Segmentation of Organs at Risk in CT Images using Deep Anatomical Constraints Learning

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Collaborations

• Joint work with
  • S. Ruan, C. Petitjean (co-supervisors)
  • B. Dubray (radiotherapist)
  • D. Nie and Prof. D. Shen (IDEA Lab UNC)

• Funded by M2NUM Project
  • Regional and European grant
Context

• Cancer is a leading cause of death worldwide.

• Radiotherapy, alone or combined with chemotherapy, is a standard treatment.

• First step is to identify the target volumes to be treated and the healthy organs at risks to be protected.
Context

- We work on the automatic segmentation of 4 Organs at risk
Context

• Esophagus is particularly challenging due to low contrast
Related Works and Limitations

• Multi-atlas based segmentation methods (-) High accuracy registration needed
  – Majority Voting (MV)

• Learning-based segmentation methods (-) Manual designed features
  – Random Forest (RF), LINKS

CNNs could (partially) address these limitations
Convolutional Neural Networks

(+): Learn features automatically
(-): Lose spatial information
(-): Slow
Fully Convolutional Networks

(+) Retain spatial information
(+) Fast
FCN Improvement

FCNs tend to produce coarse outputs and do not encourage structure.
Conditional Random Fields (CRF)

• Discriminative graphical model that can be used to encourage structured outputs

\[ E(X) = \sum_i \phi_u(x_i) + \sum_{ij} \phi_p(x_i, x_j) \]

• Typically, CRFs has been used to boost the performance of simple classifiers
CRF Illustration

**Unary Term**
- Depends on individual nodes
- Pay a penalty if the label assignment does not agree with the initial probability (classifier)

**Pairwise Term**
- Depends on pairs of nodes
- Pay a penalty if two similar nodes have a different label assigned

\[ w_1 \exp \left( -\frac{\|I_i - I_j\|^2}{2\sigma^2} \right) + w_2 \exp \left( -\frac{\|p_i - p_j\|^2}{2\sigma^2} \right) \]
CRF to Improve FCN

- Use CRF as a post-processing step

CRF as RNN [Zheng et al. ICCV’15]

- Perform Inference using Recurrent Neural Networks (RNNs).
- Not anymore a separated step, it can be trained as an additional layer of the network.
Experimental Setting

- 60 CT scans where the patients have either lung cancer or Hodgkin lymphoma
- Volume sizes of 512x512x(150~284) voxels
- Spatial resolution of 0.98x0.98x2.5 mm³

- 6 Fold Cross Validation
- 50 subjects for training and 10 for testing at each fold

\[
\text{Dice index} = \frac{2|A \cap B|}{|A| + |B|}
\]
FCN Model
Skip-connection architecture (First Framework)
Visual Results
Visual Results

SM

SM+CRF
Anatomical Constraints Learning

• Radiotherapists use anatomical knowledge to segment the OARs.

• Our goal: learn automatically this type of anatomical constraint via deep networks
Autocontext model - ACM

Tu et al IEEE PAMI’10

- Cascade system where the classifier at one stage uses the segmentation result of the previous one

Source: http://segmentation.is.tuebingen.mpg.de/facadesegmentation/
Anatomic Information (Second Framework)
Visualizations

(a) Input

(b) SM

(c) SM+Constraints GT

(d) SM+Constraints 1st net

Esophagus
Visualizations

- **Aorta**
- **Trachea**
- **Heart**

**w/o constraints**

**With constraints**
Results

<table>
<thead>
<tr>
<th>Organ</th>
<th>Method</th>
<th>Patchmtch.</th>
<th>SM</th>
<th>SM+CRF</th>
<th>SM+ACM</th>
<th>SM+ Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Esophagus</td>
<td></td>
<td>0.39+-0.05</td>
<td>0.66+-0.08</td>
<td>0.67+-0.04</td>
<td>0.67+-0.04</td>
<td><strong>0.69+-0.05</strong></td>
</tr>
<tr>
<td>Heart</td>
<td></td>
<td>0.62+-0.07</td>
<td>0.89+-0.02</td>
<td>0.90+-0.01</td>
<td><strong>0.91+-0.01</strong></td>
<td>0.90+-0.03</td>
</tr>
<tr>
<td>Trachea</td>
<td></td>
<td>0.80+-0.03</td>
<td>0.83+-0.06</td>
<td>0.82+-0.06</td>
<td>0.79+-0.06</td>
<td><strong>0.87+-0.02</strong></td>
</tr>
<tr>
<td>Aorta</td>
<td></td>
<td>0.49+-0.10</td>
<td>0.85+-0.06</td>
<td>0.86+-0.05</td>
<td>0.85+-0.06</td>
<td><strong>0.89+-0.04</strong></td>
</tr>
</tbody>
</table>

**Dice Ratios**

Joint segmentation of multiple thoracic organs in CT images with two collaborative deep architectures. MICCAI’17 workshop Deep Learning in Medical Image Analysis, 2017.
Conclusions and Future Works

• We presented a Deep Learning based framework for the segmentation of OARs in CT images.

• Hierarchical, auto-context based architecture improves the performance

• Dynamic loss functions preform better

• Future/ Ongoing works
  • GAN for segmentation
  • Handle 3D with RNNs
  • Apply the method to other datasets
Thanks!

Questions?