Iteratively-Refined Interactive Medical Image Segmentation with Multi-Agent Reinforcement Learning

2019/9/24

Motivation

- Existing automatic segmentation methods usually cannot achieve a satisfactory performance.

- Current two-stage works usually ignore the relationship between the current prediction and previous predictions.

Contributions

- A novel voxel-wise interactive segmentation algorithm framework based on multi-agent RL for medical images.

- A reservation scheme for the prediction uncertainty via the segmentation probability.

- The segmentation is significantly improved over the iteration sequence with only a few interactions and a rapid convergence.

Background

- Usage of hints

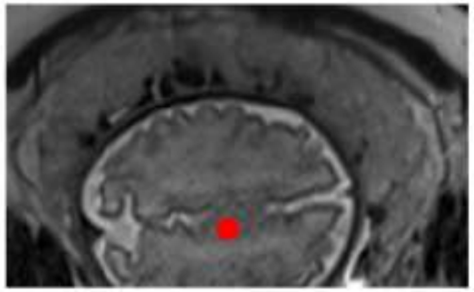
- Every step contains two hint maps:

$$\boldsymbol{h}^{(t)} = [\boldsymbol{h}_{+}^{(t)}, \boldsymbol{h}_{-}^{(t)}].$$

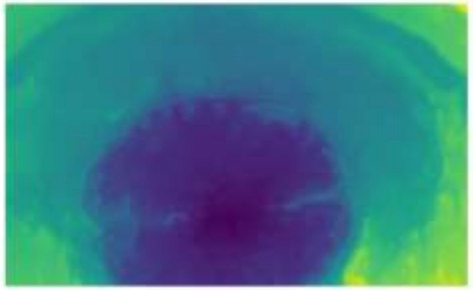
$$\boldsymbol{h}_{l}^{(t)} = (h_{l,1}^{(t)}, \cdots, h_{l,N}^{(t)}).$$

$$h_{l,i}^{(t)} = \min_{\forall x_j \in hs_l^{(t)}} Dist(x_i, x_j),\ l \in \{+, -\}$$

(a) input image
with a seed point



(b) Geodesic distance
based on fast marching



Background

- PixelRL
  - The objective of the pixelRL problem is to learn the optimal policies $\boldsymbol{\pi} = (\pi_1, \cdots, \pi_N)$ that maximize the mean of the total expected rewards at all pixels:

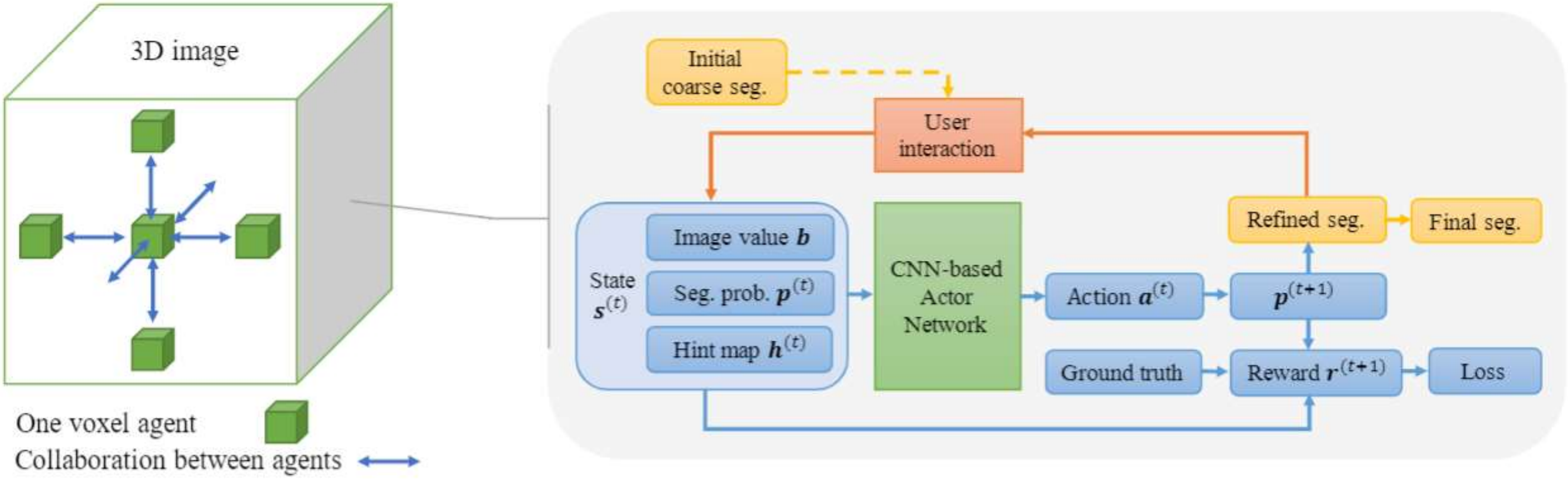
$$
\begin{aligned}
\boldsymbol{\pi}^* &= \underset{\boldsymbol{\pi}}{\operatorname{argmax}}\, E_{\boldsymbol{\pi}} \left(\sum_{t=0}^{\infty} \gamma^t \overline{r}^{(t)} \right), \\
\overline{r}^{(t)} &= \frac{1}{N} \sum_{i=1}^{N} r_i^{(t)},
\end{aligned}
$$

  - By using the FCN, all the N agents can share the parameters, and we can parallelize the computation of N agents on a GPU.

