Structure Boundary Preserving Segmentation for Medical Image with Ambiguous Boundary

Hong Joo Lee te al., CVPR, 2020

Shin Yoo Seung

usxxng@korea.ac.kr

Department of Artificial Intelligence,
Korea University

Apr. 05, 2022

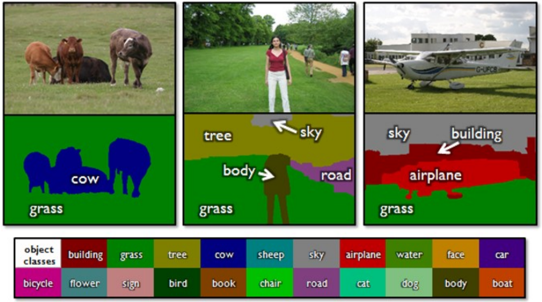
Contents

Machine Intelligence Lab

Introduction

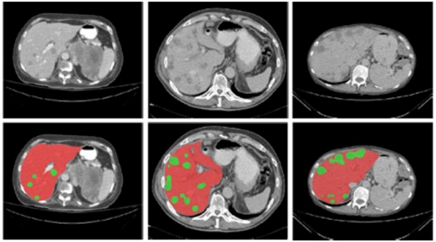
Image Segmentation

- Image Segmentation Networks aim to classify individual pixels constituting an image.
- Produce the predicted result by indicating the label value corresponding to the pixel.



Introduction

- For many medical image processing applications, it is an important key to success for the models to correctly segment anatomical structures in the medical image domain.
- Many convolutional neural networks (CNNs)-based segmentation approaches have been proposed to accurately segment the target object both in the natural and medical image domain.



Machine Intelligence Lab

Introduction

- However, it is challenging to obtain accurate segmentation results because of the ambiguity of structure boundary, heterogeneous texture and the uncertainty of the segmented region without domain knowledge.
- To deal with the ambiguous structure boundary issue, a few approaches have been reported.
  - But, these methods need manual parameter tuning as post-processing, which is labor-intensive tasks, and the results are affected by parameter tuning.
- To overcome this limitation, interactive or semi-automatic segmentation methods have been proposed where ambiguous structure boundary is dealt with interactively during test time.
- The interactive segmentation methods employ user inputs such as points, bounding boxes to segmentation network.
  - However, the interaction approaches require user interaction time and specialized domain knowledge.

Introduction

- In this paper, researchers focus on tackling the following two segmentation problems raised by medical image domain.
  - First, most of the medical images in application contain ambiguous boundaries because of poor image quality and heterogeneous textures.
  - Second, it is difficult to automatically predict the correct target region without knowledge of experts such as melanocytic lesions in ultrasound image.
- Researchers propose a novel fully automatic medical image segmentation framework that preserves structure boundary of target region.

Introduction

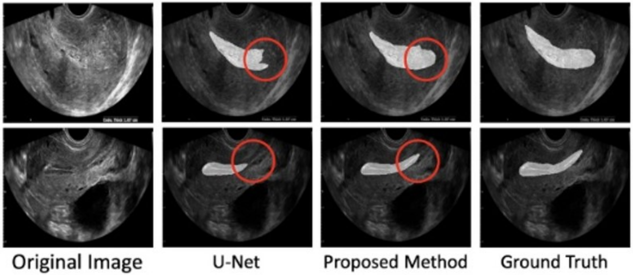


Figure 1. Results of automatic segmentation methods on medical images with the ambiguous structure boundary and heterogeneous texture image. Note that these segmentation results by U-Net have failed in preserving structure boundary.

Machine Intelligence Lab

Related Works

- **Automatic Medical Image Segmentation**
  - Fully Convolution Network (FCN) is one of the most widely used segmentation networks both on natural image and medical image. The FCN consists of consecutive convolution and max-pooling layers.
    - Roth et al. applied FCN networks cascaded way for medical image segmentation.
    - Vorontsov et al. used two types of FCNs for liver and liver lesion segmentation.
  - U-Net utilized the encoder features to decoder features by skip connections. Since the encoder feature information is transferred to decoder, it shows comparable performance in medical image segmentation.
    - Dalm et al. proposed 2 and 3 consecutive U-Nets for breast mass segmentation.

- Although these approaches have achieved reasonable segmentation results in medical image segmentation, it still has problems for preserving boundary.

