Medical Image Seminar

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Outline

Volumetric Attention Module

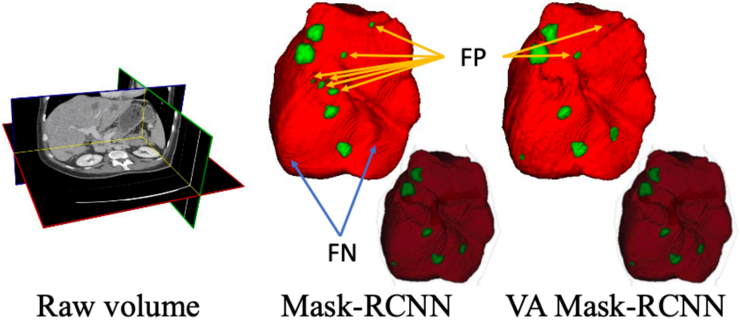
Volumetric Attention for 3D Medical Image Segmentation and Detection (MICCAI 2019)

- Propose **volumetric attention(VA) module** for 3D medical image segmentation and detection
- Inspired by Non-local Neural Networks Segmentation and Detection
- Backbone: Mask R-CNN Segmentation and Detection

Volumetric Attention Module

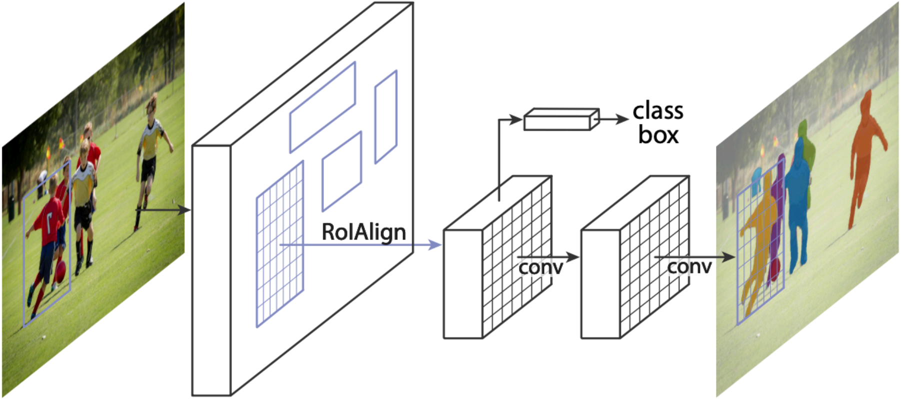
Mask R-CNN VS. VA Mask R-CNN

- 2D network but 3D
- transfer learning (pre-trained detection network)



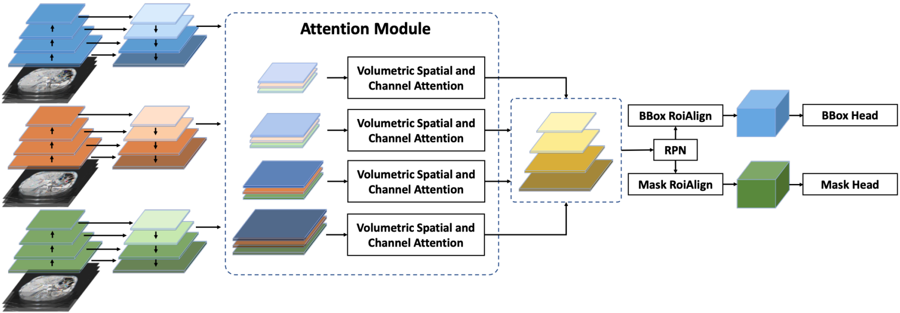
Volumetric Attention Module

Mask R-CNN Network Structure



Volumetric Attention Module

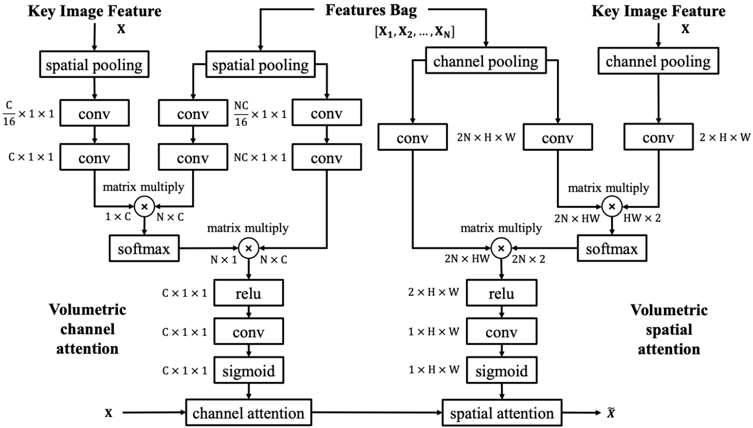
Proposed Network Structure: **Attention Module** before RPN



