VALSE ONLINE 视觉与学习青年学者研讨会 Vision And Learning SEminar

Towards Intelligent Interactive Segmentation of Medical Images

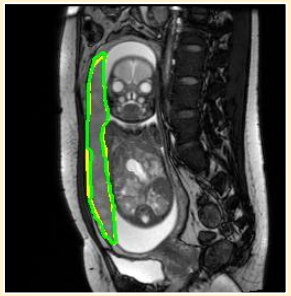
Guotai Wang

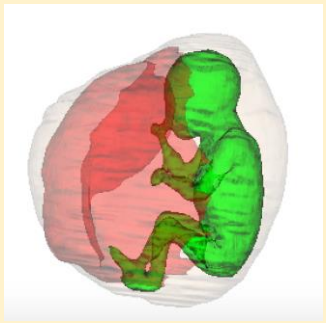
University of Electronic Science and Technology of China

2019-9-4

Content

1， Minimally interactive segmentation of the placenta from fetal MRI

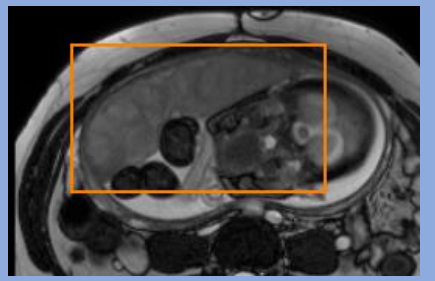




2, Interactive segmentation using deep learning and geodesic distance transform

CNN

3, Image-specific fine-tuning for interactive segmentation



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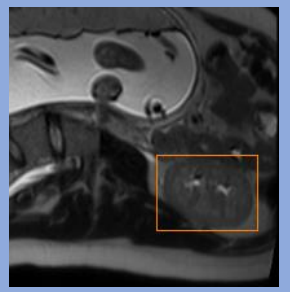

Test

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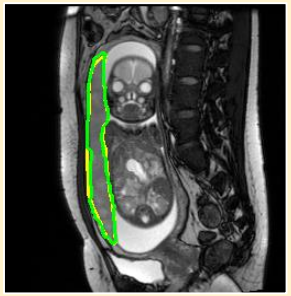

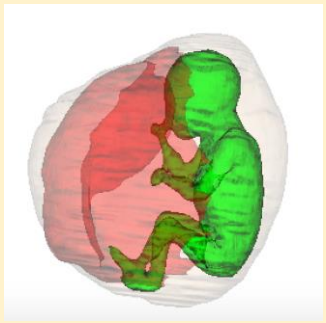

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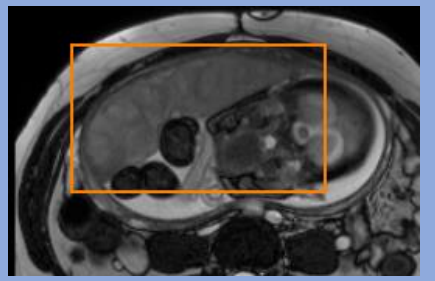

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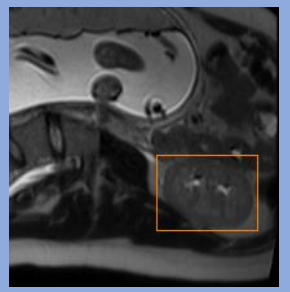
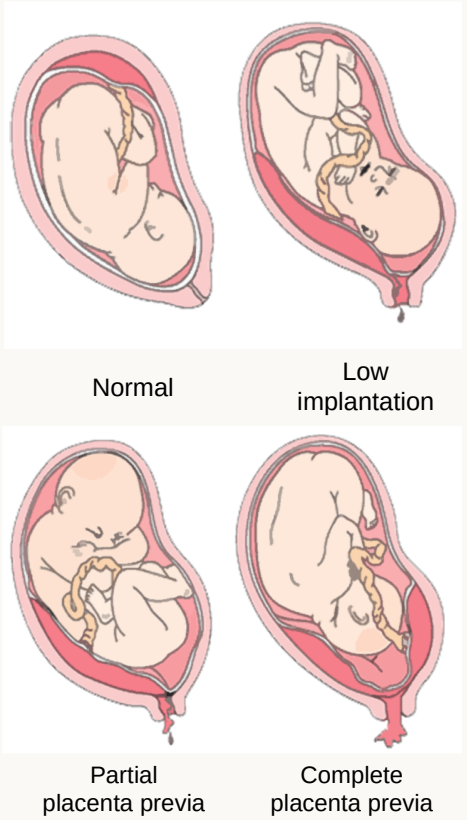
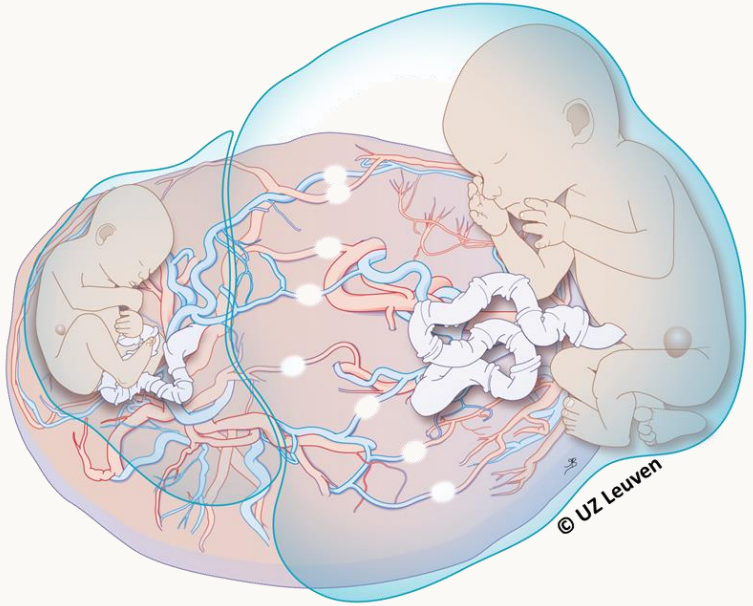


Test

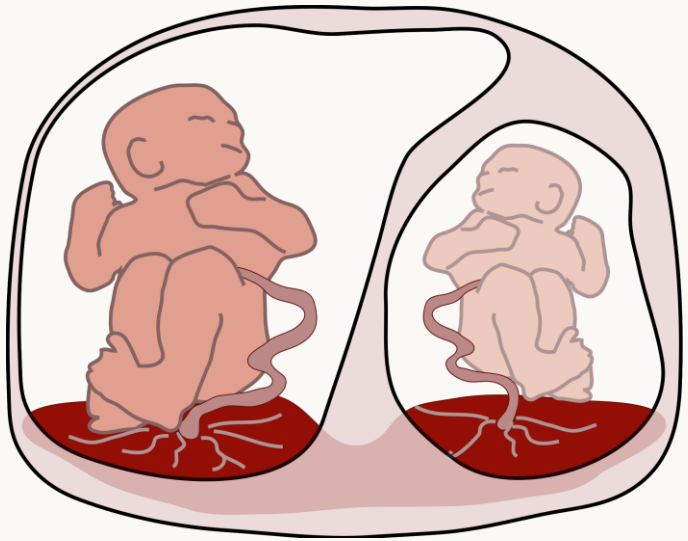
Clinical background of the placenta



Placenta has a large variation of shape and position



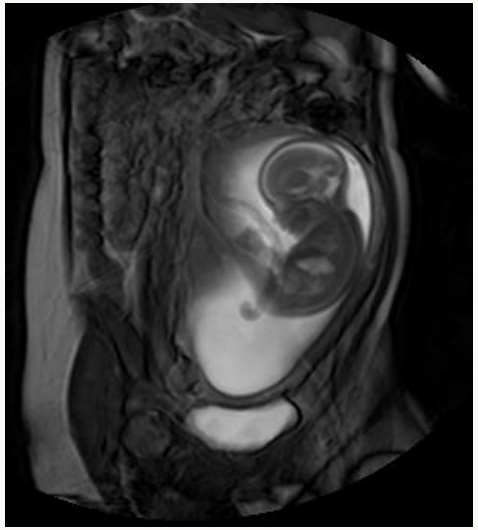
Twin-twin transfusion syndrome



Intrauterine growth restriction

Minimally Interactive Placenta Segmentation: Background

Imaging of the placenta



Fetal Ultrasound

- Low contrast
- Limited filed of view
- Noises

Fetal MRI

- Good soft tissue contrast
- Large filed of view
- Higher SNR

Minimally Interactive Placenta Segmentation: Background

Challenges of placenta segmentation from fetal MRI

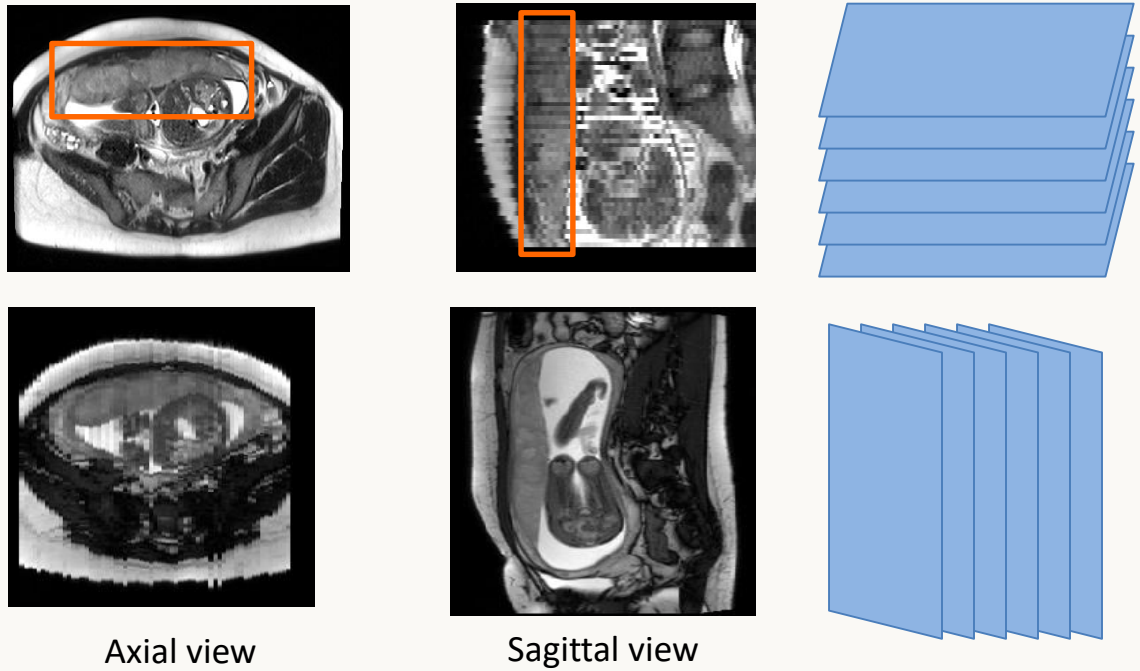
- Images are acquired as a stack of 2D Slices

Stack 1

Acquired in axial view

Stack 2

Acquired in sagittal view



Axial view

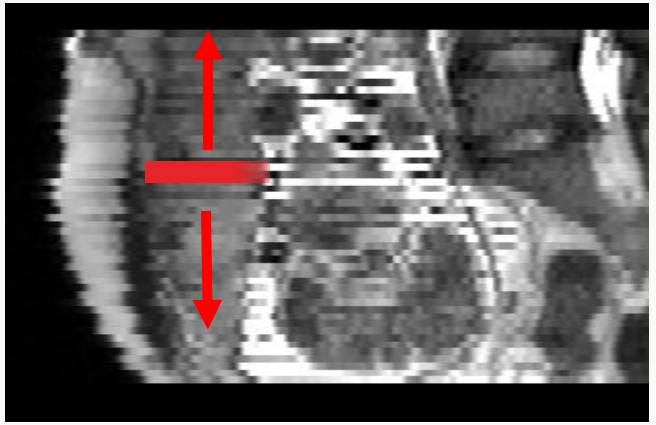
Sagittal view

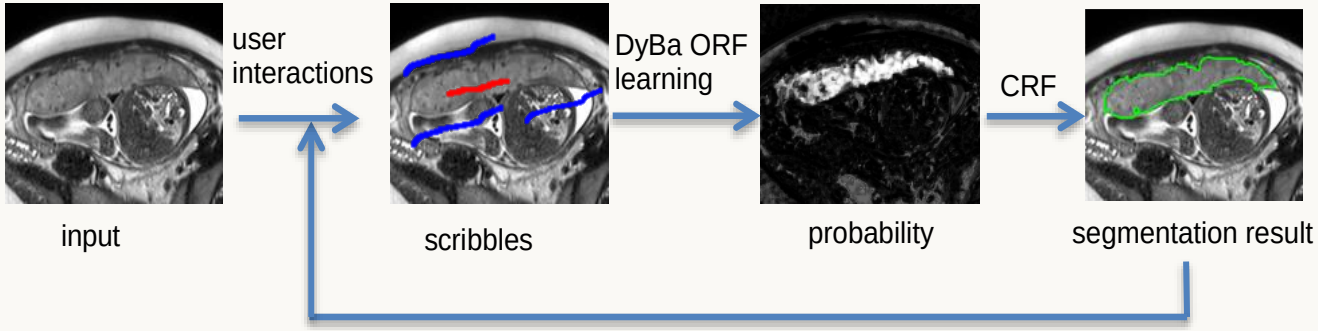
- Low 3D resolution
- Inter-slice motion
- Inhomogeneous appearance
- Large shape/position variation

The challenges make it hard to obtain accurate segmentation results of the placenta automatically

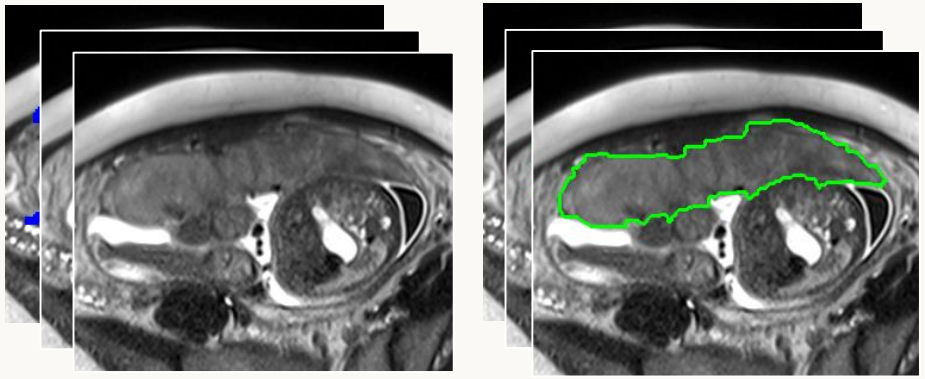
Slic-Seg: Slice-by-slice propagation

- Minimally interactive segmentation
  - Interactions only required for a single slice
  - Automatic propagation to other slices





