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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: $\mathcal{L}_{Dual-Loss} = \alpha.\mathcal{L}_{Entropy}(x, y_1|\theta)+\beta.(1-\mathcal{L}_{Dice}(x, y_1|\theta))$, where $\mathcal{L}_{Entropy}$ is the cross-entropy loss, $\mathcal{L}_{Dice}$ is the dice loss, $\theta$ denotes the network weights, $x$ is the training samples, $y_1$ is the training set label map, and $\alpha$ and $\beta$ 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.

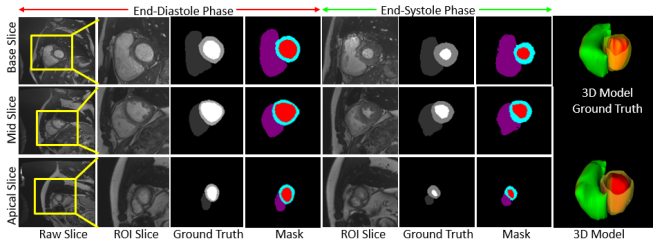


**Fig. 1**. Segmentation results at both ED & ES phases showing RV, LV, and LV-Myo in purple, red, and cyan, respectively.

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

| | UNet | DCN | MUNet | MNet | DNet | **LCON** |
|---|---|---|---|---|---|---|
| | End Diastole (ED) | | | | | |
| 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) | | | | | |
| 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 |

| | UNet | DCN | MUNet | MNet | DNet | EUNet | **LCON** |
|---|---|---|---|---|---|---|---|
| | Correlation Coefficient | | | | | | |
| LV EF | 0.987 | 0.988 | 0.988 | 0.989 | 0.989 | 0.991 | 0.997 |
| LV EDV | 0.997 | 0.993 | 0.995 | 0.993 | 0.997 | 0.997 | 0.998 |
| RV EF | 0.791 | 0.852 | 0.851 | 0.793 | 0.858 | 0.901 | 0.869 |
| RV EDV | 0.945 | 0.980 | 0.977 | 0.986 | 0.982 | 0.988 | 0.988 |
| Myo mass | 0.989 | 0.963 | 0.982 | 0.968 | 0.990 | 0.989 | 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

[1] Bai, Wenjia et al. , "Automated cardiovascular magnetic resonance image analysis with fully convolutional networks," *Journal of Cardiovascular Magnetic Resonance*, vol. 20, no. 1, pp. 65, 2018.

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