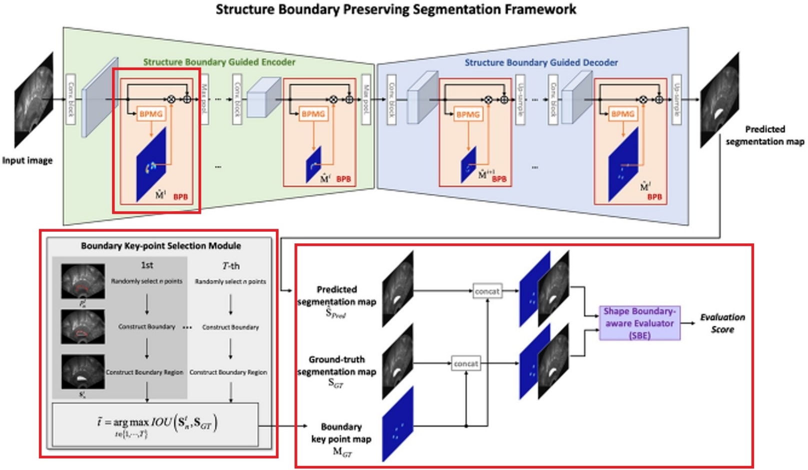
Related Works

- **Interactive Medical Image Segmentation**
  - In medical image segmentation, interactive segmentation shows great performance since it encodes the experts knowledge to segmentation network with several interactions.
    - Rajchl et al.trained the CNNs network by employing user-provided inputs.
    - Wang et al. proposed deep learning-based interactive segmentation method. They employed structure boundary information to the segmentation network.
- Although these approaches showed superior results by employing user interaction, they still need to interact with the experts at inference time.

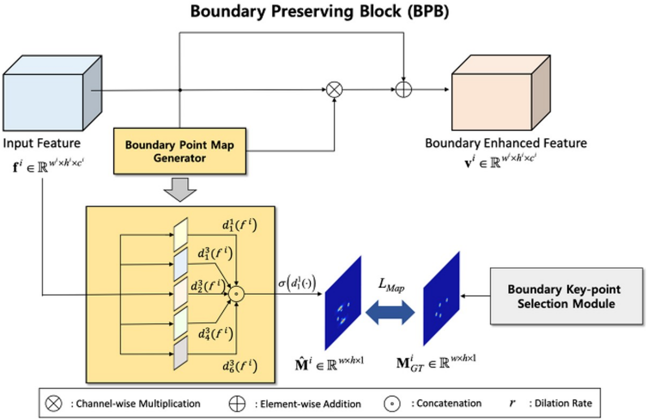
Contribution

- Researchers proposed a novel boundary key point selection algorithm that best fit the target region. The selected key points putting on the structure boundary of target region are encoded through the BPB with boundary key point map generator.
- In the proposed framework, they employ boundary key point information automatically without the user interaction. To this end, they trained the segmentation network in an adversarial way with SBE. The evaluator gives feedback to segmentation network whether given segmented region coincidences with boundary key points or not.
- To evaluate the generalization ability of the BPB and SBE, they integrate our approach with three recent state-of-the-art segmentation models, U-Net, FCN, Dilated-net. They demonstrate that the proposed method improves the prediction performance with statistical significance.

Methodology



Methodology

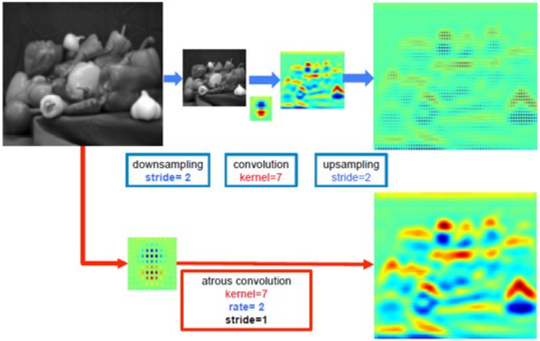


Machine Intelligence Lab

Methodology

Dilated Convolution

- Add zero padding inside the filter to force the receive field to increase the operation.



Machine Intelligence Lab

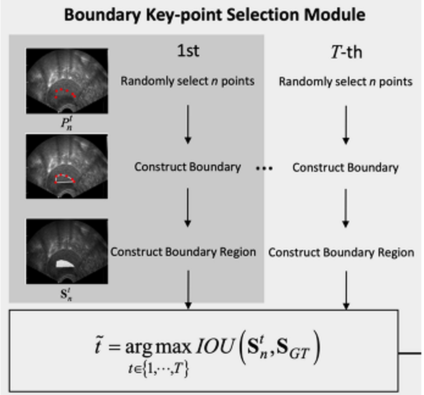
Methodology

- The boundary key point map generator is optimized by minimizing the cross-entropy loss between the estimated boundary key point map $\hat{M}^i$ and ground-truth boundary key point map M^i_{GT}.
- The objective function for the boundary key point map generation is defined as
  - $L^i_{Map} = -M^i_{GT} \cdot log\hat{M}^i - (1 - M^i_{GT}) \cdot log(1 - \hat{M}^i)$.

