MM-GAN: Multi-Modal Generative Adversarial Network for Missing MRI Pulse Sequence Synthesis

Anmol Sharma and Ghassan Hamarneh
School of Computing Science, Simon Fraser University, Burnaby, BC Canada

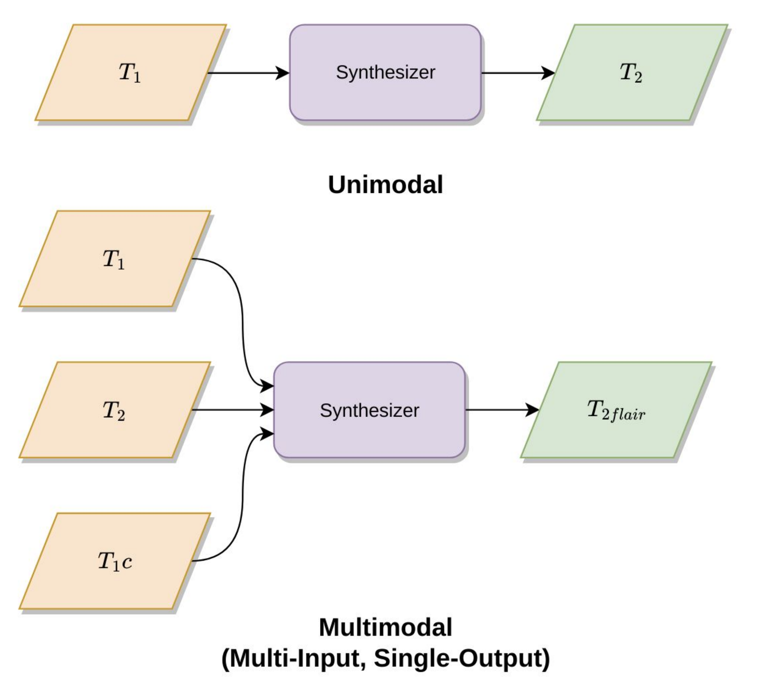
SFU

PROBLEM STATEMENT

- Magnetic resonance imaging (MRI) provides access to multiple pulse sequences, some of the commonly acquired sequences are T1, T2, T1c, and T2Flair.
- In clinical settings, however, it is common to have MRI scans acquired using varying protocols, or varying sets of sequences, which may lead to some of the common sequences missing for some patients.
- **MR Sequences** which are routinely acquired **may be unusable or missing** altogether due to scan corruption, imaging artifacts, incorrect machine settings, allergies to certain contrast agents and limited available scan time.
- This may adversely affect physician workflow, as well as any analysis pipelines that depend upon some particular sequence(s) that may have gone missing.
- **Can we synthesize the missing sequence(s) using the ones that are available?**

PREVIOUS WORK

- Single-Input, Single-Output pGAN[1].
- Multi-Input, Single-Output REPLICA[2], MM-Synthesis[3]



