Acquisition Parameter Conditioned Magnetic Resonance Image-to-Image Translation

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Abstract. A Magnetic Resonance Imaging (MRI) exam typically consists of several sequences that yield different image contrasts. Each sequence is parameterized through a multitude of acquisition parameters that influence image contrast, signal-to-noise ratio, scan time and/or resolution. Depending on the clinical indication, different contrasts are required by the radiologist to make a diagnosis. As the acquisition of MR sequences is time consuming, and acquired images may be corrupted due to motion, a method to synthesize MR images with fine-tuned contrast settings is required. We therefore trained an image-to-image generative adversarial network conditioned on the MR acquisition parameters repetition and echo time. Our approach is able to synthesize missing MR images with adjustable MR image contrast and yields a mean absolute error of 0.05, a peak signal-to-noise ratio of 23.23 dB and structural similarity of 0.78.

1 Introduction

Magnetic Resonance Imaging (MRI) is an important but complex imaging modality in radiology. An MRI exam typically consists of several MR image acquisition steps to obtain a set of MR sequences that yield different image contrasts. The sequence configurations are parameterized through a multitude of acquisition parameters that influence image contrast, signal-to-noise ratio, scan time and/or resolution. Depending on the clinical indication, different contrasts are required by the radiologist to make a reliable diagnosis. Besides the given clinical indication and imaged body part, the parameterization of an MR sequence depends on various factors, such as available hardware (1.5T vs. 3T), clinical guidelines, scan time constraints, and radiologists' preferences. This leads to large variations in MR sequence configurations across radiology sites, but also within a single site.

An MRI scan is time consuming, prone to premature scan termination due to claustrophia of the patient [1] or re-scanning due to motion artefacts [2]. Therefore, methods to shorten scan time or synthesize missing contrasts can add significant value to MRI.

One possible approach to achieve this is to use artificial intelligence (AI) to synthesize missing contrasts from existing ones. Different approaches for medical image synthesis using generative adversarial networks [3] have already been proposed [4,5,6,7,8]. However, these approaches are only trained on different categories of MR contrasts (e.g. T1-, T2- or PD-weighted) and cannot synthesize MR images with fine-tuned image contrast. Acquisition parameters influencing the image contrast are e.g. the repetition time (TR) and echo time (TE).

In order to address the variability of sequence parameterizations, we trained an MR image-to-image GAN conditioned on the acquisition parameters TR and TE to enable fine-tuned contrast synthesis for a given MR image.

2 Materials and methods

Our model consists of three networks (see Fig. 1): a generator that translates an MR image to a target image contrast, defined by the acquisition parameters TR and TE, a discriminator that learns to distinguish between synthetic and real MR images as well as an auxiliary classifier that is trained to determine the acquisition parameters TR and TE from the image itself.

The generator is based on a U-Net architecture [9] with residual blocks [10]. The acquisition parameters of the source and target contrast are normalized to values between 0 and 1 and injected into the generator through an adaptive instance normalization layer (AdaIN) [11]. The discriminator learns to distin-

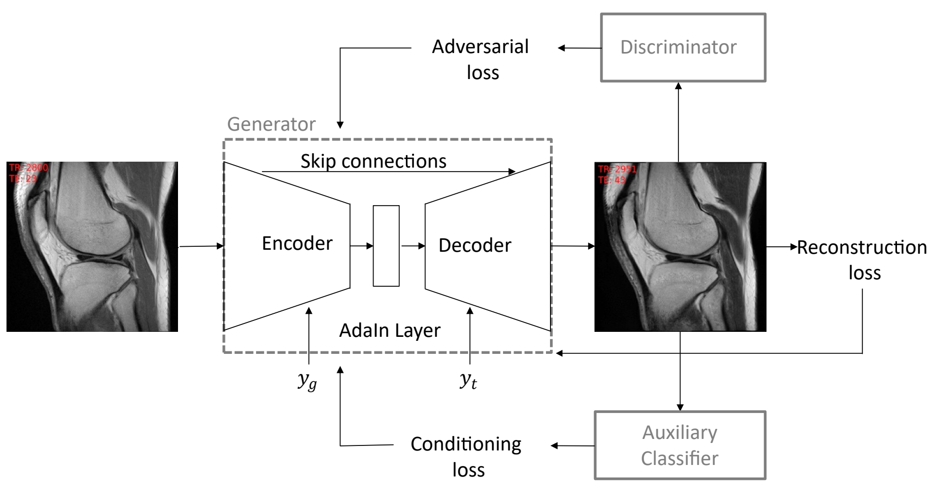

Fig. 1. Training procedure of our approach: The generator receives a real input image (left image), including its acquisition parameters TR and TE (y_g) as well as the target acquisition parameters (y_t) and translates the image to the synthesized target contrast (right image). The discriminator learns to distinguish between real and synthetic MR images, and the auxiliary classifier is pre-trained to determine the acquisition parameters from the image.

guish between real and synthetic MR images only, while the auxiliary classifier is pre-trained to determine the acquisition parameters from the image.

