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LEARNED CONDENSATION-OPTIMIZATION NETWORK: A REGULARIZED NETWORK FOR IMPROVED CARDIAC VENTRICLES SEGMENTATION ON BREATH-HOLD CINE MRI

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ABSTRACT

In this work, we implement a fully convolutional segmenter featuring both a learned group structure and a regularized weight-pruner to reduce the high computational cost in volumetric image segmentation. We validated the framework on the ACDC dataset and achieved accurate segmentation, leading to mean Dice scores of 96.80% (LV blood-pool), 93.33% (RV blood-pool), 90.0% (LV Myocardium) and yielded similar clinical parameters as those estimated from the ground-truth segmentation data.

1. INTRODUCTION

Deep neural networks have shown significant success for solving complex computer vision tasks [1]. In this work we propose a parameter- and memory-efficient, automatic segmentation framework for cardiac feature extraction and clinical parameter estimation and integrated the above with a robust technique for automatic heart localization.

2. METHODOLOGY

Our proposed LCON framework substitutes the concept of both standard convolution and group convolution (G-Conv) with learned group-convolution (LG-Conv). Our network learns group convolution automatically during training through a multi-stage scheme. Training is initiated in the first part of the pipeline by calculating the magnitude of the weights for each incoming feature, then the low-magnitude weights are screened out. Subsequently, all training occurs in the second part of the pipeline. The weights are updated by minimizing the dual loss: $\mathcal{L}_{Dual-Loss} = \alpha \cdot \mathcal{L}_{Entropy}(x, y_1 | \theta) + \beta \cdot (1 - \mathcal{L}_{Dice}(x, y_1 | \theta))$, where $\mathcal{L}_{Entropy}$ is the cross-entropy loss, \mathcal{L}_{Dice} is the dice loss, θ denotes the network weights, x is the training samples, y_1 is the training set label map, and α and β are the the weighting parameters.

3. RESULTS AND DISCUSSION

We assessed the performance of our model on the ACDA dataset based on the Dice score and clinical parameters in comparison with five other existing architectures [2] (Table 1). Our proposed model achieved a LV dice score of 96.8% in diastole and 95.1% in systole, outperforming five other models as much as 3.7%, yielding a higher than 6% improvement over traditional U-Net, with at least a 10 x fold reduction in the number of parameters.

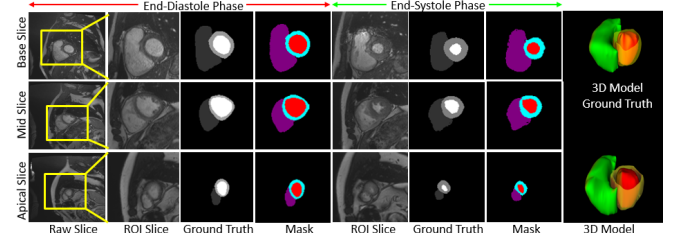


Fig. 1. Segmentation results at both ED & ES phases showing RV, LV, and LV-Myo in purple, red, and cyan, respectively.

Table 1. Comparison of mean (SD) Dice scores and clinical parameter estimates across six frameworks (*for $p < 0.05$ and ** for $p < 0.01$).

	End Diastole (ED)					
	UNet	DCN	MUNet	MNet	DNet	LCON
Dice [LV]	95.0(8.2)	96.0(7.5)	96.3(6.5)	96.1(7.7)	96.4(8.1)	*96.8(7.9)
Dice [Myo]	86.0(9.8)	86.0(11.1)	87.0(9.9)	88.9(9.8)	88.9(9.8)	*89.50(8.9)
Dice [RV]	91.0(13.5)	92.0(11.9)	93.2(12.7)	92.9(12.9)	93.5(14.0)	93.3(11.2)
	End Systole (ES)					
	UNet	DCN	MUNet	MNet	DNet	LCON
Dice [LV]	90.0(10.9)	91.0(9.6)	91.1(9.2)	91.5(7.1)	91.7(9.0)	**95.1(6.4)
Dice [Myo]	88.0(11.3)	88.0(10.7)	90.1(10.6)	88.8(8.9)	89.8(12.6)	*90.0(8.9)
Dice [RV]	83.0(18.7)	84.0(13.4)	88.3(14.7)	88.5(11.8)	87.9(13.9)	87.4(11.9)
#Parameters ($\times 10^6$)	4.1	-	19.0	2.11	0.65	0.34
	Correlation Coefficient					
	UNet	DCN	MUNet	MNet	DNet	LCON
LV EF	0.987	0.988	0.988	0.989	0.989	0.991
LV EDV	0.997	0.993	0.995	0.993	0.997	0.998
RV EF	0.791	0.852	0.851	0.793	0.858	0.901
RV EDV	0.945	0.980	0.977	0.986	0.982	0.988
Myo mass	0.989	0.963	0.982	0.968	0.990	0.993

DCN[Wolternick et al.]: Dilated Convolution Network, MUNet[Baumgartner et al.]: Modified 3D UNet, MNet[Jang et al.]: Modified M-Net, DNet[Khened et al.]: DenseNet, EUNet[isensee et al.]: Ensemble UNet, LCON: learned condensation-optimization Network

4. REFERENCES

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