Machine Intelligence Lab

Methodology

The process of generating a Ground-truth boundary map



Algorithm 1: Boundary key point selection algorithm

Input: Total number of iterations T, number of boundary key points n, ground truth segmentation map $\mathbf{S}_{GT}$
Output: Boundary key Points $\tilde{P}$
Initialize $IOU_{best} = 0$
for $t = 1, 2, \cdots, T$ **do**
  Randomly select N points
  $P_n^t \leftarrow \{(x_1^t, y_1^t), (x_2^t, y_2^t), \cdots, (x_n^t, y_n^t)\}$
  $\mathbf{S}_n^t \leftarrow c(P_n^t)$
  $IOU_t \leftarrow IOU(\mathbf{S}_n^t, \mathbf{S}_{GT})$
  if $IOU_t > IOU_{best}$ **then**
    $IOU_{best} \leftarrow IOU_t$
    $\tilde{P} \leftarrow P_n^t$
  end
end
Return: $\tilde{P}$

* In this paper, T = 40000, n=6 are used

Methodology

SBE (Shape Boundary-aware Evaluator)

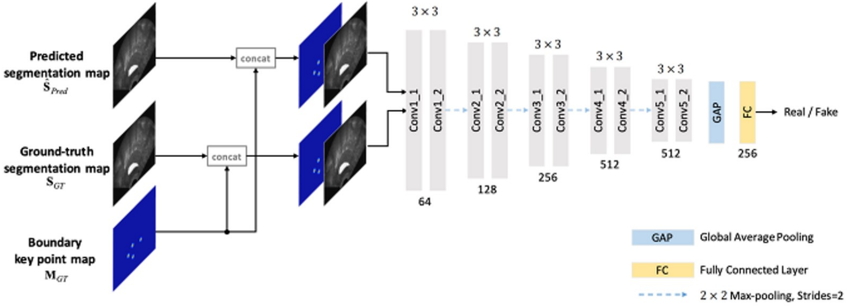


Fig. 9. The detail structure of Shape Boundary-aware Evaluator network.

Machine Intelligence Lab

Methodology

- Given the ground-truth segmentation map S_{GT} and boundary key point map, the SBE provides a high evaluation score.
- On the other hand, with the poorly predicted segmentation map and boundary key point map, the SBE provides a low evaluation score since the poorly predicted segmentation map is not consistent with the boundary key point map.
- To this end, they trained the SBE network with the following loss.

$$L_{SBE} = -log(D(S_{GT}; M_{GT})) - log(1 - D(\hat{S}_{Pred}; M_{GT})).$$

Machine Intelligence Lab

Methodology

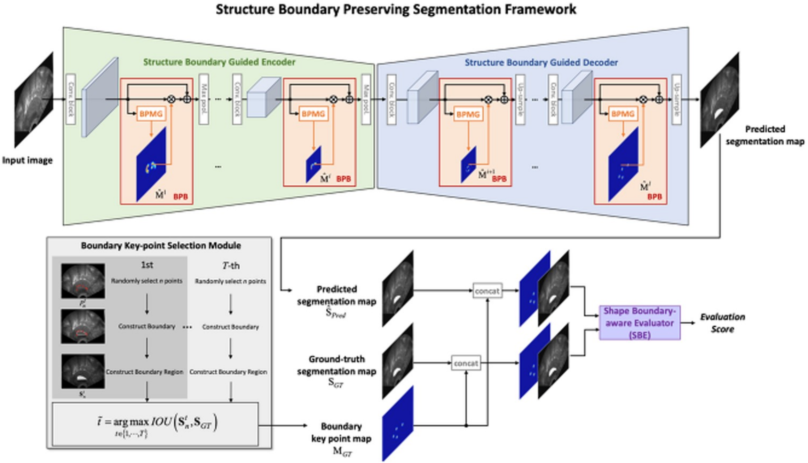
To train the segmentation network including the proposed BPBs and the proposed SBE in an adversarial way, they employ three types of loss functions.

- The first one is a segmentation loss function to reduce the difference between the ground-truth segmentation map and the predicted segmentation map.
  - $L_{Seg} = -S_{GT} \cdot log(\hat{S}_{Pred}) - (1 - S_{GT}) \cdot log(1 - \hat{S}_{Pred})$.
- The second one is a key point map loss which is devised for the proposed key point map generation.
  - $L^i_{Map} = -M^i_{GT} \cdot log\hat{M}^i - (1 - M^i_{GT}) \cdot log(1 - \hat{M}^i)$.
- The last one is a boundary aware loss considering the back-propagation of the SBE.
  - $L_{BA} = -log(D(\hat{S}_{Pred}; M_{GT}))$.

$$L_{Total} = L_{Seg} + L_{BA} + \sum_{i=1}^{l} L^i_{Map}$$

Machine Intelligence Lab

Methodology

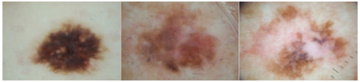


Experimental Results

- They conduct experiments to verify our proposed structure boundary preserving method on two medical image segmentation datasets.