Volumetric Attention Module

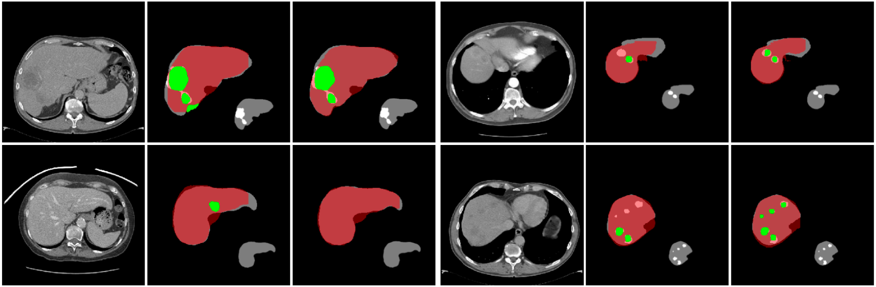
Module Detail

- Features Bag: $[\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_N] \in \mathbb{R}^{N \times C^i \times H^i \times W^i}$



Results

- enhance lesion prediction
- avoid false positive



Raw volume | Mask-RCNN | VA Mask-RCNN | Raw volume | Mask-RCNN | VA Mask-RCNN

Volumetric Attention Module

Experiment on LiTS dataset (131 training and 70 test CT scans)

Team	Model	Dice per case
3D U-Net(Ours) [5]	3D U-Net	55.0
G. Chlebus [3]	2D U-Net	65.0
E. Vorontsov et al. [16]	2D + 3D FCN	65.0
Y. Yuan [21]	Deconv-Conv Net	65.7
X. Han [9]	2D U-Net	67.0
LeHealth	-	70.2
Mask-RCNN(Ours)[10]	Mask-RCNN	70.3
X. Li et al.[13]	H-DenseUNet	72.2
VolumetricAttention	VA Mask-RCNN	**74.1**

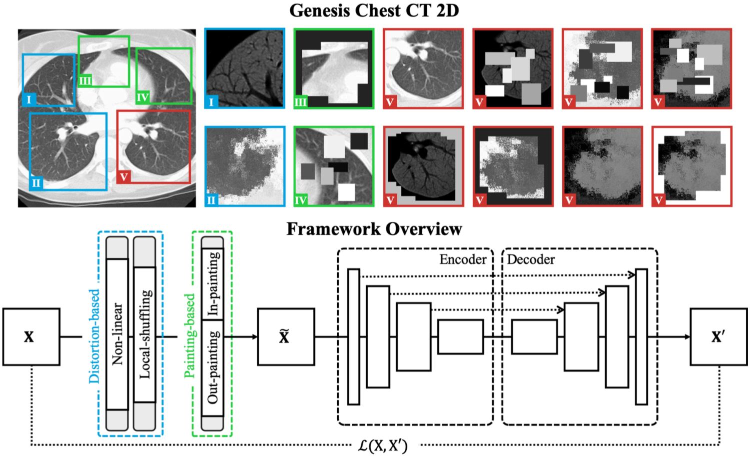
Models Genesis

Models Genesis: Generic Autodidactic Models for 3D Medical Image Analysis (MICCAI 2019)

- Propose a transfer learning pipeline for 3D Medical Image tasks Segmentation and Detection
- ImageNet is used for 2D task transfer learning, while 3D medical transfer learning is still a challenge