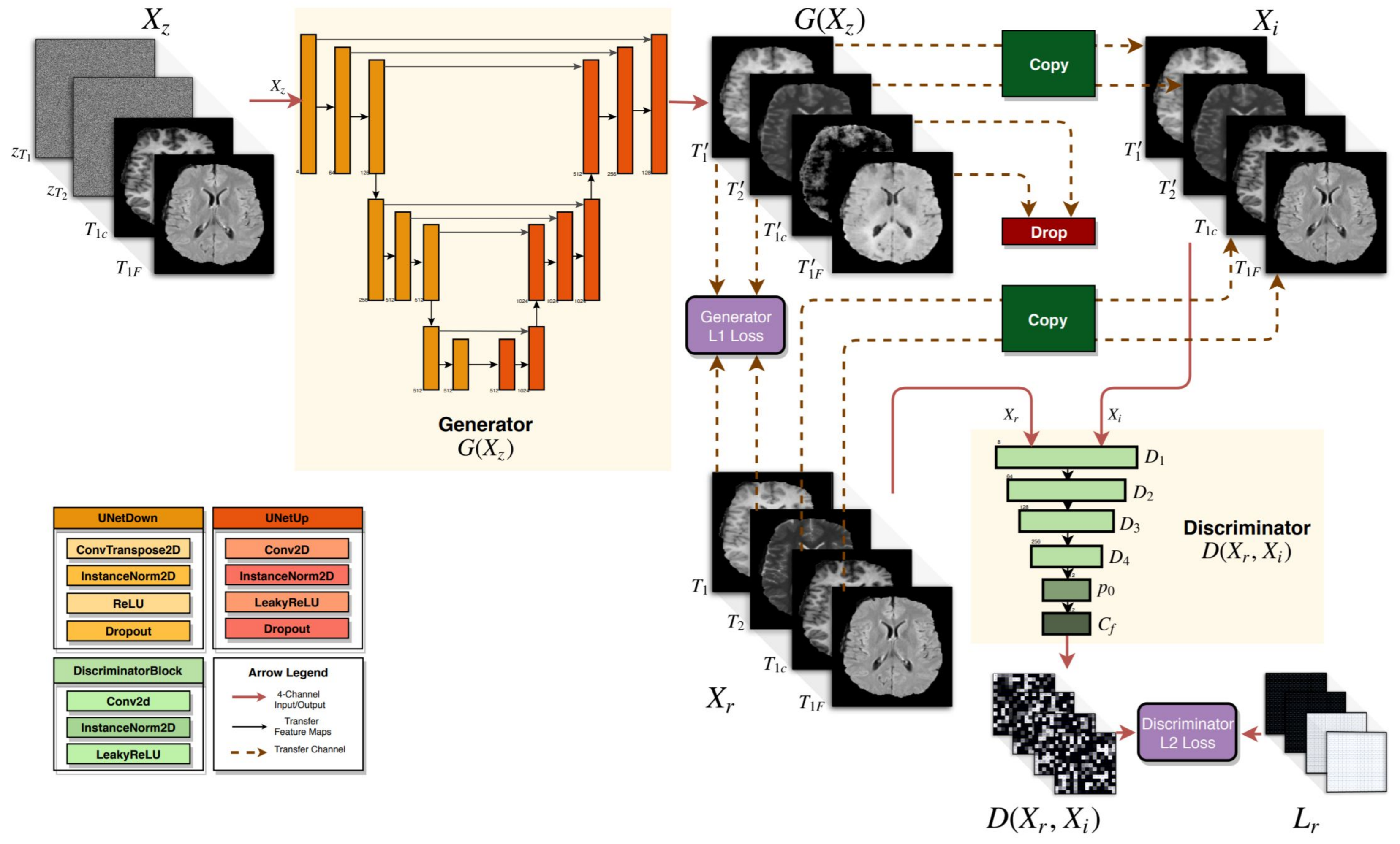
DRAWBACKS OF PREVIOUS WORK

- Unimodal (Single-Input, Single-Output)
  - For a typical use case scenario (4 sequences), we would need 12 single-input, single-output networks for all combinations of sequences.
  - Does not take into account information from multiple sequences.
- Multimodal (Multi-Input, Single-Output)
  - Multi-input networks take into account multiple information sources, although for a typical scenario would still need 4 synthesizers individually trained.

PROPOSED METHOD

We propose the first multi-input, multi-output generative adversarial network (MM-GAN) MR pulse sequence synthesizer capable of synthesizing missing pulse sequences using any combination of available sequences as input, using only a single model, in a single forward pass.

Our method is based upon a deep learning technique called generative adversarial network (GAN). A GAN is a combination of models, which act as adversary to each other. The first model ``generator" synthesizes samples with as much accuracy as possible to fool its adversary ``discriminator". The ``discriminator" tries to discern between real samples and the ones generated by its adversary ``generator".



RESULTS

- The first variant called MI-GAN outperformed the unimodal version pGAN in all three metrics.
- We show that MM-GAN outperforms the best multimodal synthesis method REPLICA[1], as well as MM-Synthesis[2] in multi-input single-input synthesis produces objectively sharper
- We set up new benchmarks using BraTS2018 dataset, in terms of PSNR, MSE and SSIM.