Experimental Results

- PH2+ISBI 2016 Skin Lesion Challenge dataset
  - ISBI 2016 Skin Lesion Challenge dataset includes 900 skin lesion images with different image size.
  - PH2 dataset includes 200 dermoscopic images.



ISBI 2016

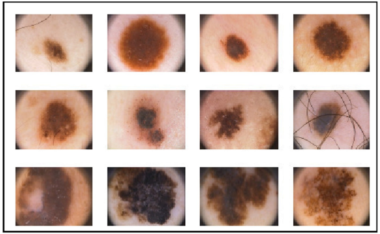
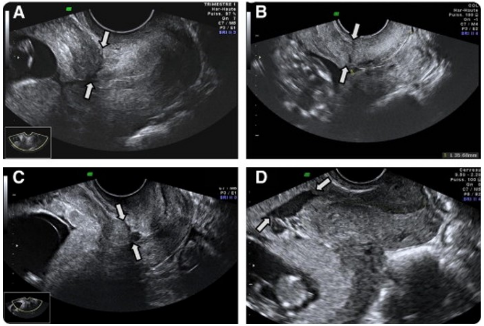


Fig. 3. Images from PH2 dataset

Machine Intelligence Lab

Experimental Results

- Transvaginal Ultrasound (TVUS) dataset
  - Conduct five-fold cross-validation
  - Use 2,688 images for training and 672 images for testing at each fold



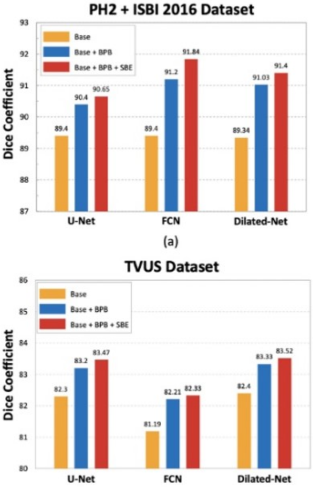
Experimental Results

Table 1. Dice and Jaccard coefficient comparison of our approach and six different approaches on PH2 + ISBI 2016 Challenge dataset.

Method	Dice Coefficient	Jaccard Coefficient
SCDRR [4]	86.00	76.00
JCLMM [23]	82.85	-
MSCA [2]	81.57	72.33
SSLS [1]	78.38	68.16
FCN [15]	89.40	82.15
Bi et al. (2017) [3]	90.66	83.99
FCN+BPB+SBE (Our method)	**91.84**	**84.30**

Table 2. Dice and Jaccard coefficient comparison of our approach and conventional segmentation network on TVUS dataset.

Method	Dice Coefficient	Jaccard Coefficient
U-Net [21]	82.30	70.38
FCN [15]	81.19	69.12
Dilated-Net [31]	82.40	70.36
Park et al. (2019) [18]	82.67	70.46
Dilated-Net+BPB+SBE (Our method)	**83.52**	**71.58**



(a)

(b)

Machine Intelligence Lab

Experimental Results

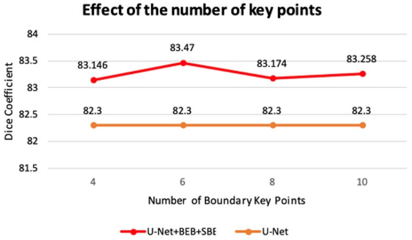
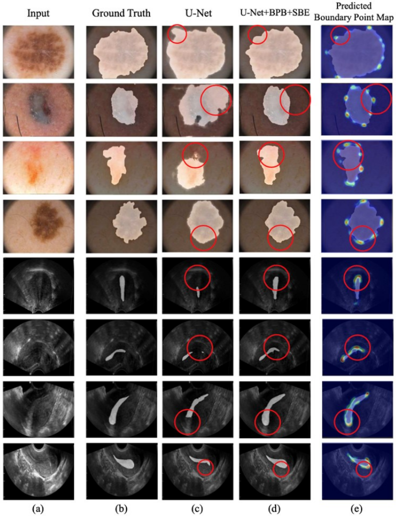


Figure 6. Performance evaluation in accordance with the number of boundary key points on TVUS dataset. It shows the comparison results between U-Net and U-Net + BPB + SBE.



Machine Intelligence Lab

Conclusion

This paper presents a novel fully automatic segmentation framework for medical image segmentation with an ambiguous boundary.

- They generate key point map through the boundary key point selection algorithm.
- The generated keypoint map is used to train the proposed novel boundary preservation blocks BPB and SBE.
- Experimental results demonstrate that the proposed framework can easily be integrated into various segmentation networks.
- The proposed method improves accuracy with statistical significance.

Thank You!

(Q & A)

usxxng@korea.ac.kr

Machine
Intelligence
Lab