Field Strength Agnostic Cardiac MR Image Segmentation

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Abstract

To train a field strength agnostic cardiac segmentation network, we propose two novel augmentation techniques that allow us to transform 3T images to synthetic 7T images: by i) simulating B_1 distribution to approximate the 7T bias field and ii) style transfer using an unpaired 3T-to-7T GAN model. Data augmentation with these two methods improved the average Dice score over all classes by 22% and 25% respectively, on our 7T test dataset. Furthermore, the average performance on a 1.5T and 3T dataset were maintained.

Keywords: 7T Cardiac MRI, segmentation, synthesis, style transfer, bias field simulation.

1. Introduction

Automatic cardiac segmentation of 7T images is a challenging task. Conventional intensity based methods suffer from performance degradation due to the increased inhomogeneity. Learning based methods are faced with a shortage of publicly available data. To our knowledge, the paper by (Ankenbrand et al., 2021) is thus far the only work that uses transfer learning for cardiac segmentation at 7T. In this work we aim to train a 7T segmentation network without using any annotated 7T images, while ensuring no significant performance drop on 1.5T and 3T data; i.e. field strength agnostic segmentation. To this end we develop two novel augmentation techniques to imitate 7T images based on labeled 3T images. The first technique is based on a simulated bias field at 7T, while the second utilizes an unpaired image-to-image translation network based on the contrastive GAN to generate synthetic 7T images. We train two segmentation networks with each augmentation technique using the nnUNet framework (Isensee et al., 2018) and evaluate their performance on manually segmented short axis 7T images of 16 volunteers, acquired using a 7T Philips Achieva multi-transmit system (Philips Healthcare, Best, The Netherlands). Each volunteer signed an informed consent prior to inclusion in the study.

2. Methods

Bias field data generation: To approximate the bias field of a 7T image, we use simulated B_1 distributions of the coil array setup (eight-channel dipole array(Steensma et al., 2018)). The 3D B_1 field distribution of each array element has been simulated for 15 unique custom-built human models using Sim4Life (ZMT, Zurich MedTech AG, Zurich, Switzerland) (Steensma et al., 2021). Alignment to SA cardiac images is done by slicing and registering the data with Elastix(Klein et al., 2010)(Shamonin et al., 2014). Subsequently, the synthetic 7T image is obtained by multiplying the registered B1 distributions with a 3T image;$X_{7T} = X_{3T} \cdot B_1^- \cdot B_1^+$. Assuming low tip angle approximation

Synthetic data generation: For the task of 3T-to-7T style transfer we use a GAN model based on contrastive learning, known as CUT (Park et al., 2020), to transfer the appearance (style) of 7T images on the anatomical information (content) of the 3T images as shown in

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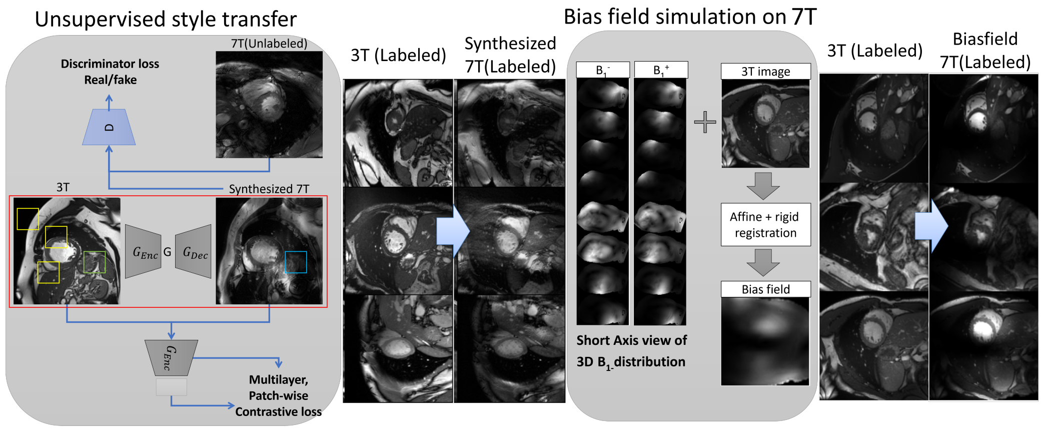

Figure 1: Data creation using GAN-based style transfer and bias field simulation.