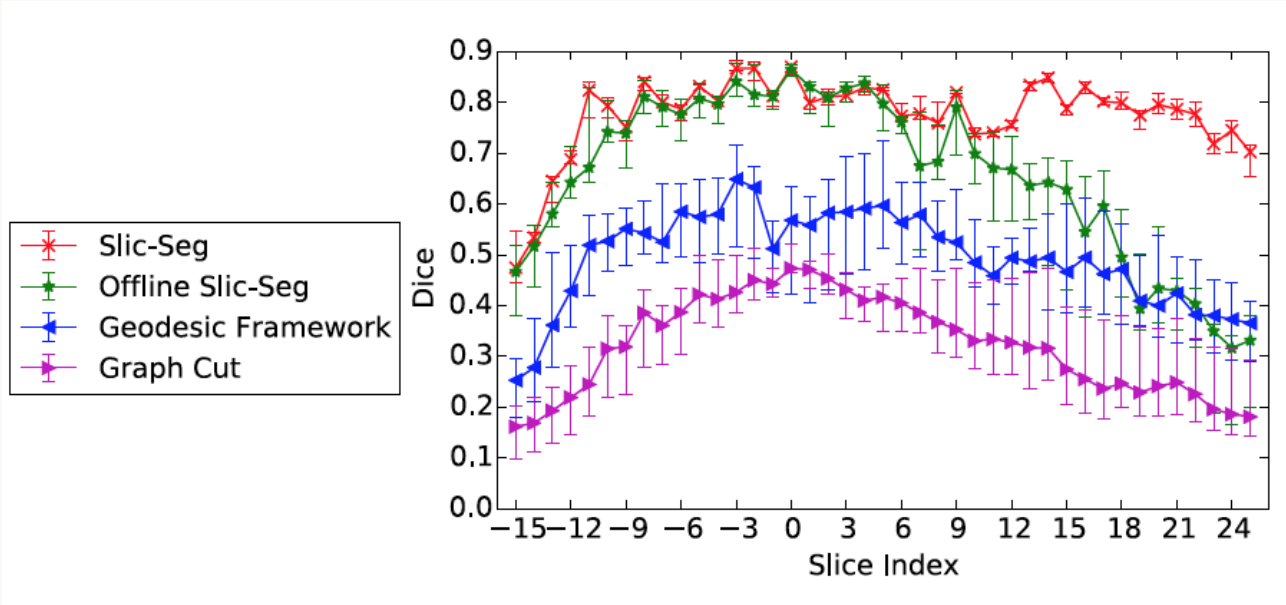
Segmentation of the start slice



Automatic propagation

Slic-Seg: Slice-by-slice propagation

- Segmentation Results



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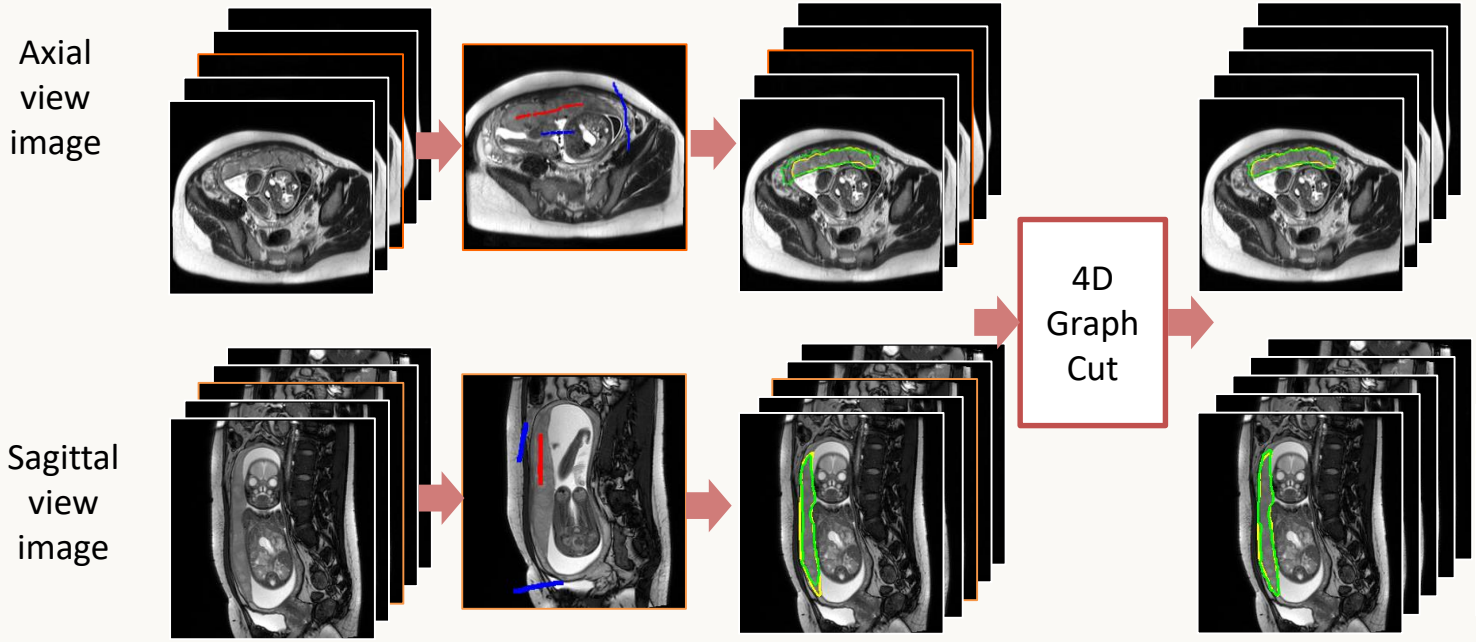
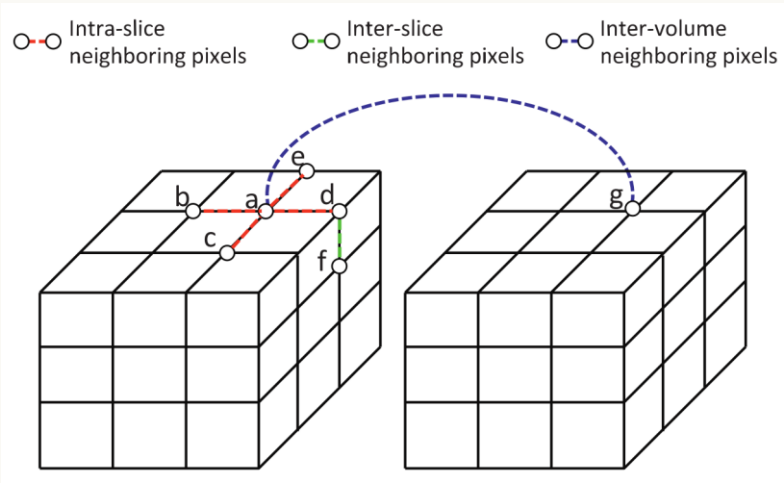
Interactive Segmentation using Online Random Forest

Co-segmentation of images acquired in different views

- Making use of the complementary resolution





$$E(C_1,...,C_K) = \sum_{k}\sum_{i\in I_k} \Psi(\mathbf{c}_i|\mathbf{x}_i, I_k) + \lambda_1 \sum_{I_k}\sum_{i,j\in N_1} B_{i,j}\cdot\delta_{i,j} + \lambda_2 \sum_{\{i,j\}\in N_2} B'_{i,j}\cdot\delta_{i,j} + \lambda_3 \sum_{\{i,j\}\in N_3} B''_{i,j}\cdot\delta_{i,j}$$

Pixel-wise probability | Intra-slice consistency | Inter-slice consistency | Inter-volume consistency

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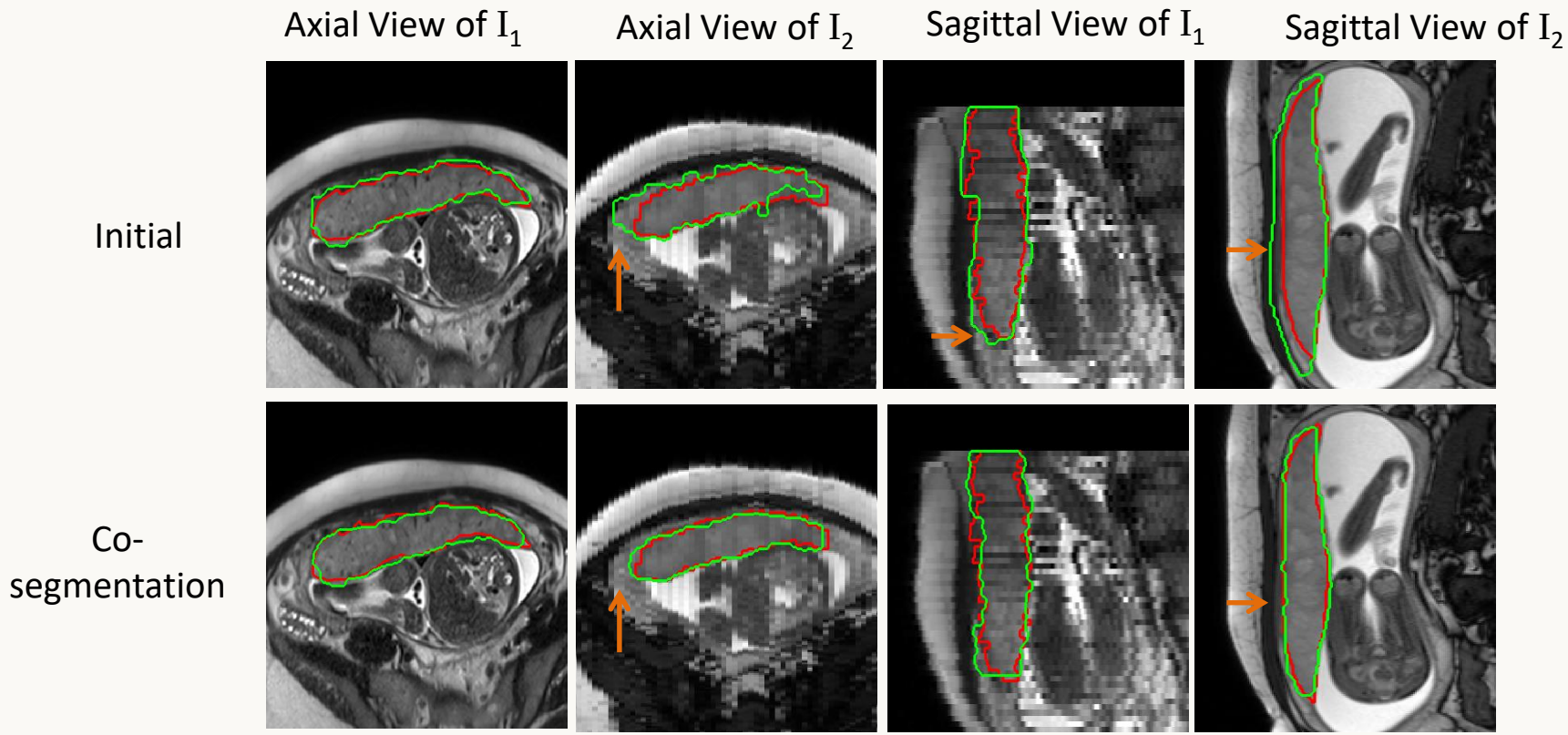

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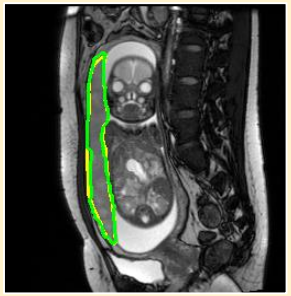

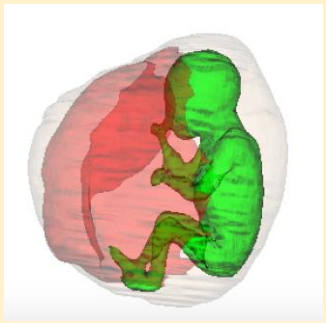

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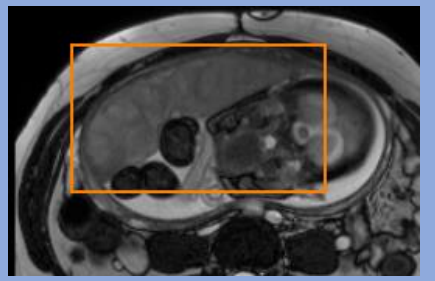

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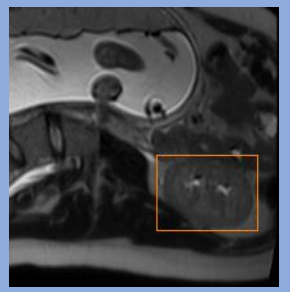
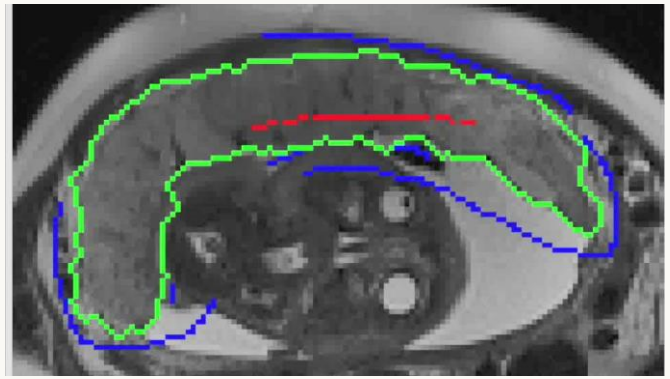


Test

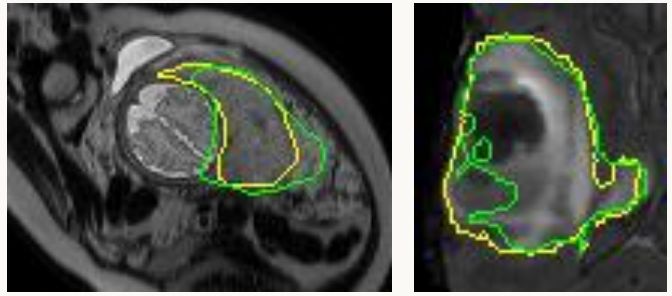
Interactive segmentation using deep learning

