MICCAI Journal Club

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December 12, 2019

Fully Convolutional Boundary Regression for Retina OCT Segmentation

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Outline

Introduction

Paper link

- Optical Coherence Tomography images
- Making use of interference of light to generate tomogram

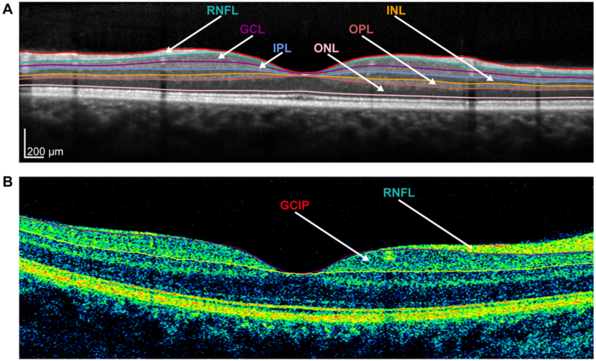

Figure 1: Spectral-Domain(A) and Time-Domain(B) OCT image

Introduction

Expected output

- Continuous layer **surfaces**, with correct hierarchy (topology)

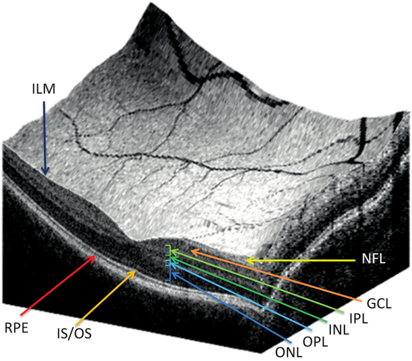

Figure 2: Retina Layers

Related work

Fully Convolutional Boundary Regression

Related work of Retina segmentation

- Pixel-wise labeling: Deep networks
- Surface estimation: Level set and graph methods

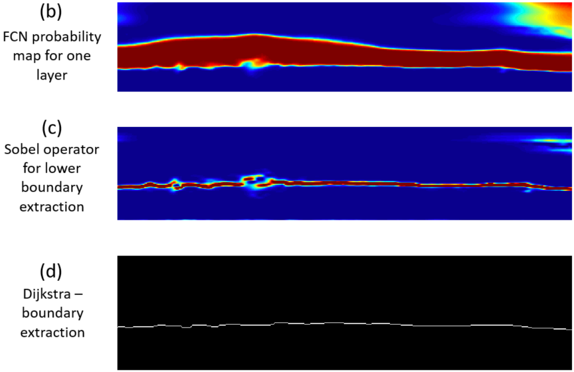

Figure 3: Sobel filter and shortest path

Current problem

Fully Convolutional Boundary Regression

- Layer topology not guaranteed:
  Pixel-wise labeling, methods separating each layer
- Hard to be integrated into deep networks:
  Current graph methods

Proposed Method

Fully Convolutional Boundary Regression

- Model the pixel-wise segmentation and topology-correct surfaces
- End-to-end training

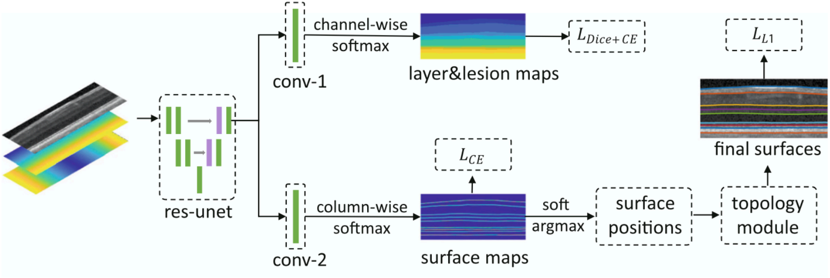

Figure 4: Proposed method

Network structure

Fully Convolutional Boundary Regression

- conv-1: Segmentation of layers and lesion $L_{Dice+CE}$
- conv-2: Surface boundaries maps L_{CE}

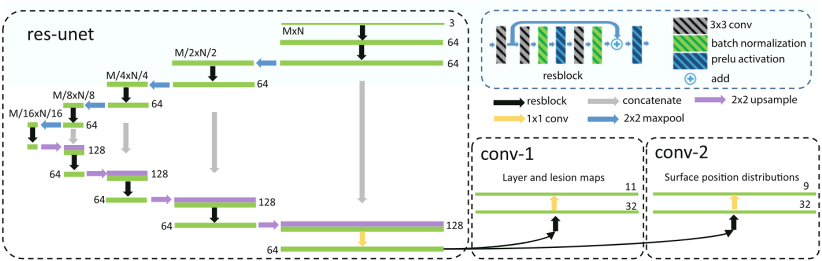

Figure 5: Network structure

Surface Modeling

For a M * N image, consider the form of a surface boundary, The ground truth is an list of N row indexes $(x_1^g, ..., x_N^g)$

They want to model the surface position distribution

$$p = p\left(x_1, \cdots, x_N, I\right)$$

by approximating it with

$$q = \Pi_{i=1}^{N} q_i\left(x_i | I; \boldsymbol{\theta}\right) p(I)$$

Then, they update the network parameters by minimizing the K-L divergence, which is similar to Variational Bayesian methods.

