Segmentation for Out of Distribution T1ρ Cardiac MRI

Nicholas Jacobs[1] NICHOLAS.JACOBS@UTAH.EDU
Ganesh Adluru[2] GANESHSHARMA.ADLURU@HSC.UTAH.EDU
Jason Mendes[2] JASON.MENDES@HSC.UTAH.EDU
Ravi Ranjan[3] RAVI.RANJAN@HSC.UTAH.EDU
Andrew Arai[2.3] ANDREW.ARAI@HSC.UTAH.EDU
Shireen Elhabian[1] SHIREEN@SCI.UTAH.EDU
Edward DiBella[2] EDWARD.DIBELLA@HSC.UTAH.EDU
[1] *University of Utah Department of Computer Science*
[2] *University of Utah Department of Radiology and Imaging Sciences*
[3] *University of Utah Division of Cardiology*

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Abstract

Prior research has shown that Magnetic Resonance Imaging (MRI) with T1ρ weighted contrast images has the potential to detect disease, such as scar tissue (Han et al., 2014). This makes it a useful imaging modality to help cardiologists diagnose and treat cardiac patients, especially patients with kidney disease who cannot receive contrast. Our work shows that segmentation networks trained on clinical T1 datasets, which are more common and abundant than T1ρ datasets, can be used to segment out-of-distribution T1ρ images from pre-clinical studies given sufficient data augmentation during training.

Keywords: MRI, Segmentation, T1, T1ρ

1. Introduction

Past research by Han et al., 2014 and Bustin et al., 2023 suggests that "T1ρ MRI is a promising non-contrast method for tissue characterization" in the heart (Han et al., 2014). This would give cardiologists better insights into diseased and scarred heart tissue, allowing them to better treat patients suffering cardiac disease. T1ρ measures magnetic relaxation under a spin-locking pulse. This is a different mechanism than T1 and T2 decay and gives a different contrast. Additionally, T1ρ imaging does not require injected contrast agents, which makes the procedure cheaper, faster, and available to patients with kidney failure. Patients with kidney failure cannot properly filter all injected contrast agents from their blood after imaging (Bustin et al., 2023).

Segmentation of T1ρ weighted contrast images is needed for quantitative tissue analysis. For example, in the heart, it is useful to segment the left ventricle so that the T1ρ statistics of that tissue can be calculated. While state-of-the-art segmentation techniques are deep learning-based, the scarcity of labeled training and testing data creates a barrier to entry for the medical domain. Additionally, labeling cost is significantly higher in the medical domain than general-purpose computer vision as patient privacy and labeling expertise prevent the use of low-cost online labeling services that have helped power the success of supervised deep learning over the past decade.

This work aims to reduce the data requirements for training segmentation models for T1ρ MRI images by training a model on existing T1 data and treating T1ρ as an external validation dataset.

2. Methods

2.1. Datasets

An internal short-axis cardiac T1 dataset with human subjects was used for this work. The dataset contains 66 series, where each series contains eight contrast-weighted images and a T1 map that are all co-registered with motion correction and correspond to the same slice of the same patient. As images in a series are co-registered, a single mask for the left ventricle corresponds to all images.

The out-of-distribution T1ρ dataset was an internal mid-short-axis cardiac dataset from preclinical subjects. The left ventricle was manually labeled to serve as the true segmentation. This dataset contains 15 T1ρ weighted contrast images from different subjects. The images with the shortest spin lock time were used as they have the highest SNR (signal-to-noise ratio). As all of the weighted contrast images and the T1ρ map for a given series are co-registered, they share the same segmentation label, and at inference time, only a single image needs to be segmented. This work focuses on segmenting weighted contrast images as opposed to contrast maps, as our preliminary work showed a smaller distributional shift between T1 and T1ρ contrast weighted images than between T1 and T1ρ maps. Example images from both the T1 and T1ρ datasets are shown in Figure 1 below.