Why combine them

- Interactive segmentation
  - Widely used in practice
  - Higher robustness for challenging cases
- Existing interactive tools
  - Graph Cuts, Random Walker, ITK-SNAP, …
  - Often require a lot of user interactions
  - Not intelligent and fast enough
- Existing deep learning methods
  - Mainly used for automatic segmentation
  - Require a large number of annotated training images
  - Still need to be refined in complex cases



Graph Cuts (Y. Boykov, 2001)

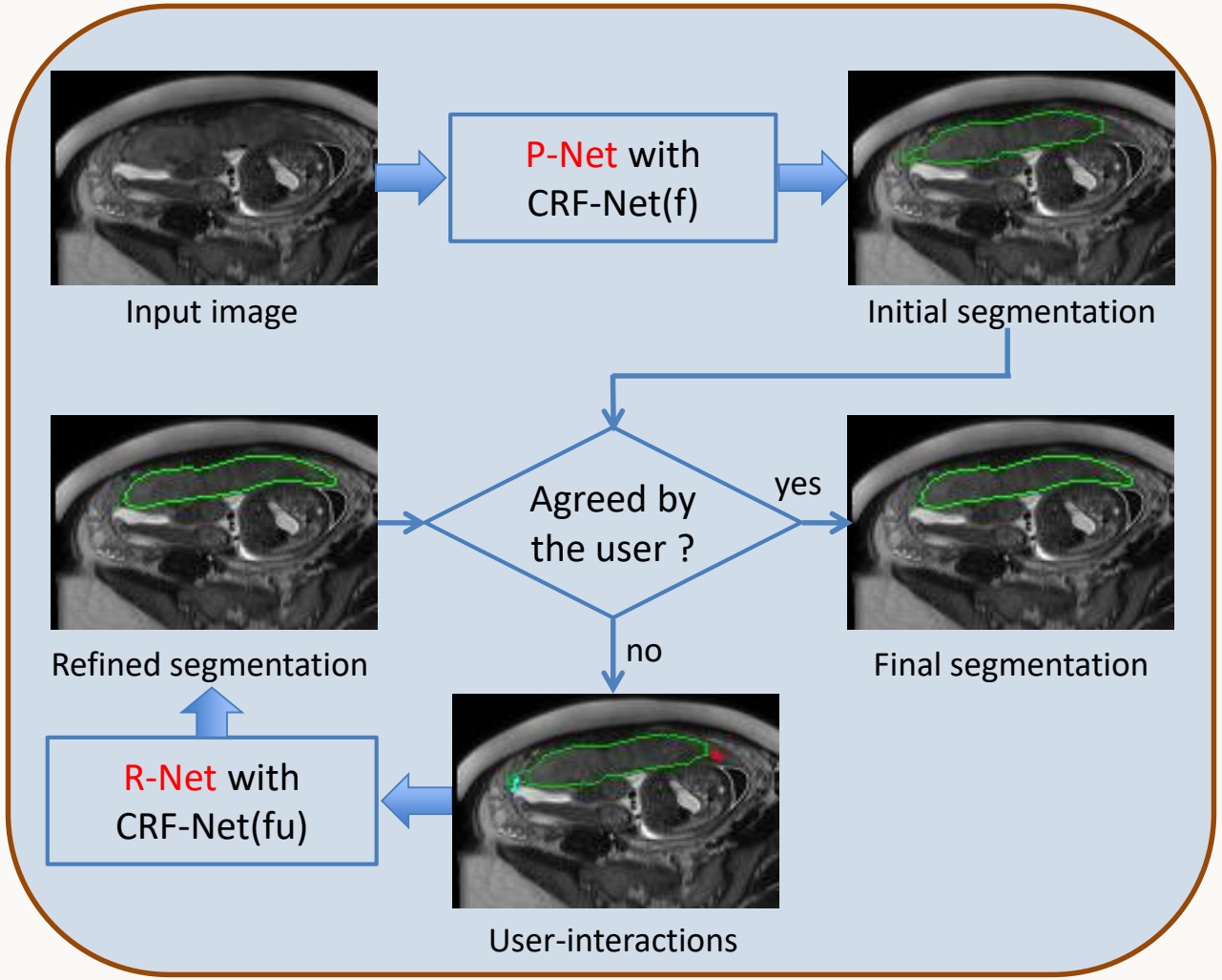


Mis-segmentations obtained by CNNs

DeepIGeoS: Deep Interactive Geodesic Framework for Segmentation

Interactive segmentation using CNNs

- Two-stage framework
  - P-Net: propose an initial segmentation
  - R-Net: refine the initial segmentation
- User interactions
  - Given on the output of P-Net
  - Used as input of R-Net



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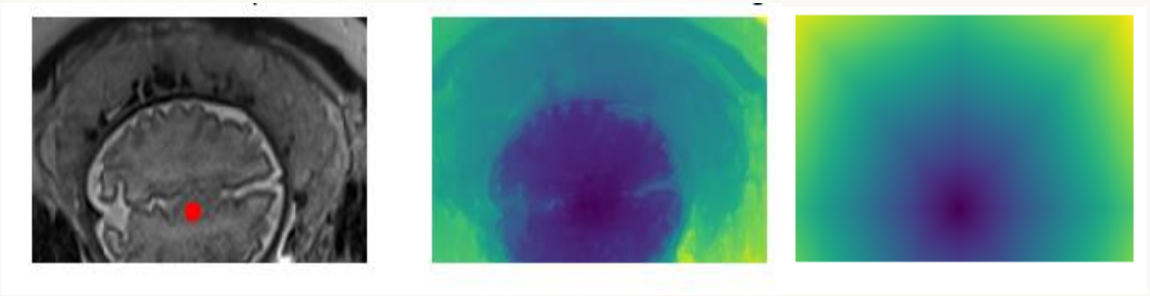
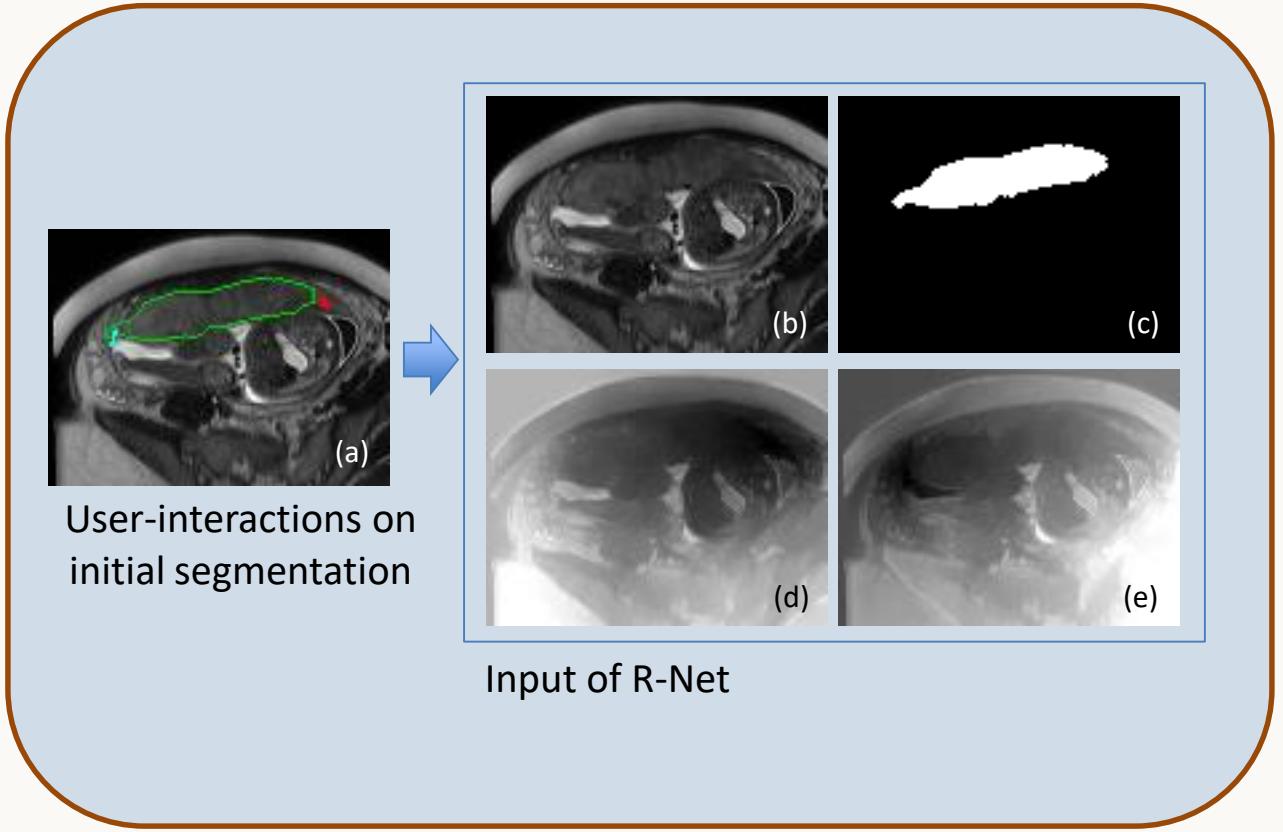
How to encode user interactions

- Geodesic distance transforms
  - For each class respectively
  - Obtain additional two distance maps
  - Encode contextual information



A seed point Geodesic distance Euclidean distance



User-interactions on initial segmentation

Input of R-Net

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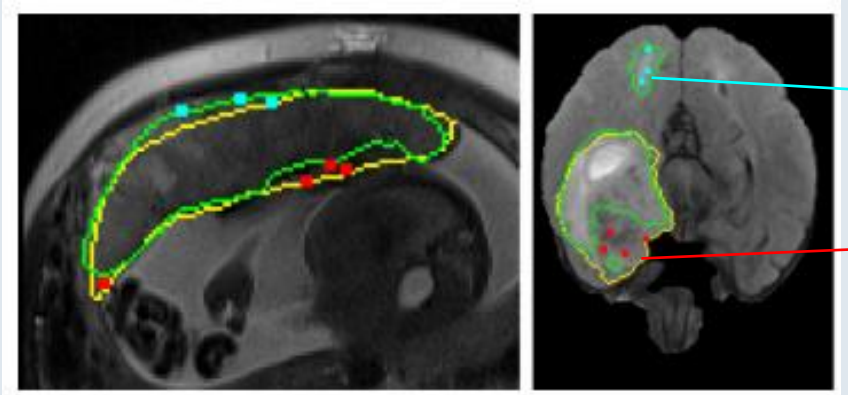
Simulated user interactions during training

- Interactions are based on mis-segmentations
  - Compare an initial segmentation with the ground truth
  - Randomly sample points from mis-segmented regions



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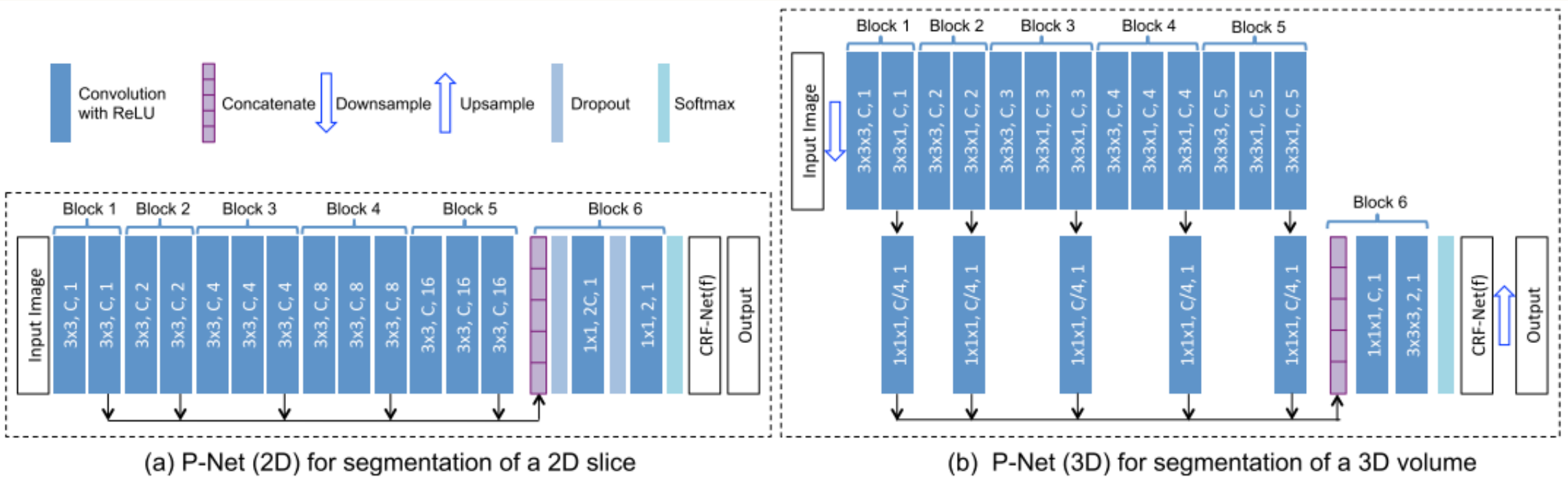
Network structure

- P-Net and R-Net share the same structure
  - Except the number of input channels