We use a non-saturating adversarial loss with R1 regularization [12], combined with a reconstruction and conditioning loss to train the GAN. The reconstruction loss is given by the L1-loss of the predicted and target image, if a target image is available, and by the cycle consistency loss [13], if no target image is available. The mean squared error between predicted and target acquisition parameters is used as conditioning loss.

For training and validation, we used the clinical part of the fastMRI dataset [14] containing knee MR images from different MR scanners with different sequence parameterizations. We used the DICOM images from the image series without fat saturation from 1.5 T Siemens scanners (Siemens Healthcare, Erlangen, Germany). After applying several data filters, this results in a dataset of 67,956 MR images (2,114 paired and 65,842 unpaired images) of which 60 unique DICOM studies (1,022 images) are used for testing and the rest for training (66,934 images).

Fig. 2. Example of two paired MR images with different acquisition parameters including their synthesized images. The first column shows the real image g with acquisition parameters y_g (top) and the real target image pair t with acquisition parameters y_t (bottom). The second column shows the result and the absolute error map, when synthesizing image g with the generator G, and the third column shows the result of the image synthesis of image t. The image annotations show the real (first column) and predicted TR and TE values.

3 Results

The auxiliary classifier reached a mean absolute error of 247 ms for the determination of TR and 1.8 ms for TE on the test set, respectively. Thus, it is able to reliably guide the training of the generator to produce MR images with the correct image contrast.

Besides visual assessment (see Fig. 2 and 3), we computed the mean absolute error (MAE), peak signal-to-noise ratio (PSNR), and the structural similarity (SSIM) index [15] to measure both pixel-wise intensity differences and structural similarities between reconstructed and reference images.

The performance metrics were computed on the test set with cyclic reconstruction and randomly selected acquisition parameters, since slice pairs were not available for all test images. Our approach reached the following MAE, PSNR and SSIM values:

- MAE: 0.05
- PSNR: 23.23 dB
- SSIM: 0.78

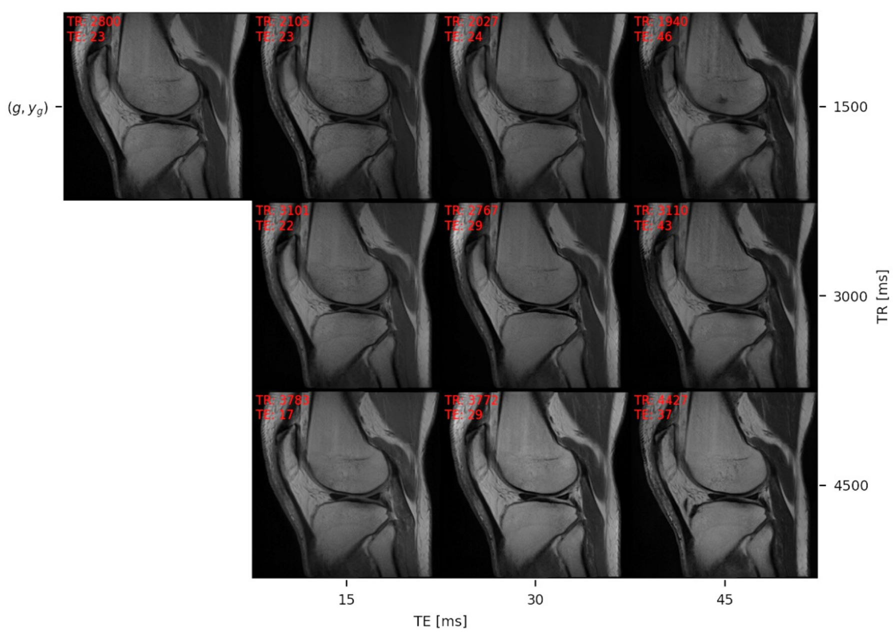

Fig. 3. Example of acquisition parameter interpolation for a given real image g with acquisition parameters y_g (first column). The image grid shows the synthesized images with varying acquisition parameters in the TE intervals [15, 30, 45] ms and TR intervals [1500, 3000, 4500] ms including their predicted TR and TE values.