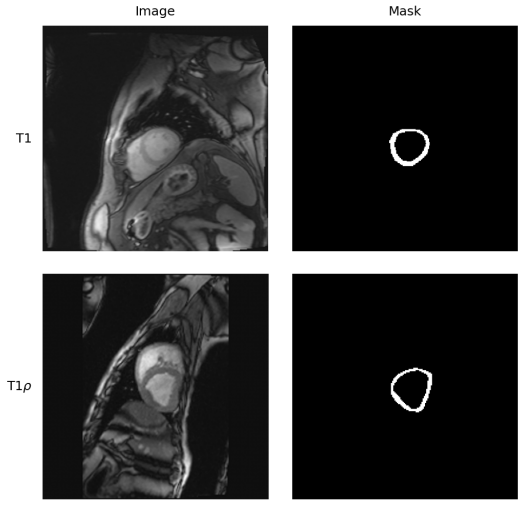

Figure 1: Example contrast weighted images from the T1 (human clinical) and T1ρ (preclinical) and their corresponding ground truth masks of the left ventricle.

2.2. Network Architecture and Training

The experiments in this paper used a modified UNet (Ronneberger et al., 2015) with a ResNet-50 encoder containing randomly initialized weights and a single output class. The final layer of all networks was a sigmoid layer, and networks were trained with a loss of one minus the dice score. All models were trained with the ADAM optimizer, with a learning rate of $3 * 10^{-4}$, for 512 epochs and without any regularization. Weights were randomly

initialized, as our preliminary work showed that initializing the UNet's encoder with weights trained on ImageNet led to no performance improvement.

3. Experiments

Our experiment studied how image augmentations can be used to help a segmentation network generalize from human clinical T1 weighted images to preclinical T1ρ weighted images. We used 5-fold cross-validation to study the difference in performance between networks trained with rotation and scaling augmentations and others with rotation, scaling, intensity, and additional geometric augmentations. Contrast images from both the T1 training set and T1 testing set were restricted to the two images with the shortest spin lock time. This is because they have the highest SNR, and as all images in an acquisition series are co-registered, it does not matter which image is segmented as they share the same mask.

All images were normalized between zero and one and scaled to a common size of 384 x 384 pixels. Aspect ratios were preserved by scaling the longest side to 384 and then zero-padding. All networks were trained with random horizontal, vertical, and 90-degree rotations. The networks with additional augmentations had additional intensity and geometric transformations applied during training. These included random brightness, illumination, Gaussian blur, adding Gaussian noise, masking out parts of the image, an additional rotation between -90 and +90 degrees, grid distortion, and a perspective transformation.

The resulting dice scores averaged across all folds for both augmentations are shown in the table below. The T1 training and testing dice scores indicate that the rotation and scaling networks are overfitting as they perform well on the training set but not the validation set. The networks with additional data augmentations reduce the overfitting as seen in the T1 training dice score and slightly improve the T1 testing dice score. The additional augmentations more significantly improve performance on T1ρ from 0.564 to 0.641. See Appendix A for sample T1ρ predictions.

Augmentations	T1 Train	T1 Test	T1ρ Validation
Scaling and rotation	0.96 $\pm$ 0.002	0.80 $\pm$ 0.041	0.56 $\pm$ 0.042
Scaling, rotation, and additional	0.90 $\pm$ 0.011	0.83 $\pm$ 0.021	0.64 $\pm$ 0.049

Table 1: Dice scores for all data splits averaged across all five folds with standard deviation.

4. Conclusion

T1ρ MRI has the potential to improve the standard of care for cardiac patients. Our experimentation shows that additional data augmentations improve segmentation network generalization between T1 human clinical and T1ρ preclinical datasets. This shows that existing datasets can be used to train models for T1ρ images.