(a) P-Net (2D) for segmentation of a 2D slice

(b) P-Net (3D) for segmentation of a 3D volume

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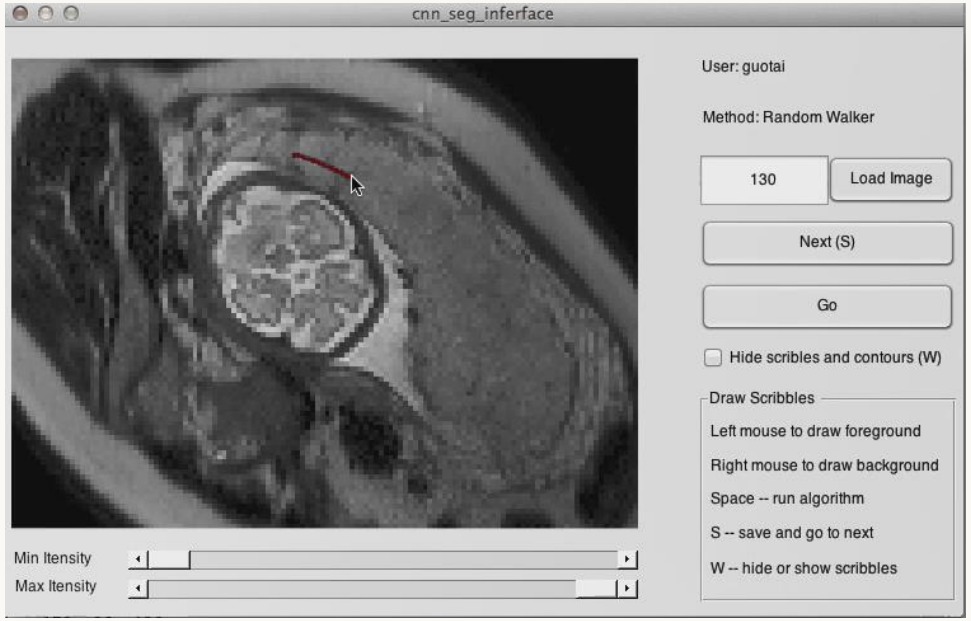
DeepIGeoS: Deep Interactive Geodesic Framework for Segmentation

2D placenta segmentation from fetal MRI

Random Walker (L. Grady, 2006)



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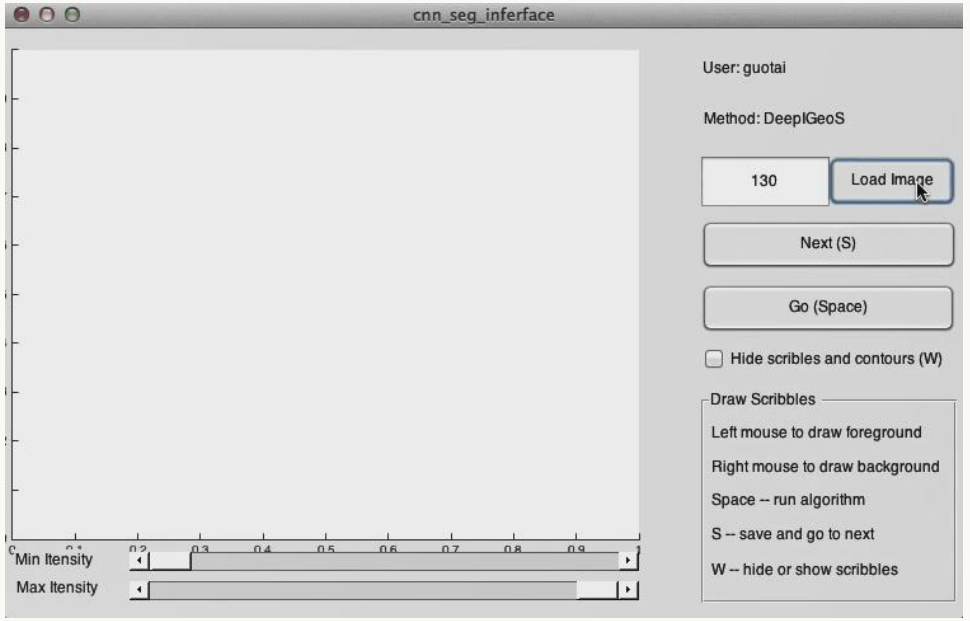

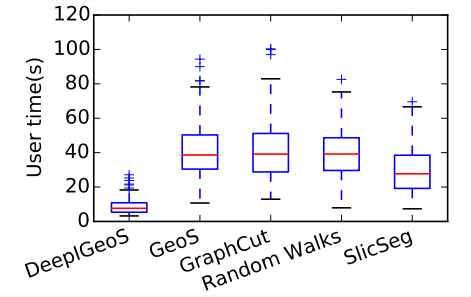

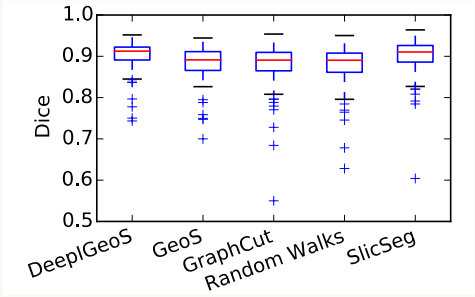

DeepIGeoS is 4-5 times faster than traditional interactive segmentation tools

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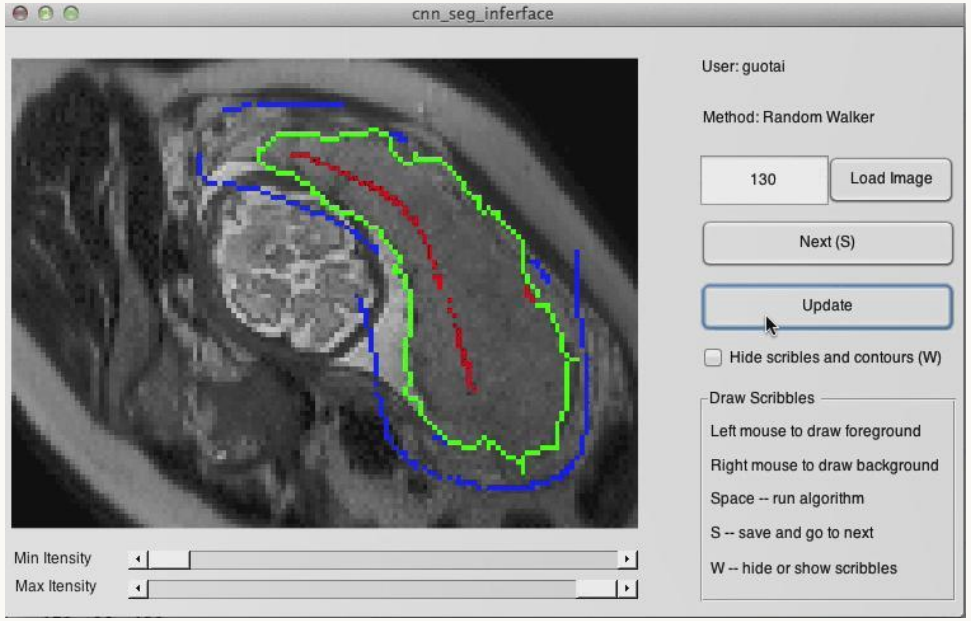

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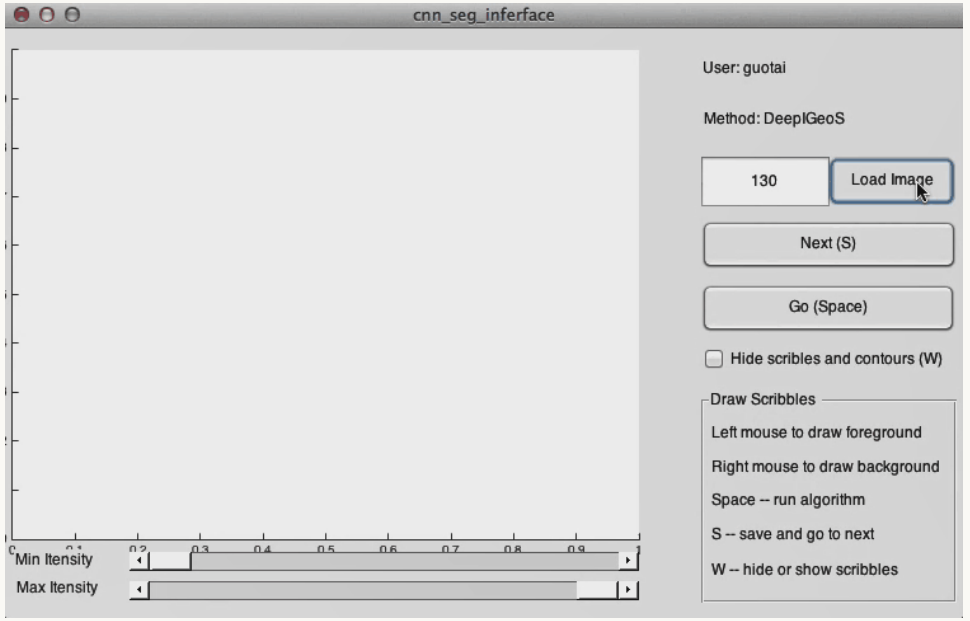

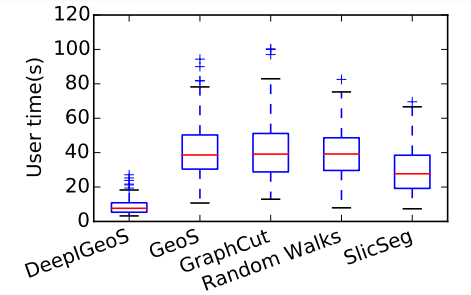

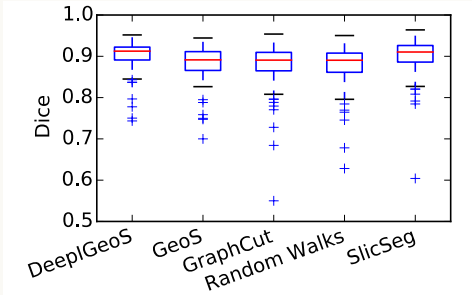

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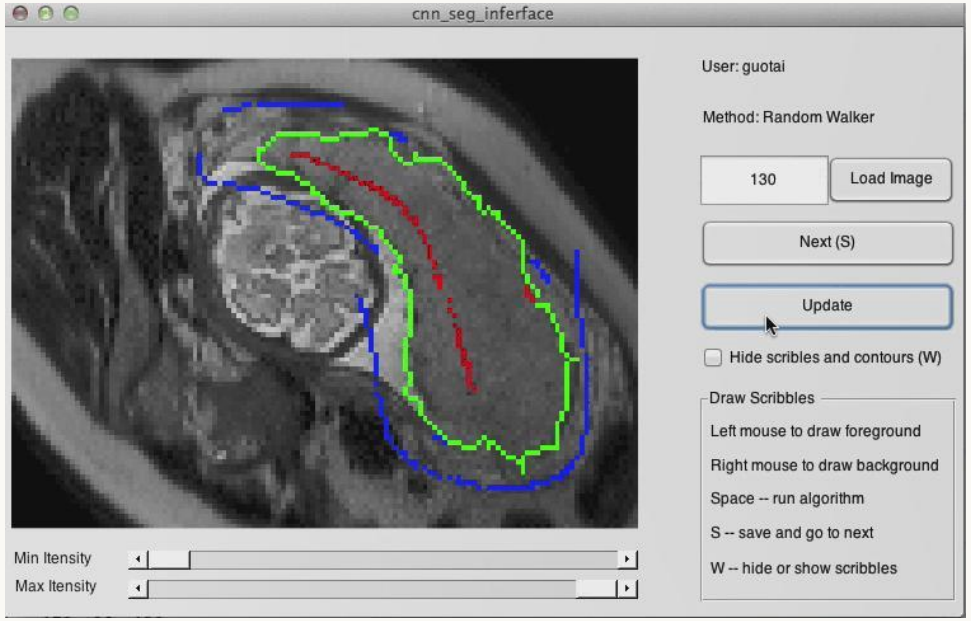

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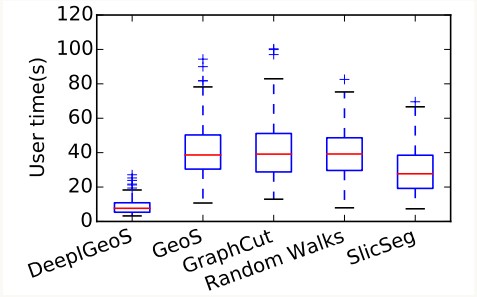