4 Discussion

The generator is able to produce realistic and sharp MR images that also show fine anatomical structures within the image. Although several approaches have already been published that apply image-to-image GANs to synthesize MR image contrasts, these results are difficult to compare due to the fact that our presented approach is the first to condition the contrast translation of MR images on acquisition parameters and not only on different categories of contrasts. Moreover, a different dataset (including body regions trained on) was used in our work, since the recently published fastMRI dataset offers the required image contrast variations. However, the reported performance metrics are comparable to reference literature [4,5,6,7], demonstrating the potential of our presented approach.

One limitation of the dataset is that it only contains different parameterizations of PD-weighted MR images. Consequently, the network is not able to translate an existing image into a T1- or T2-weighted MR image as it has not been trained on such. However, it is anticipated that the approach is transferable to a wider range of acquisition parameters given a proper dataset. A limitation of the cycle consistency loss is that it may hallucinate features in the generated images [16]. Consequently, a reader study must evaluate the diagnostic value of the synthesized MR images.

This work has the potential to synthesize missing or replace corrupted contrasts and therefore is anticipated to reduce the duration of an MRI exam.

In future work, we aim at extending the capabilities of the network on additional acquisition parameters (e.g. scan options such as fat-saturation) and evaluate the work on data with additional body regions.

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References

1. Munn Z, Moola S, Lisy K, et al. Claustrophobia in magnetic resonance imaging: A systematic review and meta-analysis. Radiography. 2015 May;21(2):e59–e63.
2. Andre JB, Bresnahan BW, Mossa-Basha M, et al. Toward quantifying the prevalence, severity, and cost associated with patient motion during clinical MR examinations. J Am Coll Radiol. 2015 Jul;12(7):689–695.
3. Goodfellow I, Pouget-Abadie J, Mirza M, et al. Generative adversarial nets. In: Adv Neural Inf Process Syst; 2014. p. 2672–2680.
4. Yu B, Zhou L, Wang L, et al. Ea-GANs: Edge-aware generative adversarial networks for cross-modality MR image synthesis. IEEE Trans Med Imaging. 2019 Jul;38(7):1750–1762.

5. Sharma A, Hamarneh G. Missing MRI Pulse Sequence Synthesis Using Multi-Modal Generative Adversarial Network. IEEE Trans Med Imaging. 2020 Apr;39(4):1170–1183.
6. Zhou T, Fu H, Chen G, et al. Hi-Net: Hybrid-Fusion Network for Multi-Modal MR Image Synthesis. IEEE Trans Med Imaging. 2020 Sep;39(9):2772–2781.
7. Wang G, Gong E, Banerjee S, et al. Synthesize High-Quality Multi-Contrast Magnetic Resonance Imaging From Multi-Echo Acquisition Using Multi-Task Deep Generative Model. IEEE Trans Med Imaging. 2020 Oct;39(10):3089–3099.
8. Stimpel B, Syben C, Würfl T, et al. Projection-to-projection translation for hybrid X-ray and Magnetic Resonance Imaging. Sci Rep. 2019 Dec;9(1).
9. Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. In: Med Image Comput Comput Assist Interv. Springer; 2015. p. 234–241.
10. He K, Zhang X, Ren S, et al. Deep residual learning for image recognition. In: Proc IEEE Comput Soc Conf Comput Vis Pattern Recognit; 2016. p. 770–778.
11. Huang X, Belongie S. Arbitrary style transfer in real-time with adaptive instance normalization. In: Proc IEEE Int Conf Comput Vis. IEEE; 2017. p. 1501–1510.
12. Lucic M, Kurach K, Michalski M, et al. Are GANs created equal? A large-scale study. In: Adv Neural Inf Process Syst. NIPS'18. Red Hook, NY, USA: Curran Associates Inc; 2018. p. 698–707.
13. Zhu JY, Park T, Isola P, et al. Unpaired image-to-image translation using cycle-consistent adversarial networks. In: Proc IEEE Int Conf Comput Vis; 2017. p. 2223–2232.
14. Zbontar J, Knoll F, Sriram A, et al. fastMRI: An open dataset and benchmarks for accelerated MRI. arXiv preprint arXiv:181108839. 2018;.
15. Wang Z, Bovik AC, Sheikh HR, et al. Image quality assessment: From error visibility to structural similarity. IEEE Trans Image Process. 2004 Apr;13(4):600–612.
16. Cohen JP, Luck M, Honari S. Distribution matching losses can hallucinate features in medical image translation. In: Frangi AF, Schnabel JA, Davatzikos C, et al., editors. Med Image Comput Comput Assist Interv. Springer; 2015. p. 234–241.