Acknowledgments

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Appendix A

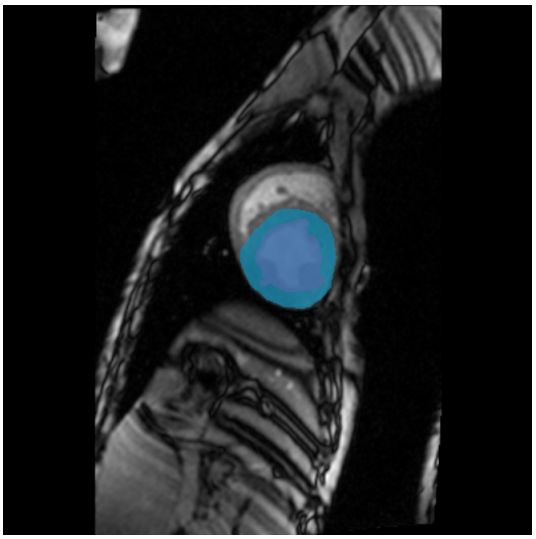

Figure 2: Best prediction with overlaid masks from best network with scaling and rotation augmentations (dice score 0.77.)

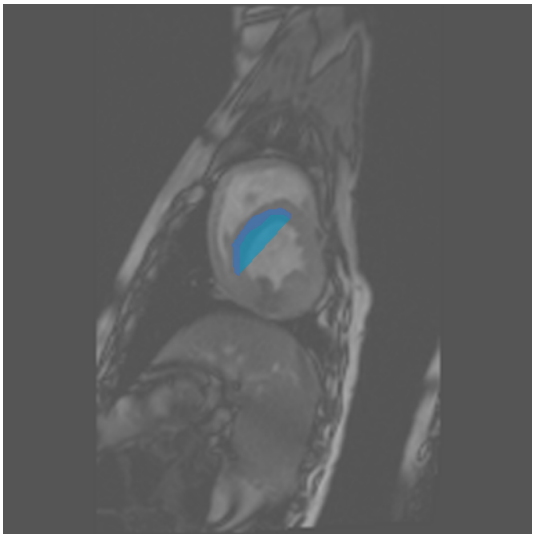

Figure 3: Worst prediction with overlaid masks from the best network with scaling and rotation augmentation (dice score 0.27.)

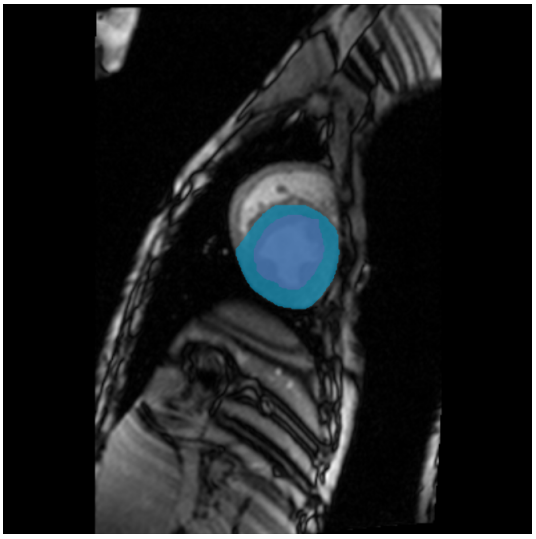

Figure 4: Best prediction with overlaid masks from the best network with scaling, rotation, and additional augmentations (dice score 0.83.)

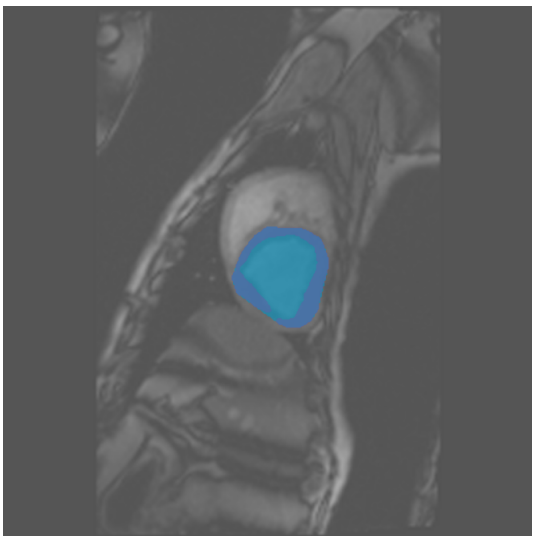

Figure 5: Worst prediction with overlaid masks from the best network with scaling, rotation, and additional augmentations (dice score 0.63.)