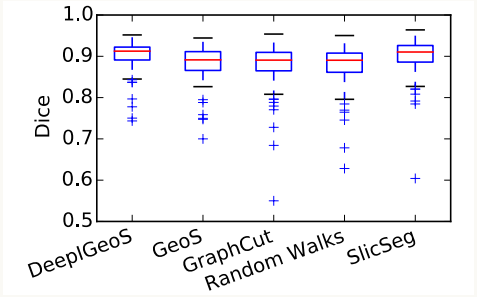

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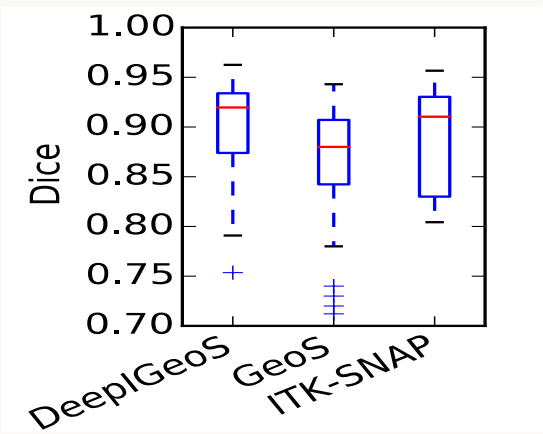
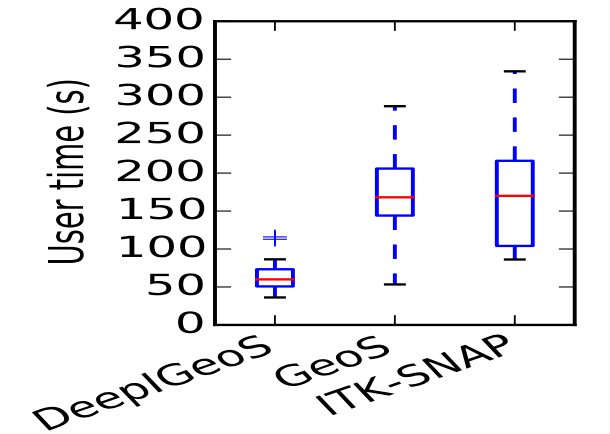
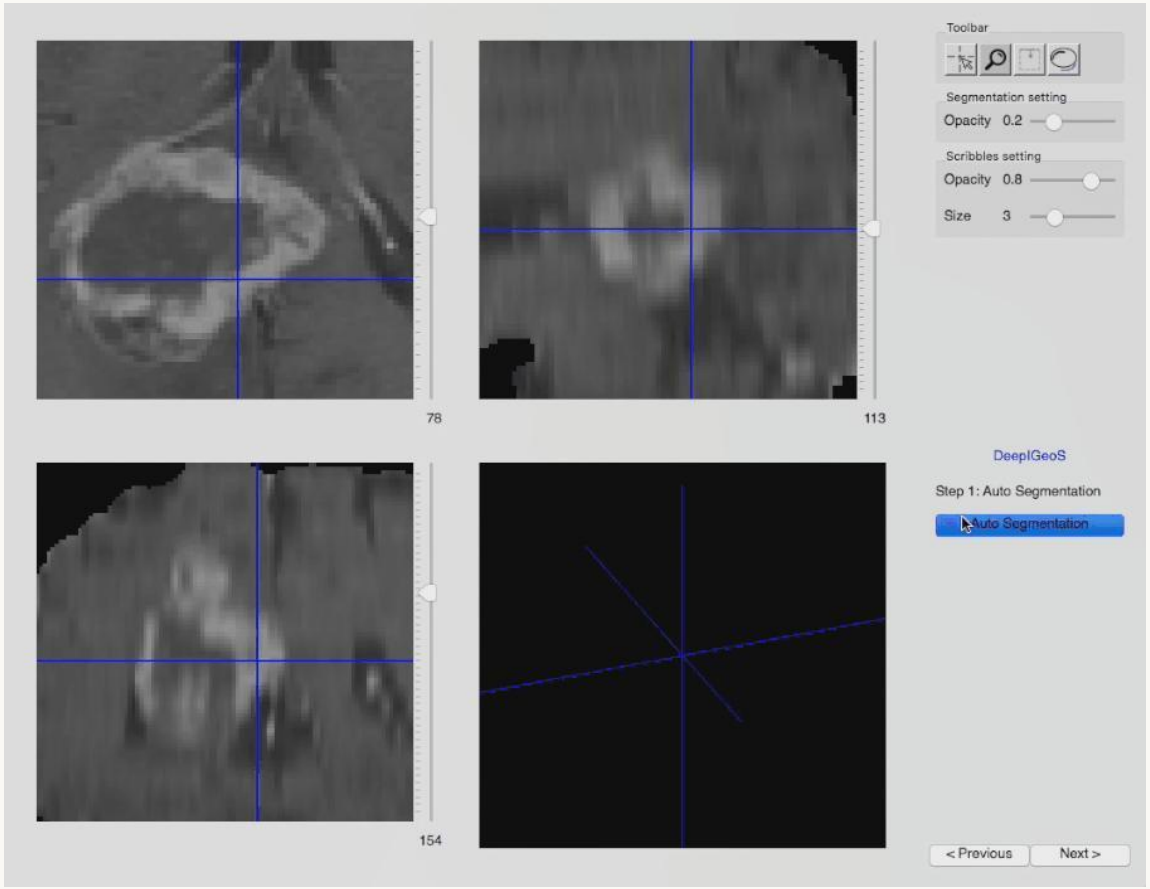
3D brain tumor segmentation from MRI

- Data from BraTS challenge 2015
  - Whole tumor segmentation from FLAIR
  - Training: 234 images
  - Testing: 40 images







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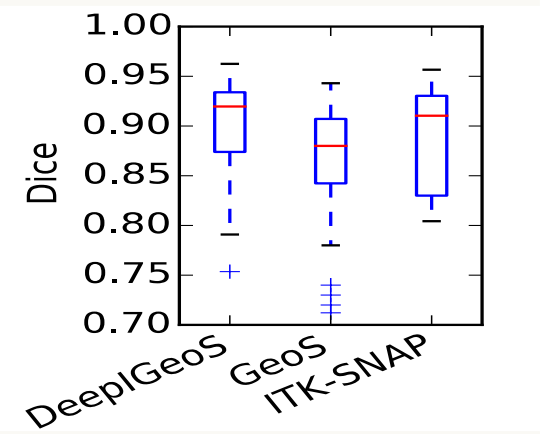

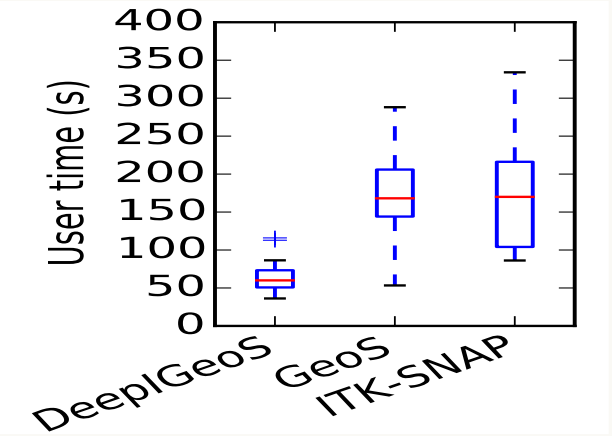

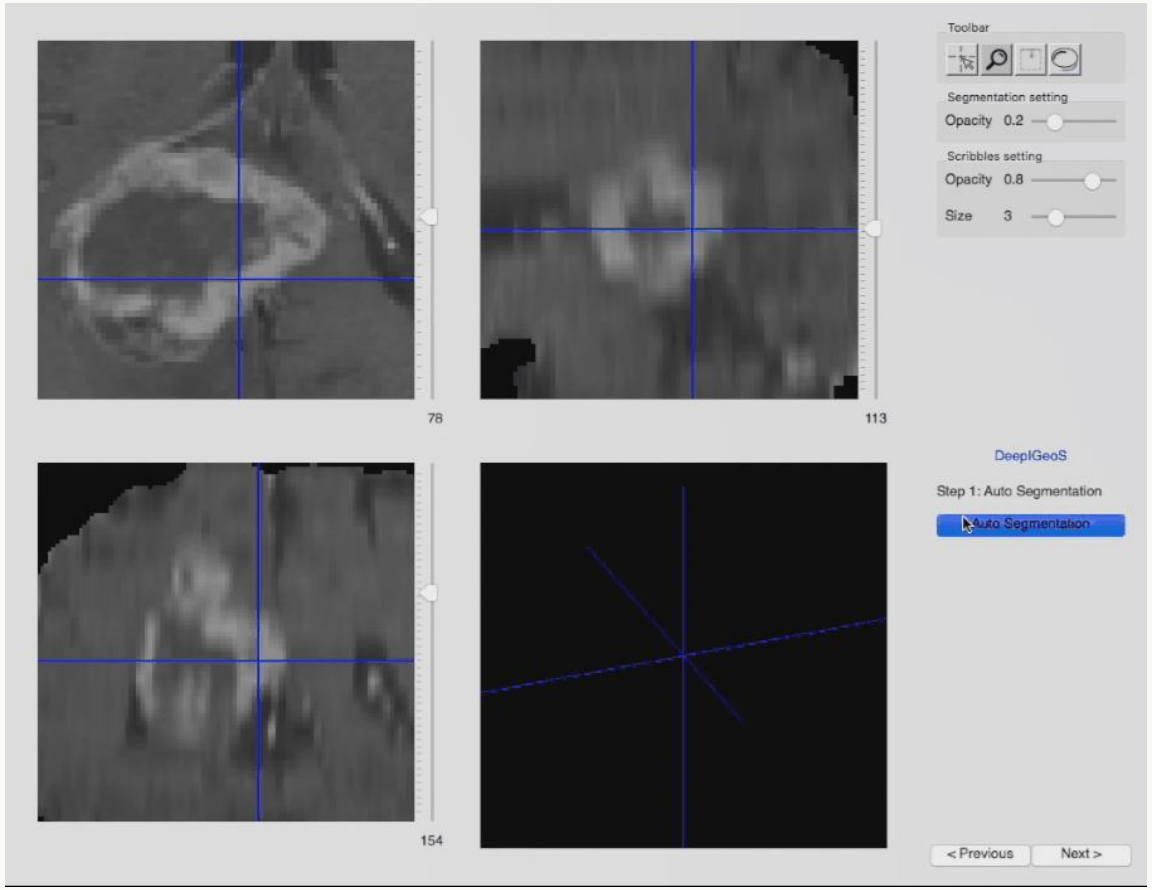

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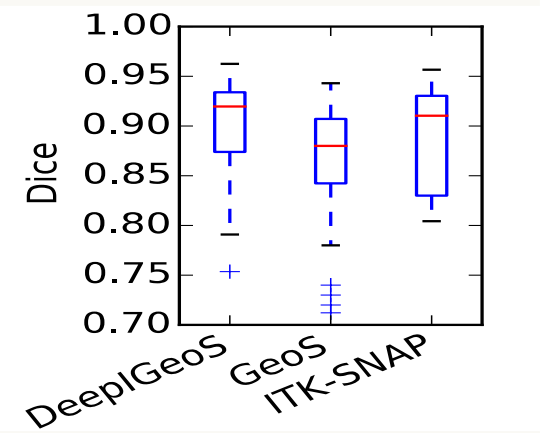
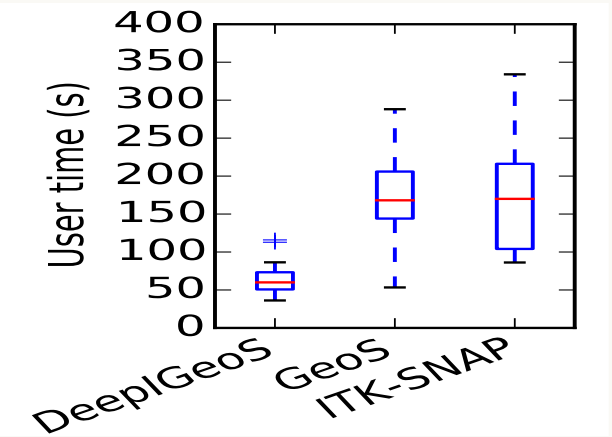
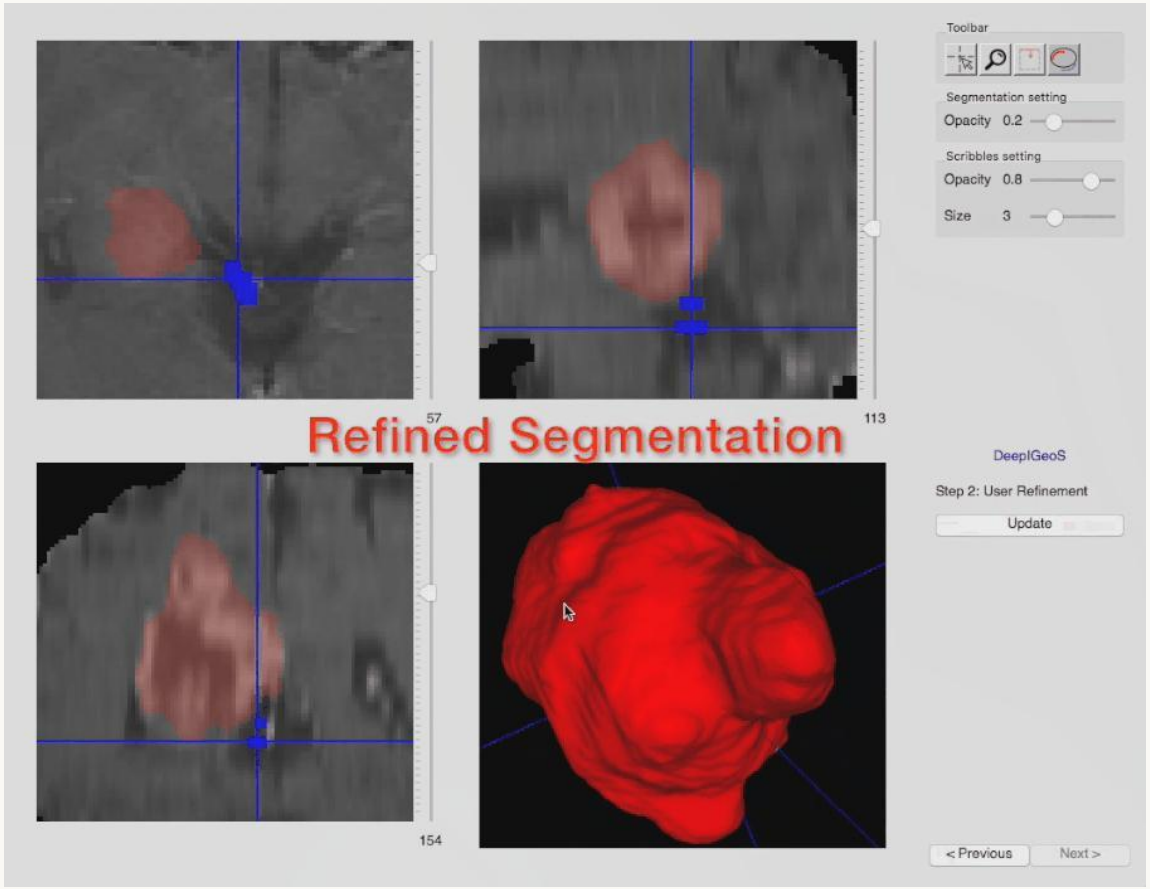
3D brain tumor segmentation from MRI

- Data from BraTS challenge 2015
  - Whole tumor segmentation from FLAIR
  - Training: 234 images
  - Testing: 40 images







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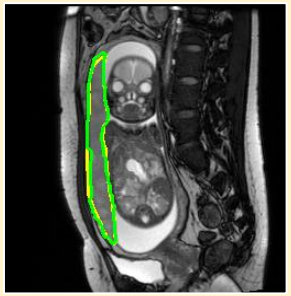
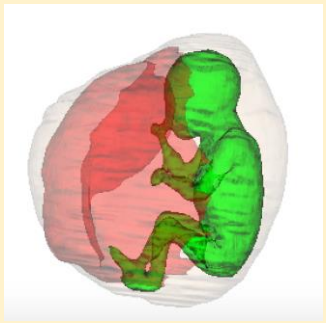
Content

1， Minimally interactive segmentation of the placenta from fetal MRI

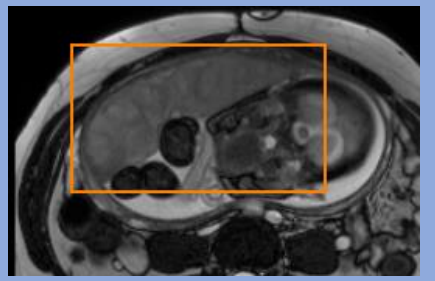




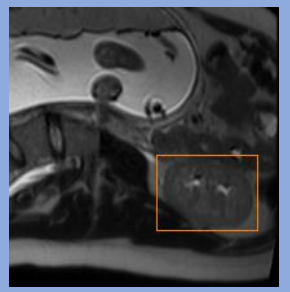
2, Interactive segmentation using deep learning and geodesic distance transform

