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Simulated CMR images can improve the performance and generalization capability of deep learning-based segmentation algorithms

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INTRODUCTION

The generalization capability of deep DL-based segmentation algorithms across different sites and vendors, as well as MRI data with high variance in contrast, is limited[1,2]. In this work, we explore the benefits of adding a highly heterogeneous simulated MRI dataset into the training procedure of the neural network for the task of cardiovascular MR ventricular cavity segmentation.

METHODS

Data: short-axis cine MR images from six different sites (A to F) and highly heterogeneous contrast with ground truth outlining right (RV) and left (LV) ventricular blood pool, and left ventricular myocardium (LVM)

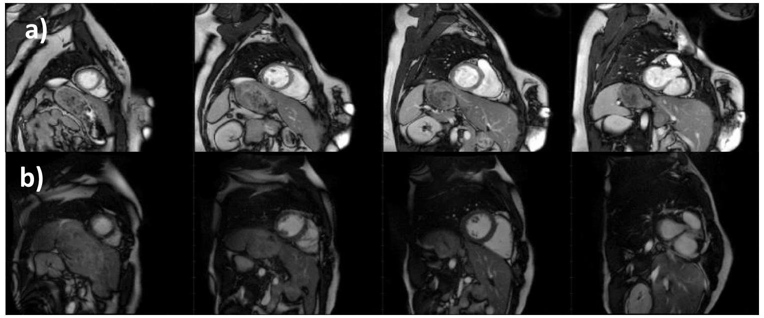

Figure 1: Representative depiction of contrast differences due to variation in scan parameters and vendors between the datasets from sites A to E (a) and site F (b) at end diastolic phase. Data from site F was acquired using Siemens Aera, while datasets A-E were acquired from various Philips scanner models.

Approach:

- To account for the variance, **augment** the training with **simulated CMR images** obtained using a human anatomical model for **XCAT[3] phantom** with controllable parameters[4] (Figure 3)
- **2D U-Net[5]** for multi-structure cardiac segmentation

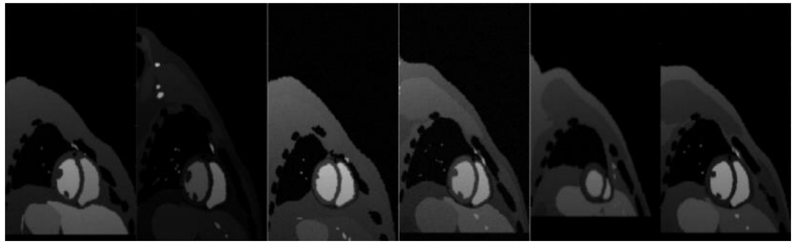

Figure 3: Sample slices from simulated images used in this study for introducing a wider variance in contrast, while providing an accurate ground truth.

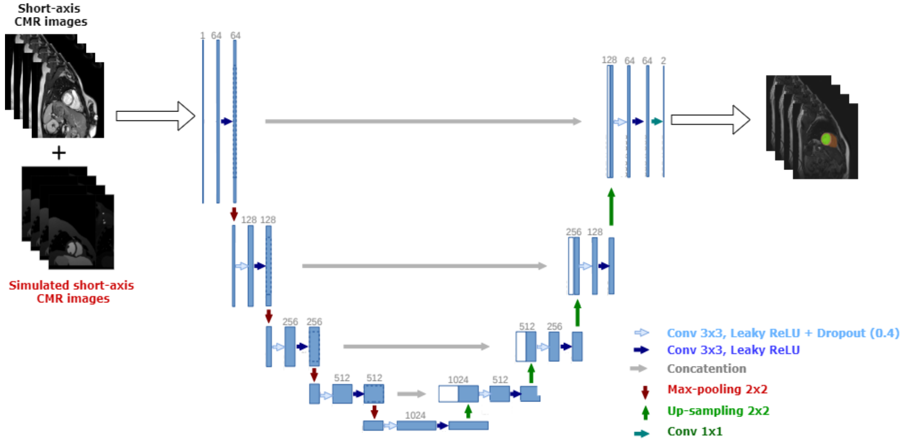

Figure 2: A 2D U-Net training strategy. All data is normalized to zero mean and unit standard deviation and resampled to a voxel spacing of 1.5 mm^3. Data augmentation is applied on the fly, using elastic deformations, random scaling and random rotations. The sum of cross-entropy and dice is used as a loss function, optimized utilizing Adam with an initial learning rate of 0.001 and a weight decay of 5×10^{-5}. All networks were trained for a maximum of 200 epochs.

RESULTS

Addition of simulated data improves the overall segmentation performance across heterogeneous datasets

#	Train set (# of subjects) Site A-F	Simulated Data	Test set (# of subjects) Site A-F	LV Dice	LV IoU	Myo Dice	Myo Iou	RV Dice	RV IoU
1	145	0	38	0.879	0.792	0.754	0.641	0.817	0.708
2	145	12	38	0.881	0.802	0.779	0.659	0.819	0.721
3	145	24	38	0.889	0.812	0.784	0.673	0.825	0.734
4	145	36	38	0.894	0.817	0.789	0.681	0.836	0.739
5	145	48	38	0.901	0.823	0.797	0.689	0.849	0.748
6	145	60	38	**0.913**	**0.834**	**0.814**	**0.705**	**0.856**	**0.759**

Improvement in the generalization capability of the network to data coming from unseen sites and acquired on different vendors

Dataset Train set	Test set	LV Dice	LV IoU	MYO Dice	MYO Iou	RV Dice	RV Iou
Sites A, B, C, D, E	Site F	0.702	0.549	0.614	0.448	0.595	0.433
Sites A, B, C, D, E + Simulated Data	Site F	**0.734**	**0.571**	**0.651**	**0.493**	**0.635**	**0.479**
Sites A, B, C, D, F	Site E	0.887	0.801	0.779	0.641	0.837	0.726
Sites A, B, C, D,F + Simulated Data	Site E	0.898	0.812	0.791	0.662	0.842	0.731

[1] Bai W et al. *JCMR* 2018. [2] Petitjean C et al. *MedIA* 2011. [3] Segars WP et al. *Med Phys* 2010. [4] Amirrajab S et al. Proc. ISMRM 2020. [5] Ronneberger O et al. MICCAI 2015

CONCLUSION

- A promising solution to address the lack of data availability and generalization capability of neural networks in medical imaging segmentation tasks
- Improvement in segmentation even without highly realistic simulations, which we hypothesize is mainly due to the availability of highly accurate "ground-truth" and inclusion of high contrast variance