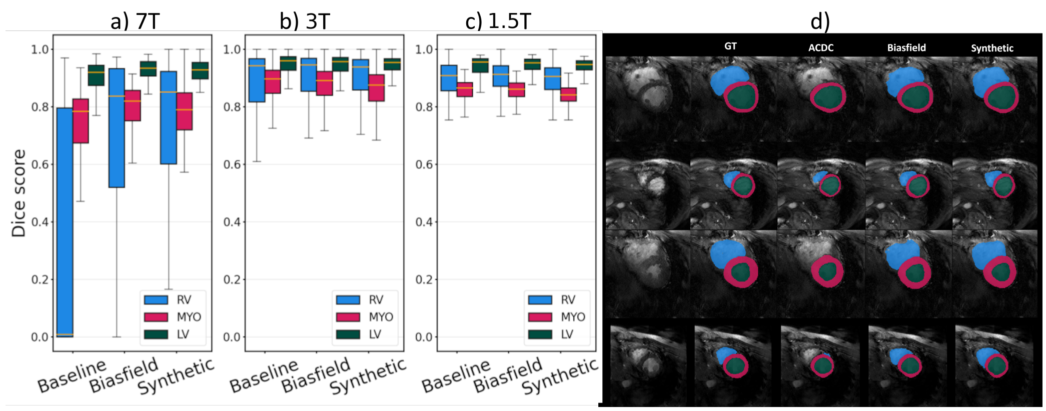

Figure 2: Dice performance on a) 7T , b) 3T (ACDC), c) 1.5T (M&Ms) dataset and d) visual comparison.

Figure 1. The content is preserved through a multi-layer patch-wise contrastive loss added to the adversarial loss. The contrastive learning encourages that the encoded features of two patches from the same location in the real and translated images are similar and in contrast to other patches. Compared to CycleGAN (Zhu et al., 2017), CUT is a one-sided network with a much lighter generator architecture hence requiring less amount of data for training.

3. Experiments & Results

Experiment: We utilize the generated bias field and synthetic data to train two different field strength agnostic cardiac MR segmentation models: (i) a **Bias field** model, trained on 69 patients (1270 slices) from the ACDC (Bernard et al., 2018) dataset and further augmented with 15 synthetic bias field 7T images and (ii) a **Synthetic** model, trained with the same ACDC dataset, but augmented with 560 CUT GAN-based synthetic 7T images. The trained networks were evaluated across datasets containing MR images acquired by scanners with varying field strengths. These include 30 patients (632 slices) of unseen 3T images acquired from the ACDC dataset, 150 1.5T images from the M&Ms data-set (Campello et al., 2021) and 14 7T images (61 slices, 14 volunteers) acquired at the UMC

Utrecht. We additionally compare the trained models to a **Baseline** model trained on 69 patients (1270 slices) from the ACDC dataset. All models were trained using a 2D nnUNet framework, under a 5-fold cross validation setup.

Results: The segmentation performance on 7T data, based on Dice score per tissue class, is shown in Figure 2 a). In addition, we evaluate the networks on 3T and 1.5T data to validate the adaptation of the networks to different field strengths and ensure there is no significant decrease in performance (b and c). Example segmentation results on 7T images from all trained networks are visualized in Figure 2 d).

4. Discussion and conclusion

We develop two novel augmentation techniques that aim to mimic the appearance of 7T images via bias field simulation and GAN-based style transfer. The 3T data from the ACDC challenge is used to train the nnUNet framework for a multi-class segmenation task, while the testing is done on 7T images acquired from 16 volunteers, for which we manually created ground truth labels. Compared to the **Baseline** model, the **Bias field** and **Synthetic** models improved the average Dice score over all classes on the 7T data from 0.64 to 0.78 and 0.80 respectively, while both models preserved the performance on 1.5T and 3T data. Next steps focus on reducing inter-/intra-observer variability on the ground truth labels and the training on a more heterogenous dataset to improve performance.

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