CNN

3, Image-specific fine-tuning for interactive segmentation



Train

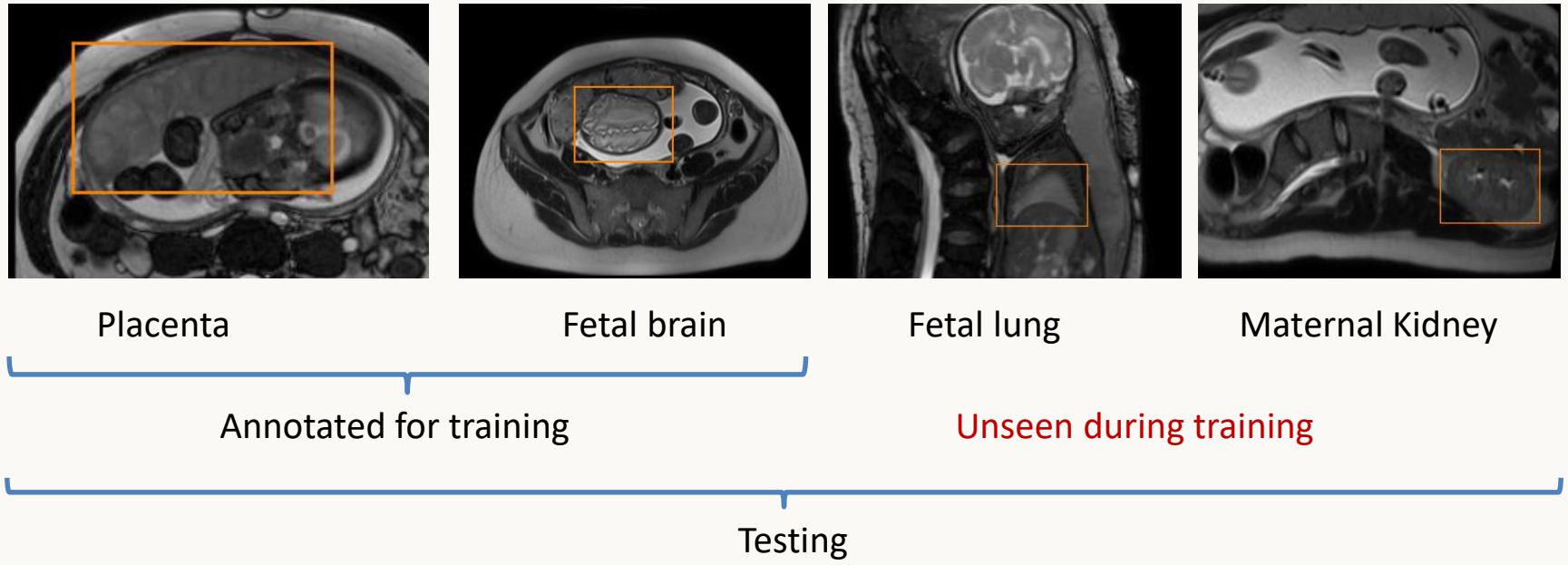


Test

BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

How to segment previously unseen objects?

- Fetal MRI segmentation
  - Multiple-organs
  - Annotation for all organs ?



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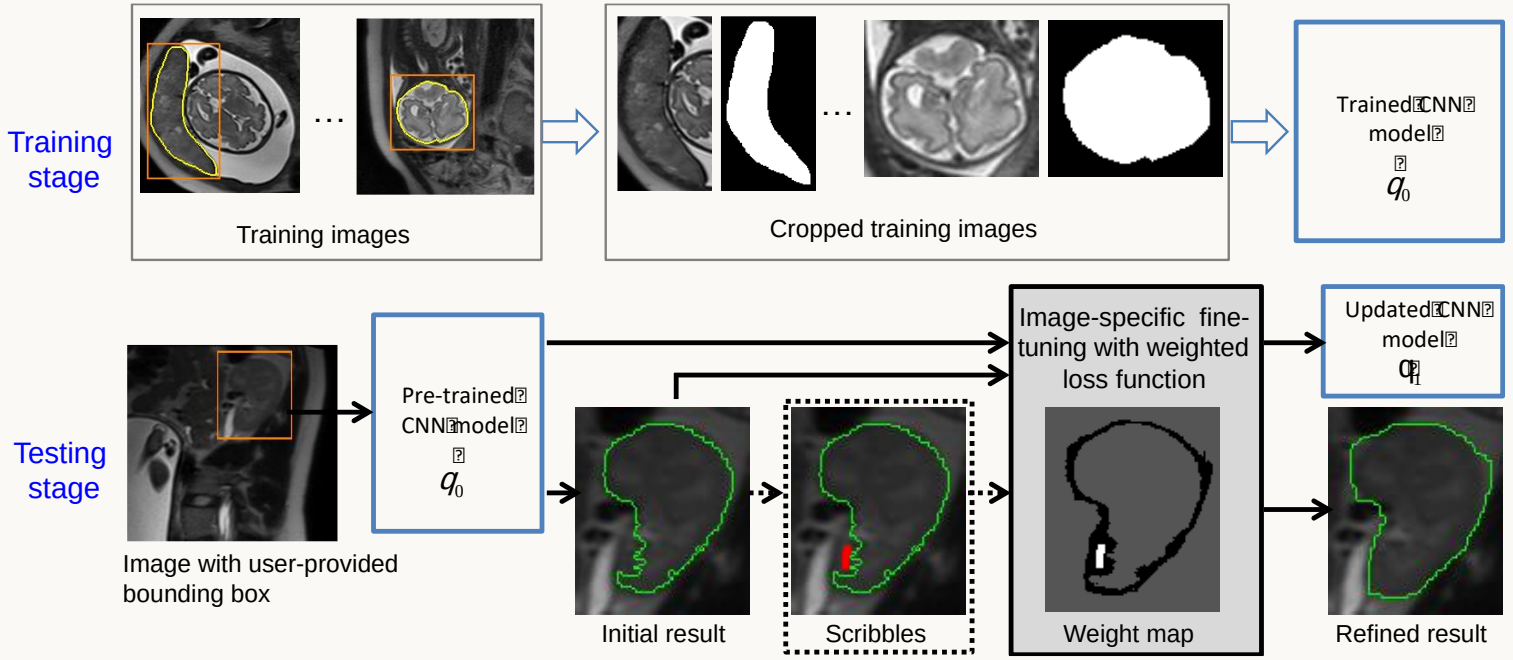
BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

Dealing with unseen objects with image-specific fine-tuning

- Proposed framework
  - 1, Use CNN to get an initial segmentation inside a bounding box
  - 2, Fine-tune the CNN with/without scribbles (supervision)
  - 3, Deal with previously unseen objects



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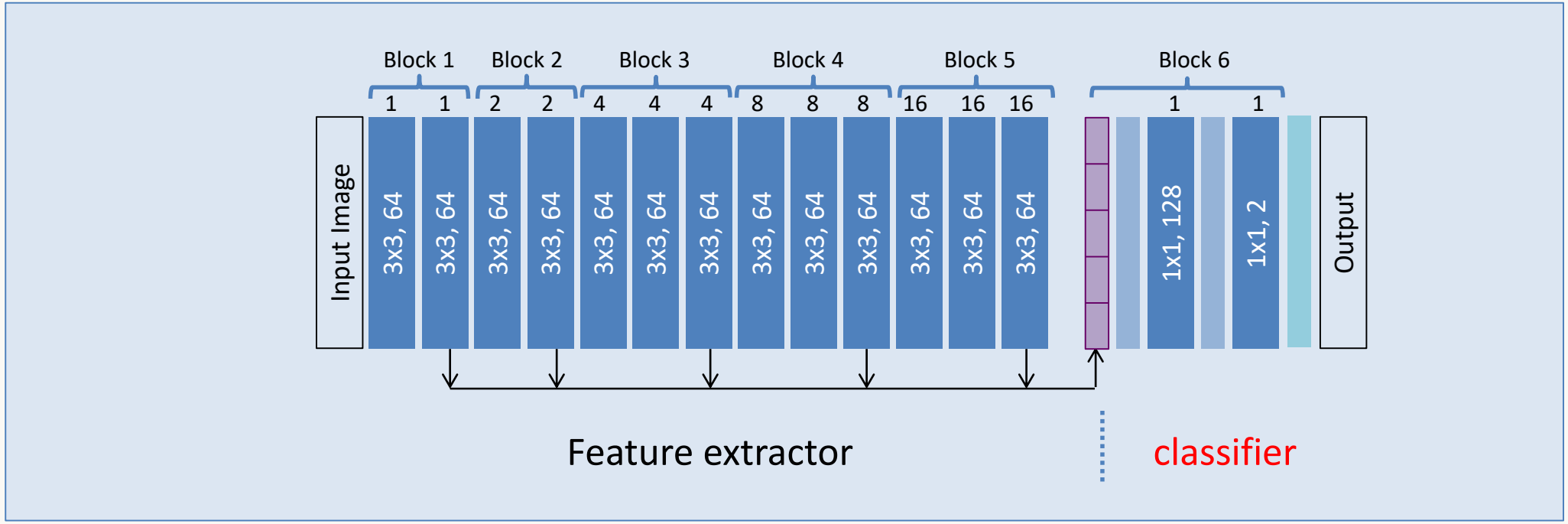
BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

Fine-tuning and image-specific model

- Fine-tuning
  - Feature extractor keep fixed
  - Classifier is fine-tuned towards a specific image
  - Update the model and label



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BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

A uniform framework for supervised and unsupervised fine-tuning

- Joint optimization
  - θ CNN parameters
  - $\hat{Y}$ Segmentation

$$\arg\min_{\hat{Y},\theta}\left\{E(\hat{Y},\theta)=\sum_i \phi(\hat{y}_i|\hat{X},\theta)+\lambda\sum_{i,j}\psi(\hat{y}_i,\hat{y}_j|\hat{X})\right\}$$

$$\text{subject to}: \hat{y}_i = s_i \quad \text{if } i \in S$$

- When θ is fixed

  (Graph Cut problem)

$$\arg\min_{\hat{Y}}\left\{\sum_i \phi'(\hat{y}_i|\hat{X},\theta)+\lambda\sum_{i,j}\psi(\hat{y}_i,\hat{y}_j|\hat{X})\right\}$$

$$\phi'(\hat{y}_i|\hat{X},\theta)=\begin{cases}+\infty & \text{if } i\in S \text{ and } \hat{y}_i \neq s_i\\ 0 & \text{if } i\in S \text{ and } \hat{y}_i = s_i\\ -\log P(\hat{y}_i|\hat{X},\theta) & \text{otherwise}\end{cases}$$

- When $\hat{Y}$ is fixed

  (Back propagation)

$$\arg\min_{\theta}\left\{-\sum_i\Big(\hat{y}_i\log p_i+(1-\hat{y}_i)\log(1-p_i)\Big)\right\}$$

Iterative update

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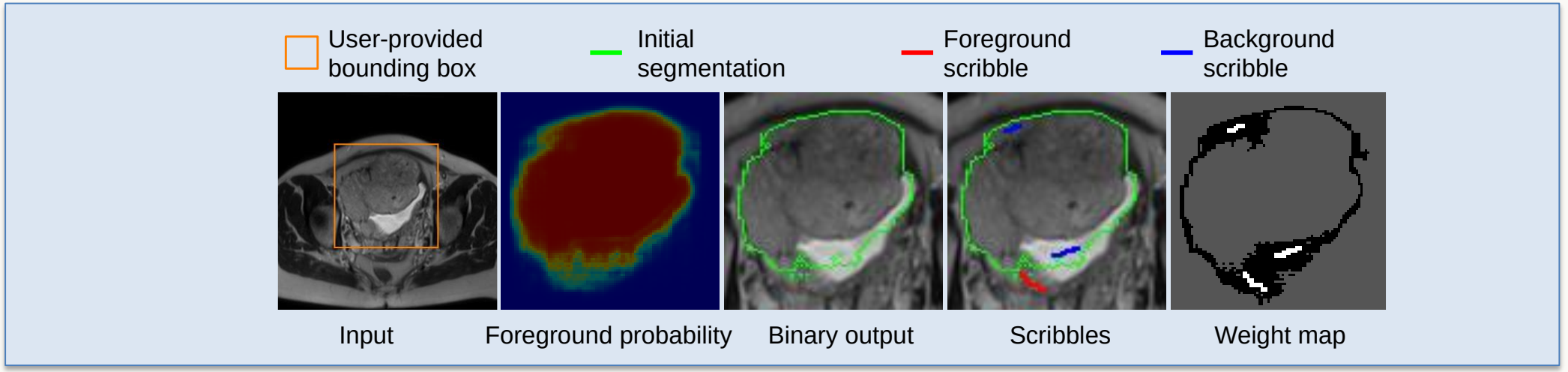
BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

Weighted loss function for fine-tuning

- Update the model based on current segmentation
  - Need to reduce the impact of mis-labeled pixels

- Pixels with different confidence
  - Network-based confidence
  - Interaction-based confidence

$$\arg\min_{\theta}\left\{-\sum_{i} w(i)\Big(\hat{y}_i \log p_i + (1-\hat{y}_i)\log(1-p_i)\Big)\right\}$$



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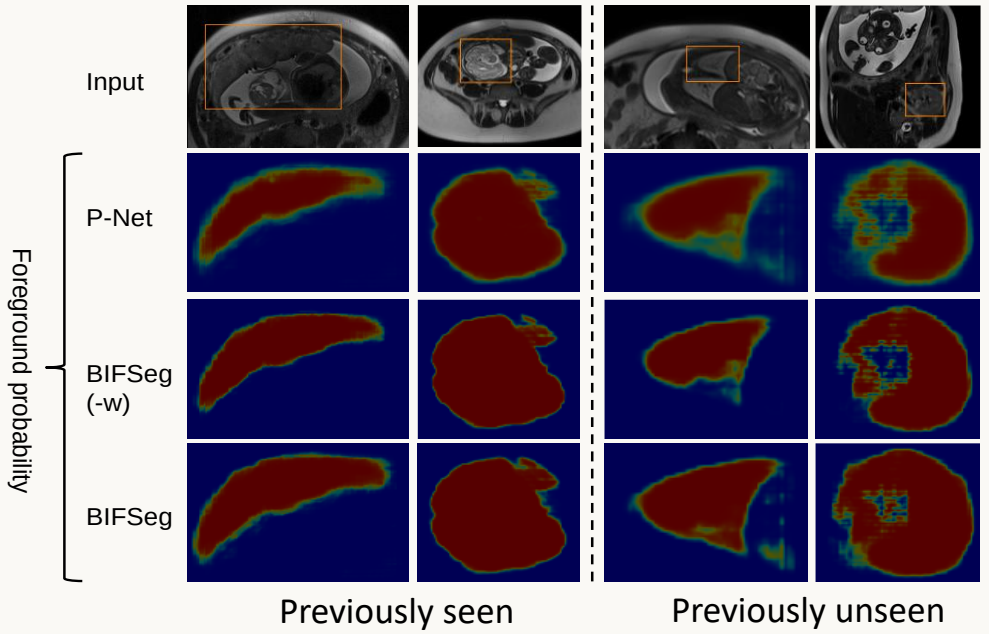
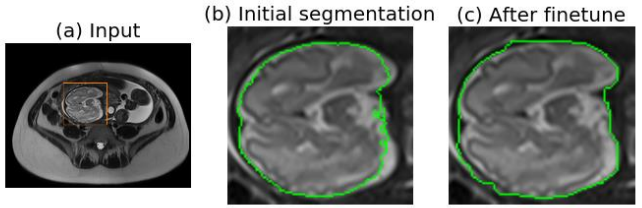
BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

