



Coronal PET AC TOF \$ 50	R24 R24	Coronal PET AC TOF<->CT Sta	andard R24 R24	Coronal CT Standard S 49	R24 R24
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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?



Patient with no breast cancer

Patient with breast cancer



Automatic axillary lymph node tumor segmentation in PET/CT

What are our contributions?





Automatic axillary lymph node tumor segmentation in PET/CT

What are our contributions?





2nd Contribution:

 Help doctors to identify quicker false positive coming from brown fat

brown fat

PET image

PET image 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







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

What is a component-tree?

≥0

≥1

 ≥ 2

≥3

≥4

3	З	3	3	З	3	З	
З	2	2	2	2	2	З	
3	2	1	2	4	2	3	
3	2	2	2	2	2	3	
3	3	3	3	3	3	3	
3	0	0	0	3	3	3	
3	3	3	3	3	3	3	• 64

Full image

- 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

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



PET image Coronal MIP view



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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



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

Goal of these descriptors?

For each node N_i , it is computed:

- f1 \rightarrow G(N_i): mean gradient of node contour
- 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

We assign to each **node** 5 descriptors

- Iymph node have high contour gradient
- lymph nodes have positive HU value brown fat has negative HU value
- Iymph nodes have low standard deviation
- Iymph nodes have high contrast with their neighbourhood
- Iymph nodes are ouside the lungs convexhull

Automatic lymph node tumor segmentation in PET/CT 3. Feature map generator

From feature vectors to feature volumes?



Automatic lymph node tumor segmentation in PET/CT 4. CNN and component-tree fusion

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Training: Validatio Patches f Loss Fund Iterations	n: or test: ction: s:	201 tumors (42 PET/CT exams) 56 tumors 63 tumors (10 PET/CT exams) 1 - Dice 1000 U-NET 3				
Type of C Number	NN: of layers:					
Resolution 3D Patch size:		1.2mm ³ 80 mm ³				
	U-PET	→ inputs {PET}				
baseline	U-PET-C	Γ → inputs {PET, CT}				

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proposed

method





U-PET -	>	inputs {PET}
U-PET-CT -	>	inputs {PET, CT}
U-PET-CT-all -	>	inputs {PET, CT, all feature maps}

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		Voxel-based metrics (Segmentation)			Region-based metrics (Detection)			
	3D CNN Model	DSC voxel	PPV voxel	SE voxel	DSC region	PPV region	SE region	
	3D U-Net (PET)	0.832703 +- 0.1327	0.827762 +- 0.1483	0.82478 +- 0.0868	0.798685 +- 0.1547	0.757925 +- 0.2206	0.890805 +- 0.0821	
baseline	3D U-Net (PET-CT)	0.865896 +- 0.08	0.844429 +- 0.1034	0.886527 +- 0.0465	0.871825 +- 0.1312	0.849864 +- 0.1893	0.926111 +- 0.0628	
method	3D U-Net (PET-CT-all)	0.867845 +- 0.1161	0.872781 +- 0.1425	0.896473 +- 0.0553	0.894624 +- 0.1431	0.851361 +- 0.1948	0.933135 +- 0.0756	

Proposed method removes false positives coming from brown fat

false positive

0 U

false positive U-PET

U-PET-CT (baseline) U-PET-all (proposed method)

Results shown on the PET/CT fusion images

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Proposed method separates visually connected tumors



U-PET

U-PET-CT (baseline) U-PET-all (proposed method)





Thank you for your attention

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