Segmentation of Axillary and Supraclavicular Tumoral Lymph Nodes in PET / CT: A Hybrid CNN / Component-Tree Approach

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Automatic axillary lymph node tumor segmentation in PET/CT

What are lymph nodes?

lymph nodes are the first organs reached by cancer

Patient with no breast cancer

Patient with breast cancer
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What are our contributions?

1st Contribution:
- Provide a prognostic factor for the staging of breast cancer

Cancer staging is determined by:
N: number of lymph nodes with cancer
T: tumor volume
M: metastasis state

Patient with no breast cancer

Patient with breast cancer
Brown fat shows up (due to exposure to cold)

- Brown fat has the same metabolism as tumor cells
- Brown fat generates false positives that can be mistaken by tumors

2nd Contribution:
- Help doctors to identify quicker false positive coming from brown fat
1. Data preprocessing

2. Component-tree extraction

3. Feature map generator

4. FCNN and component-tree fusion

5. 3D-FNCNN architecture

6. Segmentation results
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2. Component-tree extraction

What is a component-tree?

- Each node is a connected component
- Root node contains all the image
- Follows a hierarchical structure according to gray levels
- Each tree level corresponds to a gray level
- Each node belongs to its ascendants nodes

Full image
Automatic lymph node tumor segmentation in PET/CT

2. Component-tree extraction
Automatic lymph node tumor segmentation in PET/CT

2. Component-tree extraction

For each node $N_i$, it is computed:

- $f1 \rightarrow G(N_i)$: mean gradient of node contour in PET
- $f2 \rightarrow H(N_i)$: mean HU value in CT
- $f3 \rightarrow S(N_i)$: standard deviation of H
- $f4 \rightarrow R(N_i)$: relative integral volume
- $f5 \rightarrow L(N_i)$: position with respect to the lungs
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2. Component-tree extraction

Goal of these descriptors?

For each node $N_i$, it is computed:

- $f_1 \rightarrow G(N_i)$: mean gradient of node contour  
  lymph node have high contour gradient

- $f_2 \rightarrow H(N_i)$: mean HU value in CT  
  lymph nodes have positive HU value  
  brown fat has negative HU value

- $f_3 \rightarrow S(N_i)$: standard deviation of H  
  lymph nodes have low standard deviation

- $f_4 \rightarrow R(N_i)$: relative integral volume  
  lymph nodes have high contrast with their neighbourhood

- $f_5 \rightarrow L(N_i)$: position with respect to the lungs  
  lymph nodes are outside the lungs convex hull

We assign to each node 5 descriptors
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3. Feature map generator

From feature vectors to feature volumes?

For each voxel $x$ in the PET image, it is computed:

\[
\begin{align*}
G(x) &= \max_i G(N_i) & \text{lymph node have high contour gradient} \\
H(x) &= \text{mean}_i H(N_i) & \text{lymph nodes have positive HU value} \\
S(x) &= \min_i S(N_i) & \text{lymph nodes have low standard deviation} \\
R(x) &= \max_i R(N_i) & \text{lymph nodes have high contrast with their neighbourhood} \\
L(x) &= \text{or}_i L(N_i) & \text{lymph nodes are outside the lungs convexhull}
\end{align*}
\]

We assign to each voxel 5 descriptors.
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4. CNN and component-tree fusion
5. CNN

3D U-Net PET-CT for LN tumor segmentation (2 encoders + 1 decoder)

Conv 3x3 Relu

Upconv 3x3 Relu

Maxpooling 3x3

Concatenation

Input PET

Input CT

Segmentation

Contour on PET

Contour on CT
6. Results

- **Training**: 201 tumors (42 PET/CT exams)
- **Validation**: 56 tumors
- **Patches for test**: 63 tumors (10 PET/CT exams)
- **Loss Function**: 1 - Dice
- **Iterations**: 1000

- **Type of CNN**: U-NET
- **Number of layers**: 3
- **Resolution**: 1.2mm³
- **3D Patch size**: 80 mm³

The diagram shows the comparison of baseline and proposed method for accuracy over epochs, with U-PET, U-PET-CT, and U-PET-CT-all as inputs.
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6. Results

U-PET $\rightarrow$ inputs \{PET\}
U-PET-CT $\rightarrow$ inputs \{PET, CT\}
U-PET-CT-all $\rightarrow$ inputs \{PET, CT, all feature maps\}

<table>
<thead>
<tr>
<th>3D CNN Model</th>
<th>DSC voxel</th>
<th>PPV voxel</th>
<th>SE voxel</th>
<th>DSC region</th>
<th>PPV region</th>
<th>SE region</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D U-Net (PET)</td>
<td>0.832703</td>
<td>0.827762</td>
<td>0.82478</td>
<td>0.798685</td>
<td>0.757925</td>
<td>0.890805</td>
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<td>$\pm$ 0.1327</td>
<td>$\pm$ 0.1483</td>
<td>$\pm$ 0.0868</td>
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<td>3D U-Net (PET-CT)</td>
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<td>$\pm$ 0.08</td>
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<tr>
<td>3D U-Net (PET-CT-all)</td>
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<td>$\pm$ 0.1431</td>
<td>$\pm$ 0.1948</td>
<td>$\pm$ 0.0756</td>
</tr>
</tbody>
</table>
6. Results

Proposed method removes false positives coming from brown fat

Results shown on the PET/CT fusion images
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6. Results

Proposed method separates visually connected tumors

Results shown on the PET/CT fusion images

false positive joined contours separated contours

U-PET U-PET-CT (baseline) U-PET-all (proposed method)
Thank you for your attention

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