Surface Modeling

$$
\begin{aligned}
\underset{\theta}{\operatorname{argmin}} KL(p\|q) &= \underset{\theta}{\operatorname{argmin}} \iint_{\theta} p\left(x_1, \cdots, x_N, I\right) \log \frac{p\left(x_1, \cdots, x_N, I\right)}{\prod_{i=1}^{N} q_i\left(x_i | I; \theta\right) p(I)} \\
&= -\underset{\theta}{\operatorname{argmin}} \iint_{\vec{x}, I} p\left(x_1, \cdots, x_N, I\right) \sum_{i=1}^{N} \log q_i\left(x_i | I; \boldsymbol{\theta}\right) \\
&= -\underset{\boldsymbol{\theta}}{\operatorname{argmin}} \underset{\vec{x}, I \sim p}{\mathrm{E}} \left(\sum_{i=1}^{N} \log q_i\left(x_i | I, \boldsymbol{\theta}\right)\right)
\end{aligned}
$$

Replace the expectation by a training sample $\left(I, x_i^g, \cdots, x_N^g\right)$, the probability q_i is considered only if the index equals ground truth x_i^g, so they take it as cross-entropy loss function

$$
\mathcal{L}_{\mathrm{CE}} = -\sum_{i=1}^{N} \sum_{j=1}^{M} \mathbb{1}\left(x_i^g = j\right) \log q_i\left(x_i^g | I, \boldsymbol{\theta}\right)
$$

Soft-argmax

The predicted surface position can be denoted as

$$x_i = \sum_{m=1}^{M} m \times q_i(m|I, \boldsymbol{\theta})$$

Since the boundary between 2 surfaces is unique, they regularize q_i by L1 loss,

$$\mathcal{L}_{\mathrm{L1}} = \sum_{i=1}^{N} 0.5 d_i^2 \mathbb{1}\left(|d_i| < 1\right) + \left(|d_i| - 0.5\right) \mathbb{1}\left(|d_i| \geq 1\right), \quad d_i = \hat{x}_i - x_i^g$$

Topology Guarantee Module

Denote L as the number of surfaces, x_i^j as the position of the j^{th} surface at the i^{th} column, consistency of topology requires

$$x_i^1 \leq x_i^2 \cdots \leq x_i^L, i = 1, \ldots, N.$$

They update the surfaces by

$$\hat{x}_i^j = x_i^{j-1} + \mathrm{ReLU}\left(x_i^j - x^{j-1}i\right)$$

which is the output layer of Topology Guarantee Module.

Evaluation

Fully Convolutional Boundary Regression

- Healthy Controls (HC) and Multiple Sclerosis (MS) Dataset
- 35 cases, each contains 49 scans of size 496×1024
- Mean Absolution distance(MAD)

Boundary	MAD (Std. Dev.)				
	AURA	R-Net	ReLayNet	SP	Our's
ILM	**2.37** (0.36)	2.38 (0.36)	3.17 (0.61)	2.70 (0.39)	2.41 (0.40)
RNFL-GCL	3.09 (0.64)	3.10 (0.55)	3.75 (0.84)	3.38 (0.68)	**2.96** (0.71)
IPL-INL	3.43 (0.53)	2.89 (0.42)	3.42 (0.45)	3.11 (0.34)	**2.87** (0.46)
INL-OPL	3.25 (0.48)	**3.15** (0.56)	3.65 (0.34)	3.58 (0.32)	3.19 (0.53)
OPL-ONL	2.96 (0.55)	2.76 (0.59)	3.28 (0.63)	3.07 (0.53)	**2.72** (0.61)
ELM	2.69 (0.44)	**2.65** (0.66)	3.04 (0.43)	2.86 (0.41)	**2.65** (0.73)
IS-OS	2.07 (0.81)	2.10 (0.75)	2.73 (0.45)	2.45 (0.31)	**2.01** (0.57)
OS-RPE	3.77 (0.94)	3.81 (1.17)	4.22 (1.48)	4.10 (1.42)	**3.55** (1.02)
BM	**2.89** (2.18)	3.71 (2.27)	3.09 (1.35)	3.23 (1.36)	3.10 (2.02)
Overall	2.95 (1.04)	2.95 (1.10)	3.37 (0.92)	3.16 (0.88)	**2.83** (0.99)

Figure 6: Evaluation on HC and MS Dataset

Evaluation

Fully Convolutional Boundary Regression

- Diabetic Macular Edema Dataset
- From 10 patients, each with 11 B-scans (contain Lesion)

	Mean	#1	#2	#3	#4	#5	#6	#7	#8
Chiu	7.82	6.59	8.38	9.04	11.02	11.01	4.84	5.74	5.91
Karri	9.54	**4.47**	11.77	11.12	17.54	16.74	4.99	5.35	**4.30**
Rathke	7.71	4.66	6.78	8.87	11.02	13.60	4.61	7.06	5.11
Ours	**6.70**	4.51	**6.71**	**8.29**	**10.71**	**9.88**	**4.41**	**4.52**	4.61

Figure 7: Evaluation on DME dataset

Summary

Fully Convolutional Boundary Regression

Starting point

- Topology correct

Solution

- Surface position modeling
- Fully differentiable soft-argmax operation
- ? Smooth and continuous surface guarantees