Models Genesis

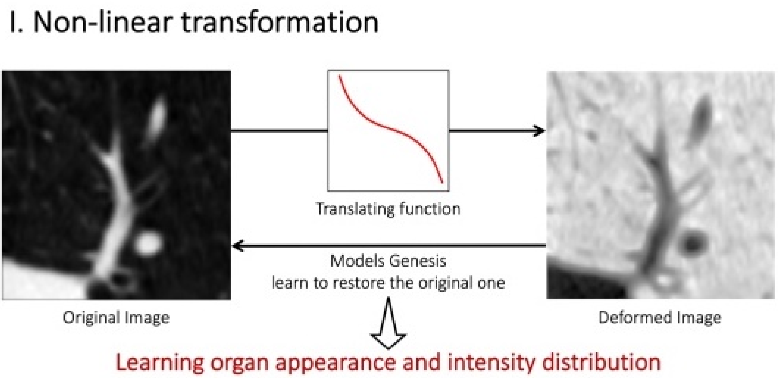
Network Structure



Models Genesis

Distribution-based

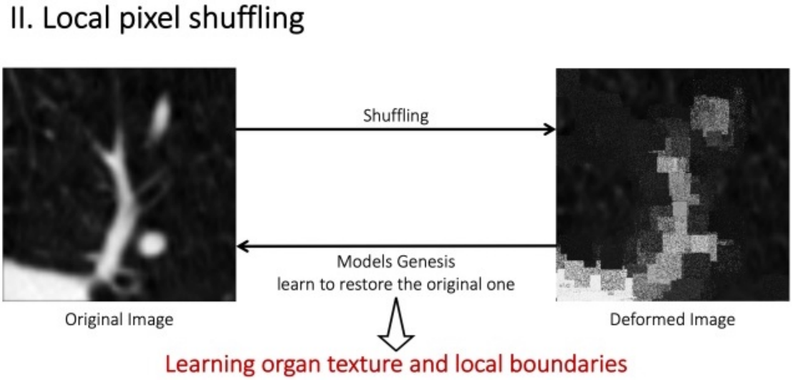
- intensity transformation



Models Genesis

Distribution-based

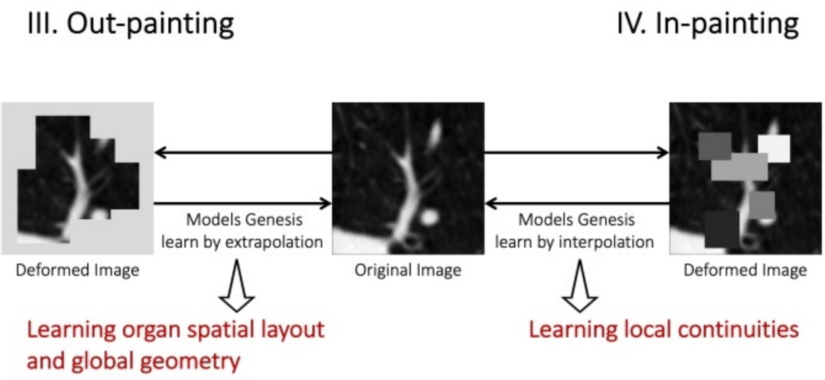
- shuffling



Models Genesis

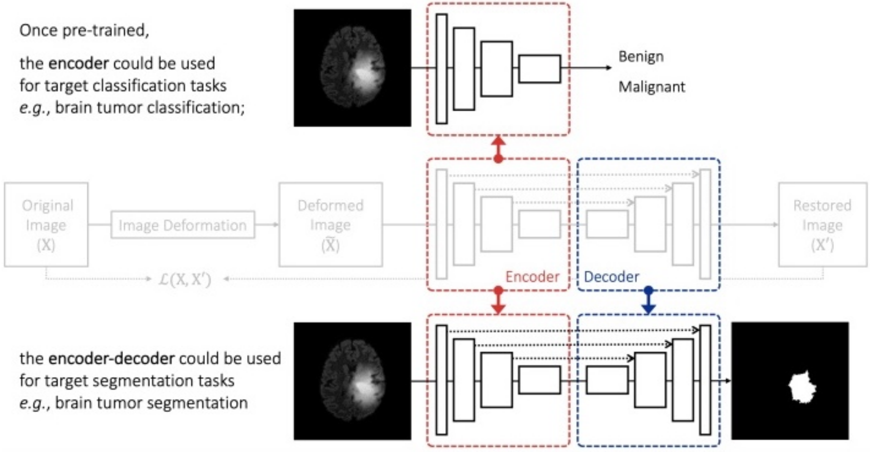
Painting-based

- in-painting
- out painting



Models Genesis

Make use of pre-trained models



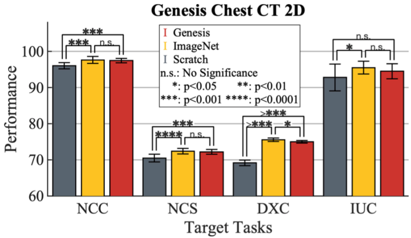
Models Genesis

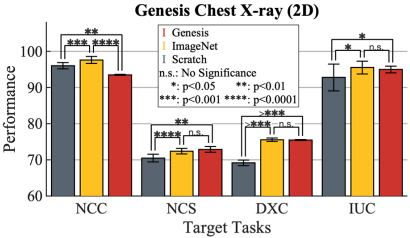
Results

- 2D score is close to ImagesNet
- for 3D, proposed method outperforms Scratch

Task	2D (%)			3D (%)			p-value†
	Scratch	ImageNet	Genesis	Scratch	ImageNet	Genesis	
NCC	96.03±0.86	97.79±0.71	97.45±0.61	94.25±5.07	N/A	**98.20±0.51**	0.0213
NCS	70.48±1.07	72.39±0.77	72.20±0.67	74.05±1.97	N/A	**77.62±0.64**	$<1e$-8
ECC	71.27±4.64	78.61±3.73	78.58±3.67	79.99±8.06	N/A	**88.04±1.40**	5.50e-4

†These p-values are calculated between our Models Genesis vs. the fine-tuning from ImageNet, which always offers the best performance (highlighted in red) for all three tasks in 2D.





