Insights into the behaviour of multi-task deep neural networks for medical image segmentation

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Agenda

Introduction  Prior art  Methods  Results  Conclusions
Gland segmentation

- Cancer diagnosis
- Glandular morphology
- Gland segmentation

Introduction

Prior art

Methods

Results

Conclusions
Why gland image is different than natural image?

1. Heterogeneous shape
2. Anisochromasia causes background noise
3. Coalescence problem
Prior art

Multi-task learning for medical image segmentation
Gland Segmentation

DCAN → Multichannel → SA-FCN

2015 → 2016 → 2017

Introduction
Prior art
Methods
Results
Conclusions
SA-FCN

**Softmax Cross Entropy Loss Function**

\[ L_{final} = L_{fb} + L_{contour} \]
Questions

1. Does loss weighting influence the final performance?

2. How do we perform instance segmentation?

3. Do we really need specialized networks?
Methods

SA-FCN
SOTA on the 2015 MICCAI dataset

Domain specific model

Mask R-CNN
SOTA on the COCO dataset

Generic model

Introduction  Prior art  Methods  Results  Conclusions
**Mask R-CNN**

\[
L_{ROI} = L_{cls} + L_{bbox} + L_{mask}
\]

Cross Entropy
Smooth L1
Binary Cross Entropy

\[
L_{RPN} = L_{cls} + L_{reg}
\]

Cross Entropy
Smooth L1

Box regression
Classification

Fully connected layers
Fixed size feature map
RoIAlign layer
Feature map
Convolutional backbone

Introduction
SA-FCN, post-processing

1. PREDICTION (FLOAT VALUES)
2. CONTOURS SUBTRACTED MAP
3. DILATED SMALL OBJECTS REMOVED
4. FINAL PREDICTION

Introduction
Our post-processing

I. Contours subtracted from the f/b prediction.
II. Small elements removed.
III. Opening operation – erosion.
IV. Opening operation – dilation, holes filled.
V. Connected-component labelling.
Comparison of post-processing

F1 SCORE

DICE INDEX

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Comparison of post-processing

1. Our post-processing method, has significantly improved the final performance.

2. SA-FCN performance strongly depends on the post-processing techniques.
Multi-task learning, loss weighting

Introduction

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Multi-task learning

1. In this particular case, the ratio value for loss weighting does not significantly affect the performance of the model.

2. Contour decoder helps f/b decoder to ignore irrelevant parts of the image and improve the performance.

3. There is no visible assistance from the f/b decoder for the contour decoder.
SA-FCN versus Mask R-CNN

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# SA-FCN versus Mask R-CNN

<table>
<thead>
<tr>
<th></th>
<th>ORIGINAL</th>
<th>BEFORE POST-PROCESSING</th>
<th>BINARIZED PREDICTION</th>
<th>AFTER POST-PROCESSING</th>
<th>GROUND TRUTH</th>
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<tbody>
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<td>MASK R-CNN</td>
<td><img src="original.png" alt="Image" /></td>
<td><img src="before.png" alt="Image" /></td>
<td><img src="binarized.png" alt="Image" /></td>
<td><img src="after.png" alt="Image" /></td>
<td><img src="ground_truth.png" alt="Image" /></td>
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**Introduction**

**Prior art**

**Methods**

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SA-FCN versus Mask R-CNN

1. **Mask R-CNN** implementation achieves higher performance than our SA-FCN implementation.

2. **Mask R-CNN** implementation requires less post-processing actions as the SA-FCN implementation.
Conclusions

1. Post-processing can have a great impact on the final performance of the deep learning architecture.

2. Mask R-CNN obtains comparable results to current state-of-the-art, for gland segmentation task.

3. It is worth to use generic models instead of design complex architectures when tackling new domains.
Thank you
Comparison of Mask R-CNN and SA-FCN

<table>
<thead>
<tr>
<th></th>
<th>F1 Score</th>
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<tbody>
<tr>
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<td>A Score</td>
<td>B Score</td>
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<tr>
<td>Our Mask R-CNN</td>
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<td>0.817</td>
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