  - The FCN is optimized by :

$$
\begin{aligned}
R_i^{(t)} &= r_i^{(t)} + \gamma V(s_i^{(t+1)}), \\
d\theta_v &= \nabla_{\theta_v} \frac{1}{N} \sum_{i=1}^{N} \left(R_i^{(t)} - V(s_i^{(t)}) \right)^2 \qquad d\theta_p = -\nabla_{\theta_p} \frac{1}{N} \sum_{i=1}^{N} \log \pi(a_i^{(t)} | s_i^{(t)}) A(a_i^{(t)}, s_i^{(t)}).
\end{aligned}
$$

Framework overview



Design of State, Action and Reward

- States

$$s_i^{(t)} = [b_i^{(t)}, p_i^{(t)}, h_{+,i}^{(t)}, h_{-,i}^{(t)}]$$

- Action

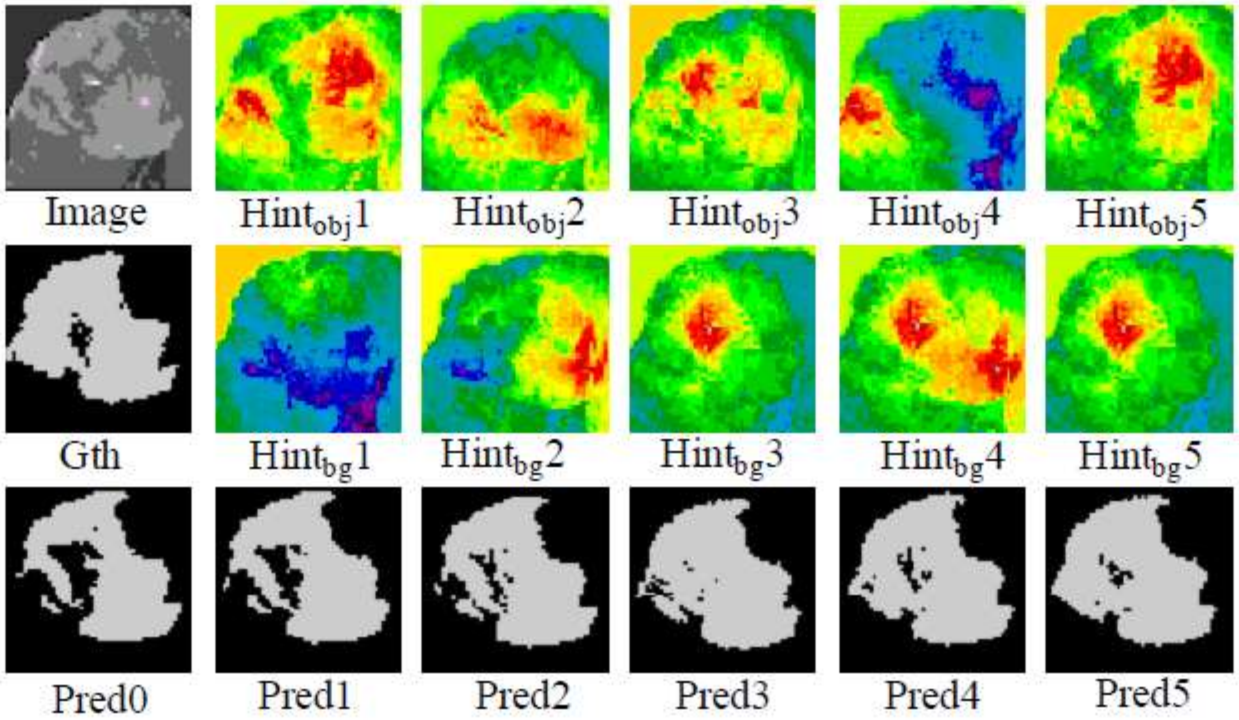
$$A = \{A_k\} \ (k = 1, 2, \cdots, K)$$

- Reward

$$r_i^{(t)} = X_i^{(t-1)} - X_i^{(t)}$$

$$X_i^{(t)} = -y_i \log(p_i^{(t)}) - (1 - y_i) \log(1 - p_i^{(t)})).$$

Experiments



The visualization of prediction and hint map for each step. The figures in the first column are [Image, Ground truth, Initial prediction]. Afterwards, each column forms one step, which corresponds to [Object hint map, Background hint map, Prediction]

Experiments

Update \ Initial	BG	V-Net	HighRes3DNet	DeepIGeoS(P-Net)
Initial	0	77.15	75.39	82.16
Min-cut	27.46	80.69	77.05	84.08
DeepIGeoS(R-Net)	82.97	85.80	85.72	84.83
InterCNN	85.17	85.56	87.29	86.54
IteR-MRL	**86.14**	**88.53**	**87.43**	**87.50**