Models Genesis

Experiment on 5 tasks

Task	Metric	Disease	Organ	Dataset	Modality	Scratch (%)	Genesis (%)	p-value
NCC[1]	AUC					94.25±5.07	**98.20±0.51**	0.0180
NCS[2]	IoU					74.05±1.97	**77.62±0.64**	1.04e-4
ECC[3]	AUC	✗		✗		79.99±8.06	**88.04±1.40**	0.0058
LCS[4]	IoU	✗	✗	✗		74.60±4.57	**79.52±4.77**	0.0361
BMS[5]	IoU	✗	✗	✗	✗	90.16±0.41	**90.60±0.20**	0.0041

[1] LUNA winner holds an official score of 0.968 vs. 0.971 (ours)
[2] Wu *et al.* holds a Dice of 74.05% vs. 75.86%±0.90% (ours)
[3] Zhou *et al.* holds an AUC of 87.06% vs. 88.04%±1.40% (ours)
[4] LiTS winner w/ postprocessing (PP) holds a Dice of 96.60% vs. 91.13%±1.51% (ours w/o PP)
[5] BraTS winner w/ ensembling holds a Dice of 91.00% vs. 92.58%±0.30% (ours w/o ensembling)

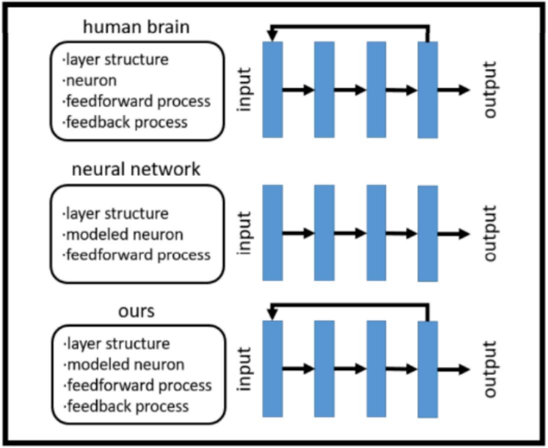
Feedback U-net

Feedback U-net for Cell Image Segmentation (CVPR 2020 workshop)

- Imitate feedback processing of human neural system
- 2 round forward using **Convolutional LSTM**

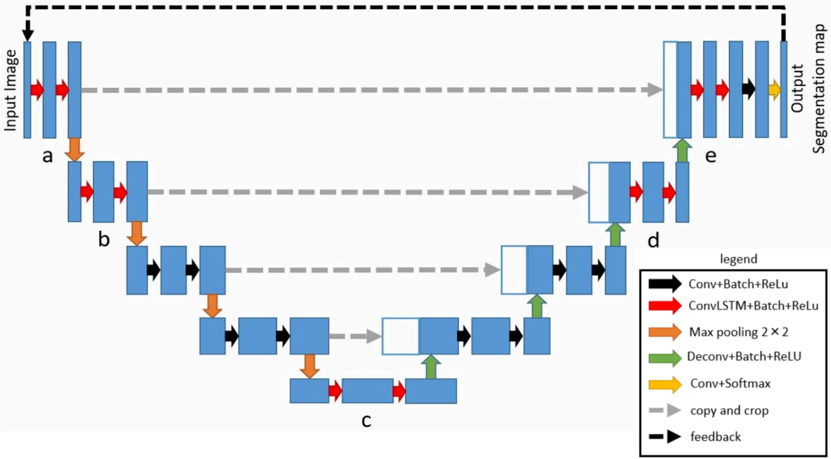
Feedback U-net

Pipeline



Feedback U-net

Network Structure



Feedback U-net

Experiment on Drosophila cell image dataset
achieved the best accuracy which is 71.5% on mean IoU

Method	cytoplasm (%)	cell membrane (%)	mitochondria (%)	synapses (%)	meanIoU (%)
U-Net	92.0	74.9	73.1	40.9	70.2
RU-Net (time-step=2)	92.2	75.8	74.3	**43.2**	71.4
Feedback U-Net with Recurrent Neural Layer	92.2	75.1	73.8	37.9	69.8
Feedback U-Net without Convolutional LSTM	92.1	76.0	74.9	38.4	70.4
Feedback U-Net with Convolutional LSTM	**92.4**	**76.4**	**75.2**	42.3	**71.5**

Feedback U-net

Visual results