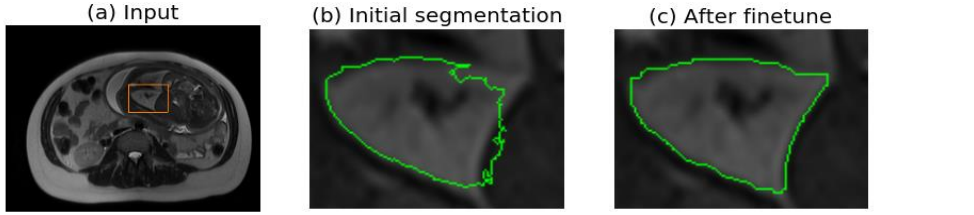
2D segmentation of multiple organs from fetal MRI

- Unsupervised Fine-tuning
  - No additional user interactions provided

	Train	Test
Placenta	√	√
Fetal brain	√	√
Fetal lungs		√
Maternal kidneys		√
Patient number	10	6







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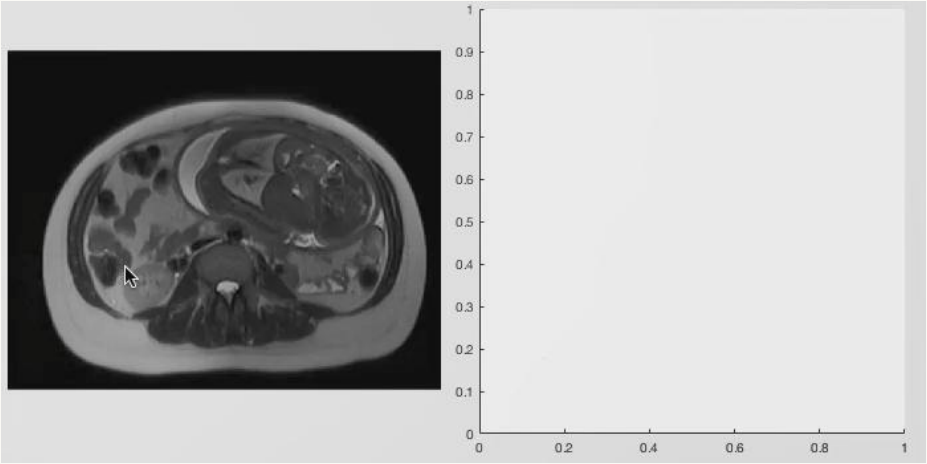
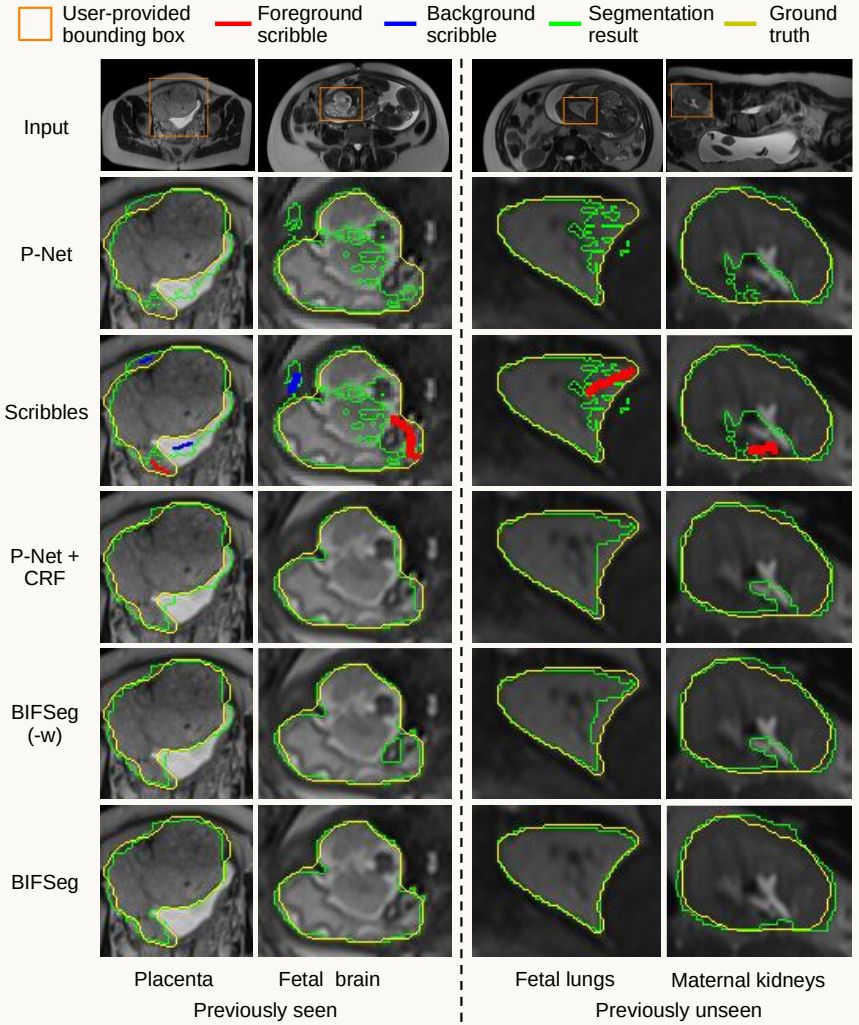
BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

2D segmentation of multiple organs from fetal MRI

- Supervised Fine-tuning
  - Guided by scribbles
  - Only few interactions
  - Real-time update

Segmentation of previously unseen kidney





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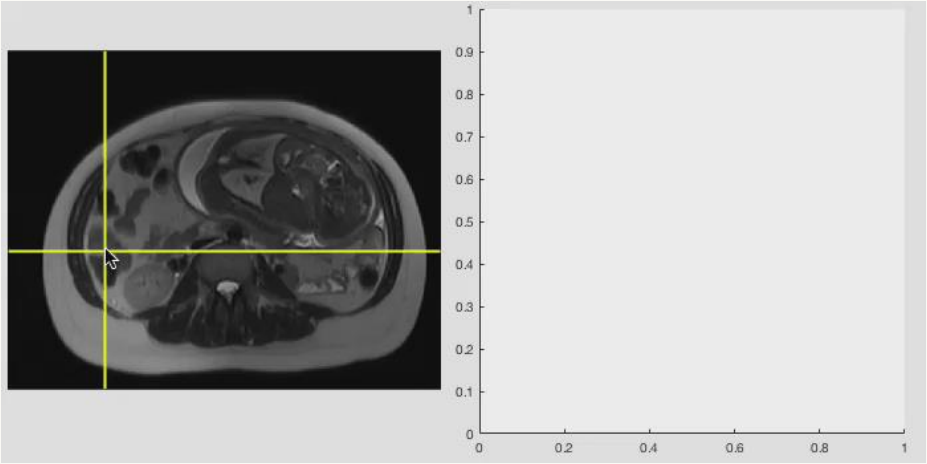

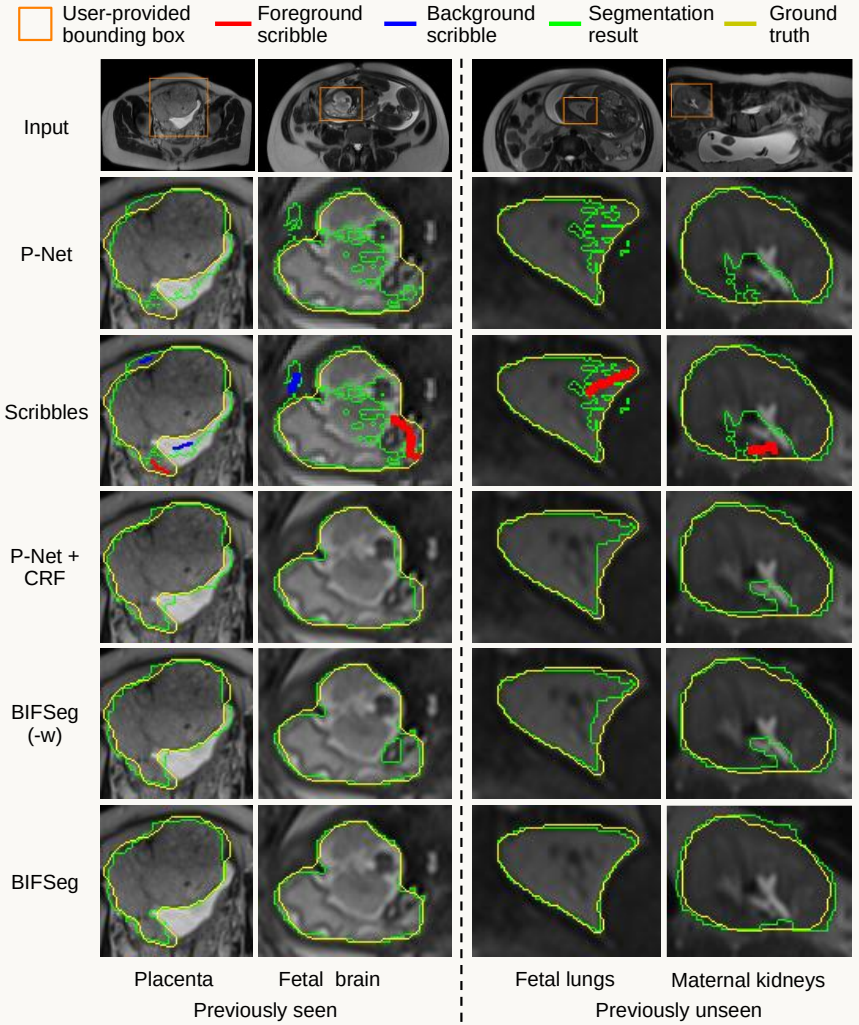

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BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

2D segmentation of multiple organs from fetal MRI

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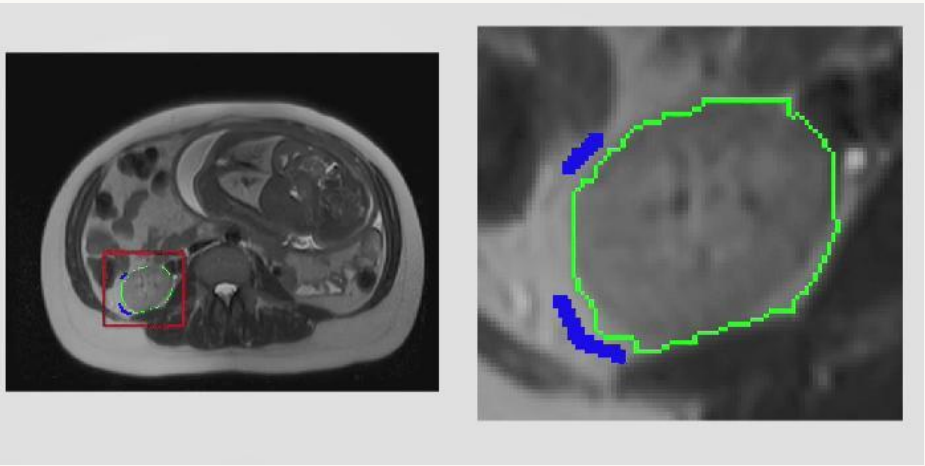
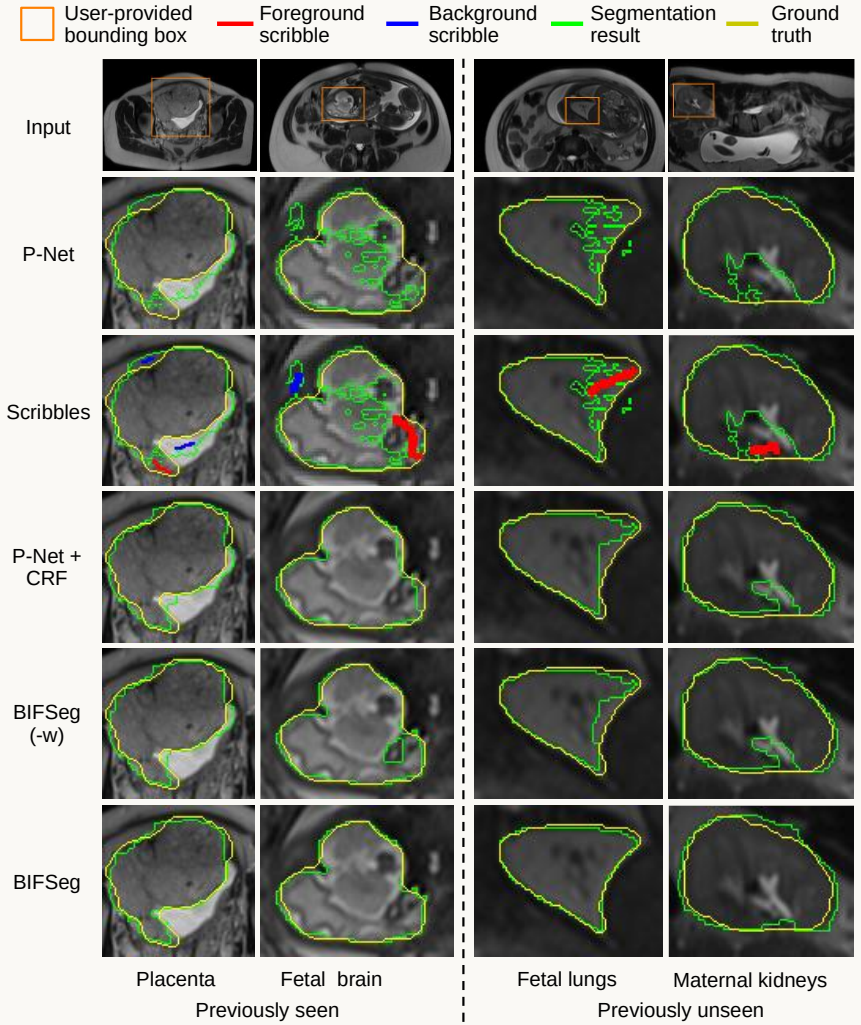
Segmentation of previously unseen kidney





