications & Limitations

### Implications

- Proposed a new multi-contrast MRI synthesis method based on conditional GANs
- Leverages information across neighboring cross-sections within each volume to increase accuracy of synthesis
- Proposed method outperformed state-of-the-art synthesis methods
- Holding great promise for improving the diagnostic information available in clinical multi-contrast MRI

### Limitations

- Optimization required according to alignment direction between source and target images
- Future work to assess the optimal weighting of perceptual loss as a function of noise level for specific contrasts

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