CHANGING THE CONTRAST OF MRI SIGNALS USING DEEP LEARNING

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An unsupervised GAN is trained to classify and generate MRI signal from five spin-echo contrasts. The novel architecture implements the signal equation into the output of the generator, so what the model *actually* learns is to deconstruct the input signal into the quantitative maps which are unknown during training. This allows the model to retrospectively transfer signal to *any* desired contrast.

INTRODUCTION

The optimal contrast of MRI data often depends on the subsequent tasks, therefore it might not be known at the time of signal acquisition. There is a desire for the reliable, retrospective transfer between contrasts, however current methods are limited for the supported input contrasts or the contrasts they transfer to. This also severely limits the usefulness of such methods.

METHOD

A Categorical GAN [1] is used where the discriminator and generator compete to correctly classify signal by the five contrasts included in the training data, and to create synthetic signal that resembles the target contrast.

The novelty of the method comes from implementing the signal equation on the three unknown output layers of the generator by using the Echo and Repetition time of the target contrast. This uniquely defines the three layers as the quantitative maps for proton density (PD), T1- and T2-relaxation times (T1 and T2 respectively). With the quantitative maps, any contrast can be reconstructed retrospectively.

Transferring between contrasts and obtaining quantitative information is achieved through a training process that does not require paired contrasts or quantitative data.

CONCLUSIONS

Trained in an unsupervised fashion, the method retrospectively reconstructs any MRI contrast.

No multi-contrast scans are required for the training process, therefore the experiments are easy to reproduce with any number of training contrasts and anatomies.

The trained model together with a tool for visualizing the results is available online, follow the QR code:

EVALUATIONS

CONTRAST TRANSFER

The model was evaluated for each of the five available input contrasts transferred to each available target contrast. The model improved all four metrics (MSE, NRMSE, SSIM, PSNR) over a simple baseline error, except for reconstructing the input contrast (where the baseline is zero).

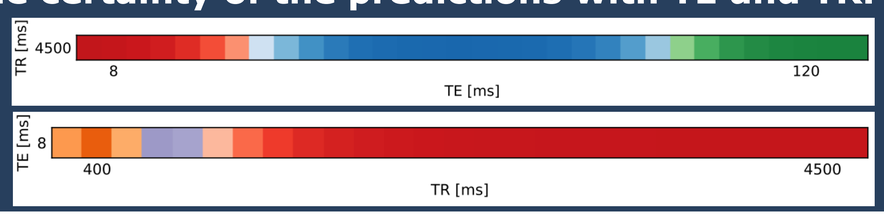
QUANTITATIVE MAPS

For better insight, we evaluate the quantitative maps extracted from the model prior to the implemented signal equation. The mean values for four manually selected tissues compared to a least-squares method (LSQ) and common values in literature [2] are similar for PD and T1, however the T2 values are generally smaller. The errors in T2 are not reflected in the errors of the reconstructed contrasts. Including a wider range of contrasts in the training dataset is expected to improve the results for T2.

	PD		$T1$ [s]		$T2$ [s]	
	LSQ	Model	LSQ	Model	LSQ	Model
Fat	0.60 ± 0.09	0.58 ± 0.09	0.38 ± 0.07	0.43 ± 0.07	0.21 ± 0.05	0.06 ± 0.01
Muscle	0.31 ± 0.08	0.30 ± 0.06	0.76 ± 0.19	0.72 ± 0.17	0.07 ± 0.03	0.04 ± 0.01
Bladder	0.54 ± 0.16	0.38 ± 0.13	3.07 ± 0.90	1.97 ± 0.78	2.71 ± 1.89	0.12 ± 0.04
Prostate	0.43 ± 0.04	0.37 ± 0.08	1.20 ± 0.16	1.34 ± 0.52	0.11 ± 0.02	0.06 ± 0.03

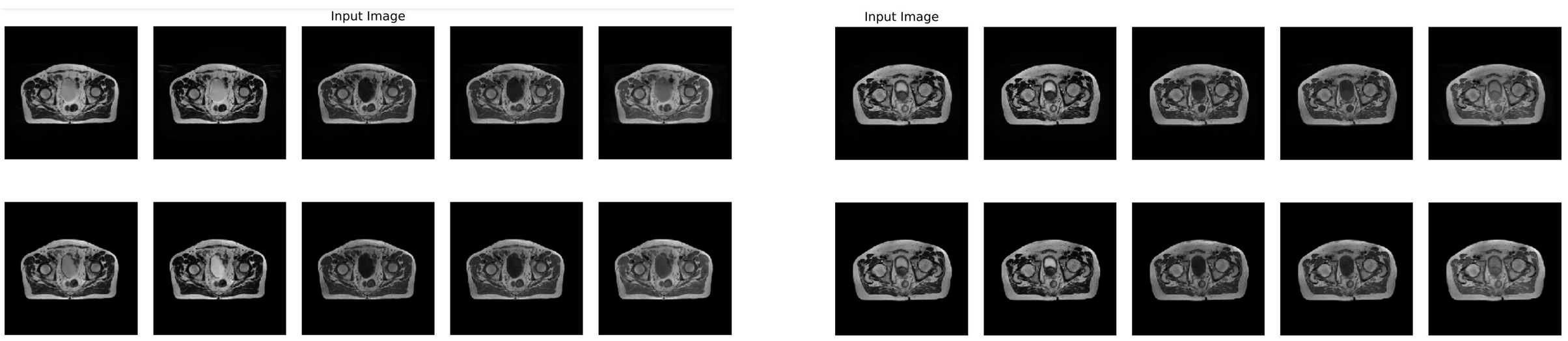
DECISION BOUNDARIES

The discriminator was trained only on five contrasts, however its classification of synthetic contrasts from a range of TE and TR shows a smooth transition. This affirms the correlation of the certainty of the predictions with TE and TR.



EXAMPLES

Two examples (left and right) showing the ground truth (top row) and the corresponding predictions (bottom row) using 'Input Image'.



REFERENCES

[1] Tim Salimans, et al. Improved techniques for training GANs. Proceedings of the 30th International Conference on Neural Information Processing Systems, 2016.

[2] Jorge Zavala Bojorquez et al. What are normal relaxation times of tissues at 3 T?, Magnetic Resonance Imaging. 2017 Jan.

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