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BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

2D segmentation of multiple organs from fetal MRI

- Quantitative evaluation

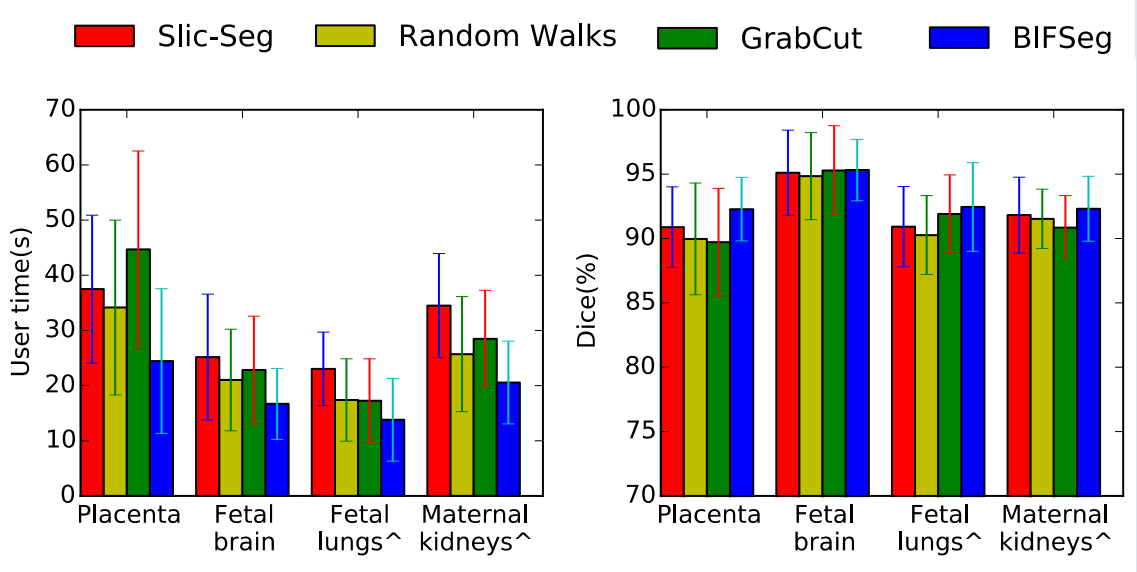
Dice score of different objects

TABLE II
QUANTITATIVE COMPARISON OF P-NET AND THREE UNSUPERVISED REFINEMENT METHODS FOR FETAL MRI SEGMENTATION. T_m IS THE MACHINE TIME FOR REFINEMENT. ^ DENOTES PREVIOUSLY UNSEEN OBJECTS. IN EACH ROW, BOLD FONT DENOTES THE BEST VALUE. * DENOTES p-VALUE < 0.05 COMPARED WITH THE OTHERS.

		P-Net	P-Net+CRF	BIFSeg(-w)	BIFSeg
Dice (%)	P	84.57±8.37	84.87±8.14	82.74±10.91	**86.41±7.50***
	FB	89.44±6.45	89.55±6.52	89.09±8.08	**90.39±6.44**
	FL^	83.59±6.42	83.87±6.52	82.17±8.87	**85.35±5.88***
	MK^	85.29±5.08	85.45±5.21	84.61±6.21	**86.33±4.28***
T_m (s)		-	**0.02±0.01***	0.71±0.12	0.72±0.12

P: Placenta, FB: Fetal brain, FL: Fetal lungs, MK: Maternal kidneys.

Comparison with traditional methods



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BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

3D segmentation of brain tumor from MRI

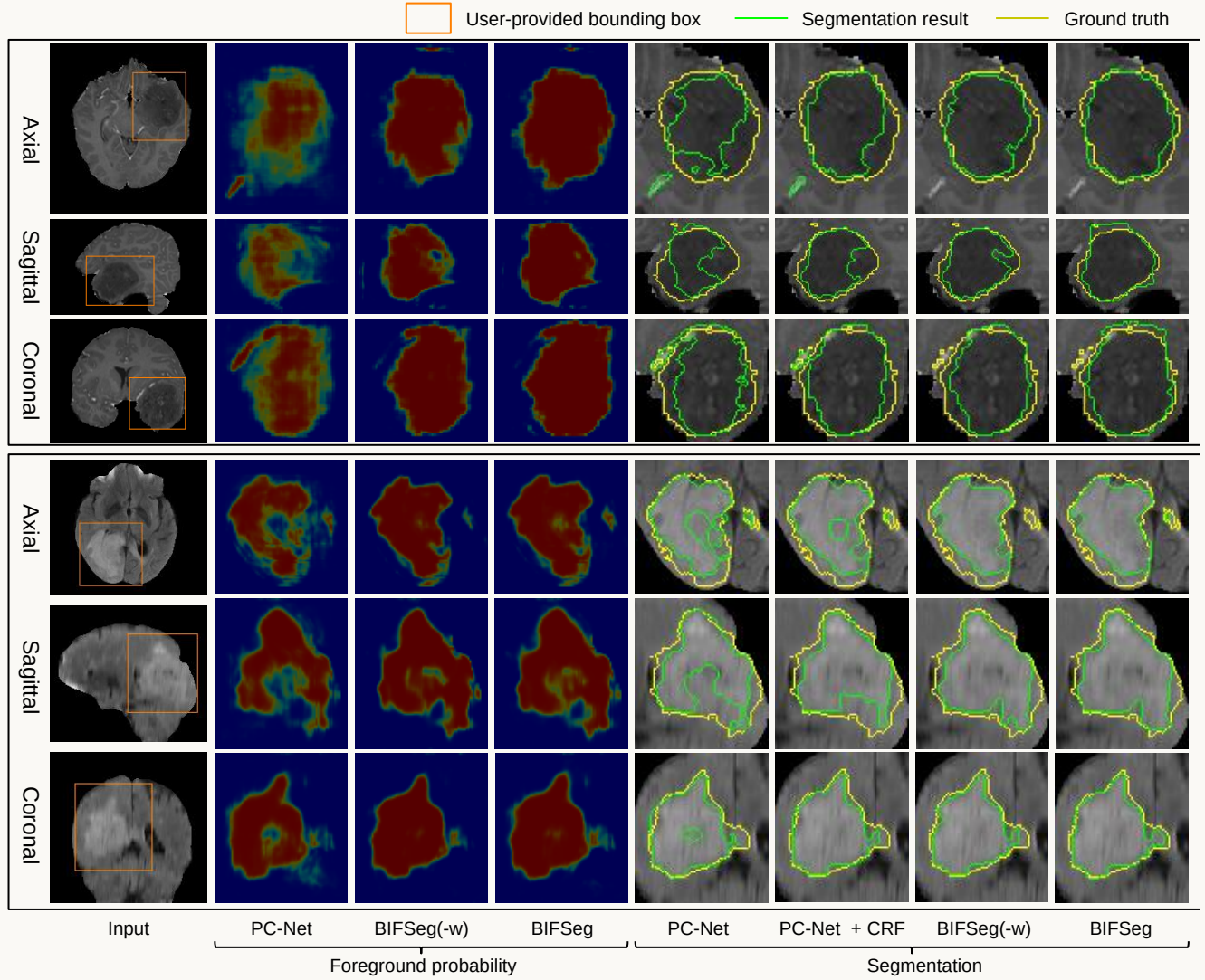
- Data
  - T1ce: tumor core (train and test)
  - Flair: whole tumor (test only)
- Unsupervised fine-tuning
  - No interactions provided

TABLE V

QUANTITATIVE COMPARISON OF PC-NET AND UNSUPERVISED REFINEMENT METHODS WITHOUT ADDITIONAL SCRIBBLES FOR 3D BRAIN TUMOR SEGMENTATION. T_m IS THE MACHINE TIME FOR REFINEMENT. $\wedge$ DENOTES PREVIOUSLY UNSEEN OBJECTS. IN EACH ROW, BOLD FONT DENOTES THE BEST VALUE. * DENOTES p-VALUE < 0.05 COMPARED WITH THE OTHERS.

		PC-Net	PC-Net+CRF	BIFSeg(-w)	BIFSeg
Dice (%)	TC	82.66±7.78	84.33±7.32	84.67±7.44	**86.13±6.86***
	WT$^\wedge$	83.52±8.76	83.92±7.33	83.88±8.62	**86.29±7.31***
T_m(s)	TC	-	**0.12±0.04***	3.36±0.82	3.32±0.82
	WT$^\wedge$	-	**0.11±0.05***	3.16±0.89	3.09±0.83

TC: Tumor core in T1c, WT: Whole tumor in FLAIR.



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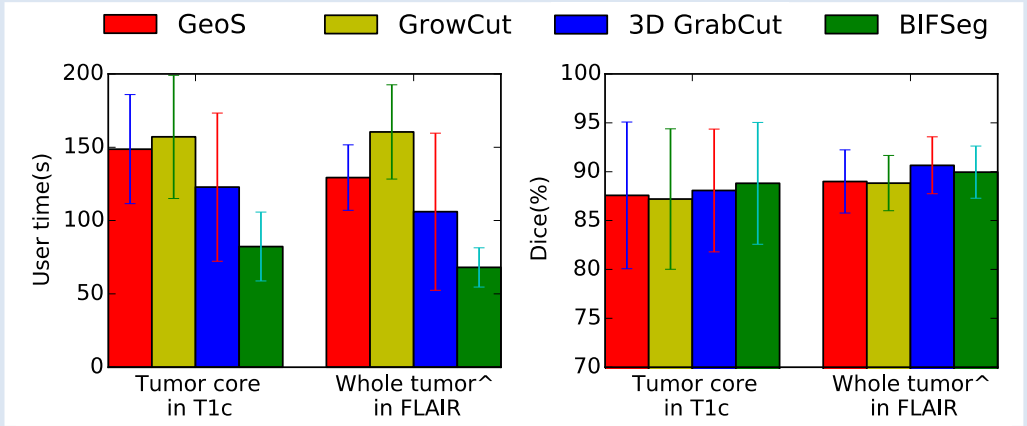
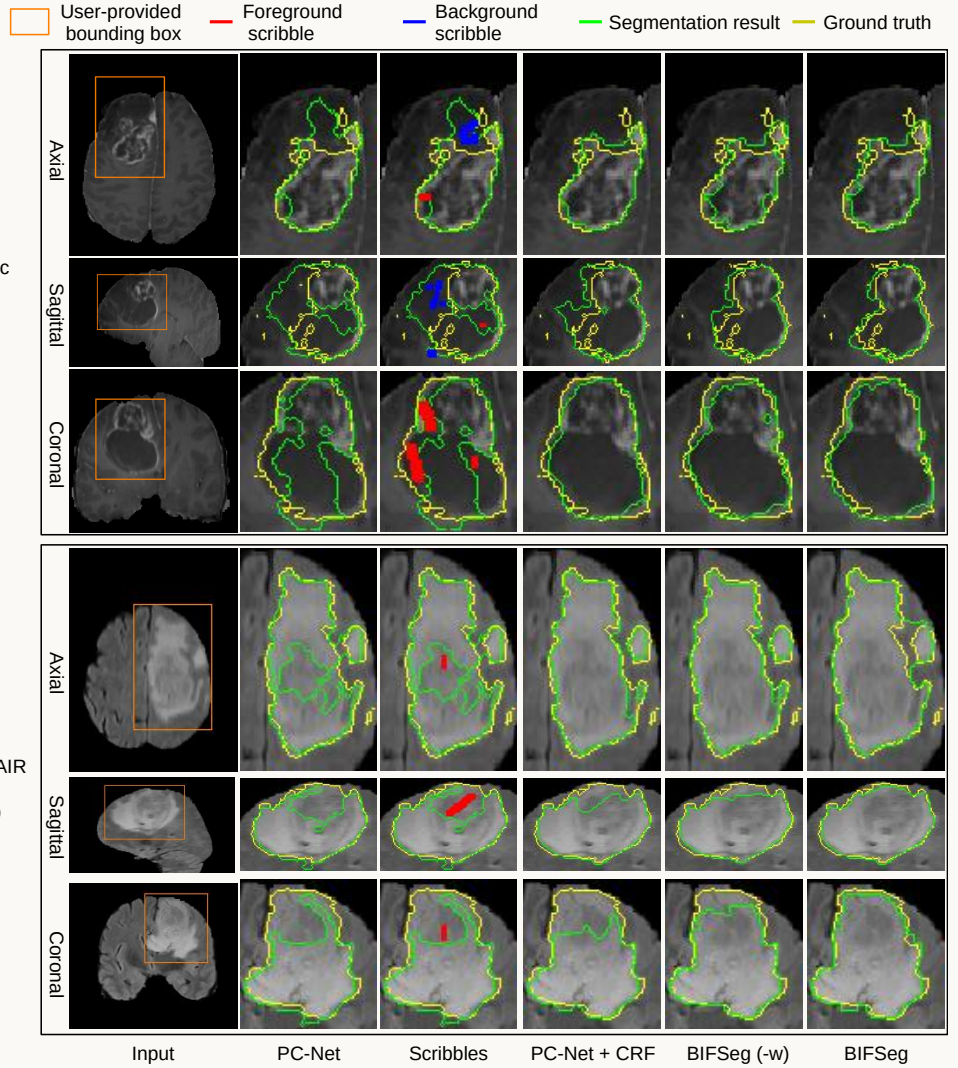
BIFSeg: Segmentation by Bounding Box + Image-Specific Fine-Tuning

3D segmentation of brain tumor from MRI

- Supervised fine-tuning
  - Guided by scribbles for refinement

Comparison with traditional methods





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Conclusion

- Using deep learning for interactive segmentation is promising
  - Outperforms traditional interactive segmentation methods
  - High accuracy and fast
  - Only few interactions needed

- Future works
  - Segment previously unseen modality
  - Intelligent guidance for user interactions

Thanks

Q&A