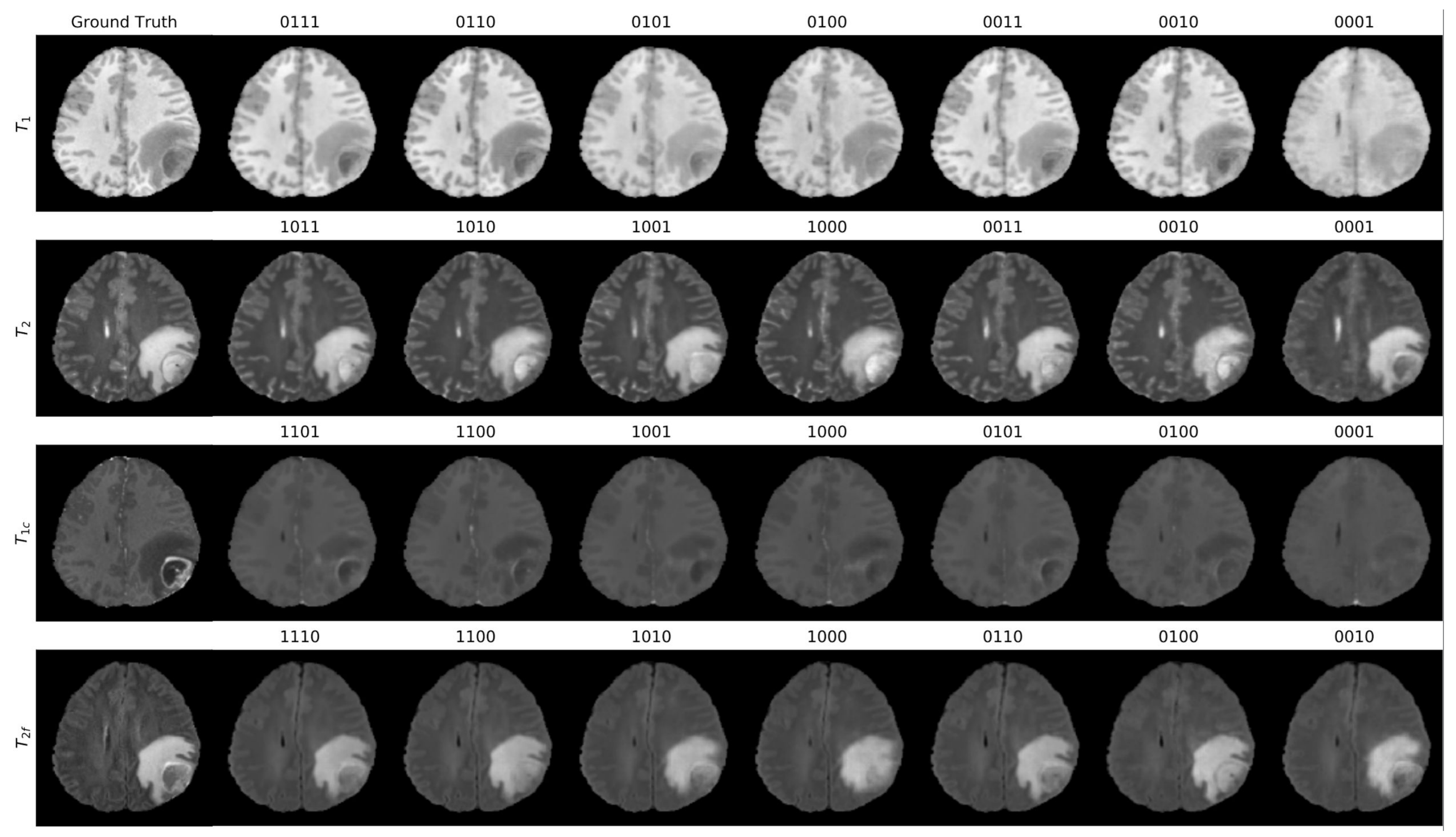


TABLE I
COMPARISON BETWEEN pGAN AND MI-GAN. VALUES IN BOLDFACE REPRESENT WINNING PERFORMANCE VALUES.

Model	MSE	PSNR	SSIM
pGAN$_{T_1}$	0.1191	24.1158	0.8895
MI-GAN$_{T_1}$	**0.0702**	**26.5179**	**0.9162**
pGAN$_{T_2}$	0.2043	24.5725	0.8895
MI-GAN$_{T_2}$	**0.1814**	**25.9927**	**0.9194**

TABLE II
COMPARISON WITH UNIMODAL METHOD REPLICA AND MULTIMODAL METHOD MM-SYNTHESIS. THE REPORTED VALUES ARE MEAN SQUARED ERROR (MSE). BOLDFACE VALUES REPRESENT LOWEST VALUES OF THE THREE METHODS FOR A PARTICULAR SCENARIO.

Scenarios T_1	T_2	DW	REPLICA	MM-Synthesis	MM-GAN (Proposed)
-	-	✓	0.278 (0.09)	0.285 (0.13)	**0.2109 (0.0575)**
-	✓	-	0.374 (0.16)	0.321 (0.12)	**0.2799 (0.0550)**
-	✓	✓	0.235 (0.08)	0.214 (0.09)	**0.1826 (0.0332)**
✓	-	-	0.301 (0.11)	**0.249 (0.09)**	0.2813 (0.0711)
✓	-	✓	0.225 (0.08)	0.198 (0.02)	**0.1918 (0.0392)**
✓	✓	-	0.271 (0.12)	**0.214 (0.08)**	0.2541 (0.0661)
✓	✓	✓	0.210 (0.08)	**0.171 (0.06)**	0.1828 (0.0412)
Mean			0.271 (0.10)	0.236 (0.08)	**0.2262 (0.0468)**

REFERENCES

1. S. Ul et al., "Image Synthesis in Multi-Contrast MRI with Conditional Generative Adversarial Networks" IEEE Transactions on Medical Imaging, pp. 1--1, 2019.
2. A. Jog et al., "Random forest regression for magnetic resonance image synthesis" Medical Image Analysis, vol.35, pp. 475--488, Jan 2017.
3. A. Chartsias et al. "Multimodal MR Synthesis via Modality-Invariant Latent Representation," IEEE Transactions on Medical Imaging, vol. 37, no. 3, pp. 803--814, Mar 2018.