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# AUTOMATIC HOT SPOT DETECTION AND SEGMENTATION IN WHOLE BODY FDG-PET IMAGES

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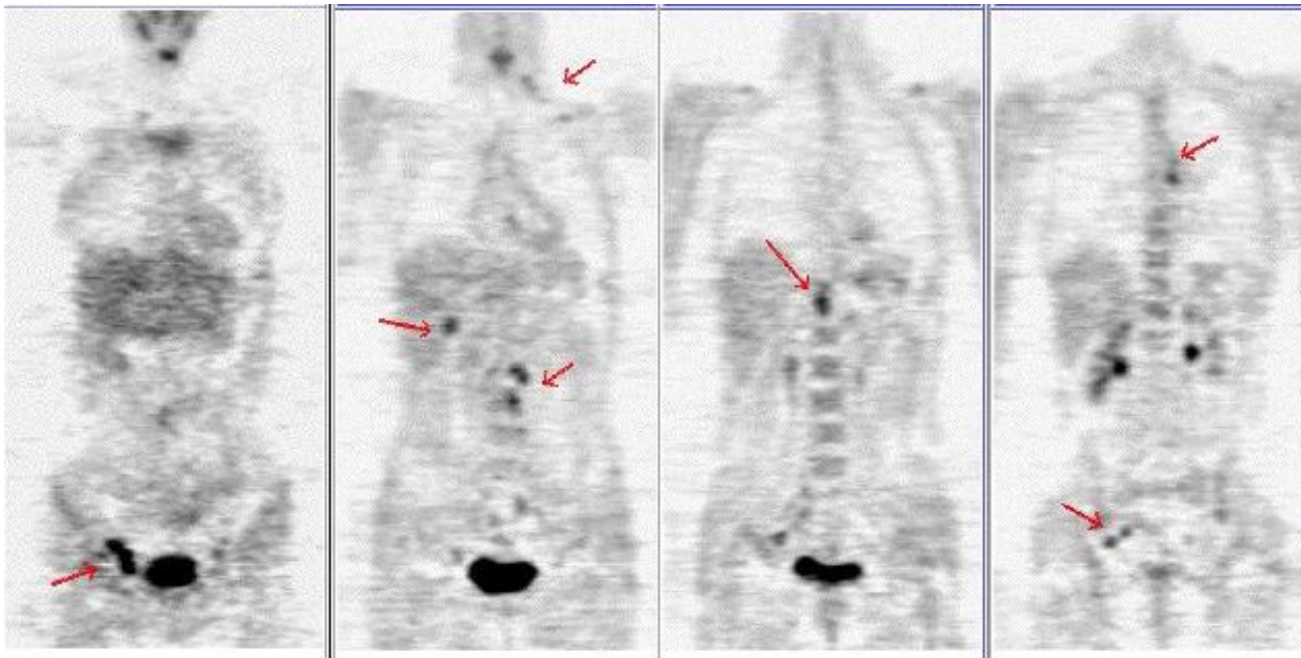
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# Overview

- Objective: To develop a PET-CAD system for whole-body hot spots detection on volumetric PET images
- Hot spots example: Metastatic ovarian carcinoma
- Solutions: image understanding and machine learning techniques based on clinical study claims



An example of Hot Spots<sup>1</sup>

<sup>1</sup><http://www.geocities.com/HotSprings/Villa/8162/mypet.html>

# Motivation

## ■ PET-FDG

- ❑ Positron Emission Tomography (PET)
- ❑ F-18 fluorodeoxyglucose (FDG)
- ❑ A nuclear medicine medical imaging technique
- ❑ 3D functional processes
- ❑ Essential and effective for detection, diagnosis and prognosis of tumors.



NIH PET image<sup>1</sup>

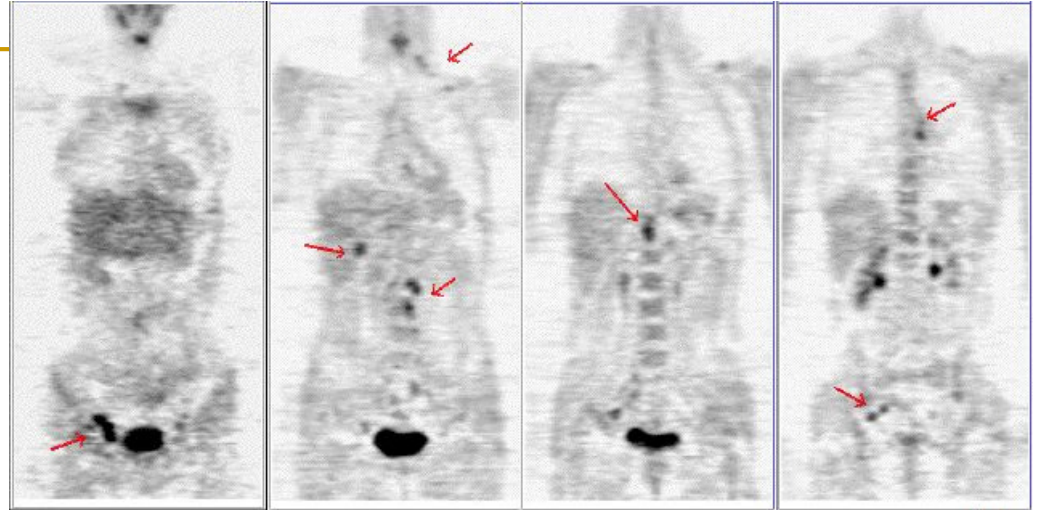
<http://clinicalcenter.nih.gov/pet/gallery/fdgcc.gif>

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## Motivation (cont.)

- Computer-aided Diagnosis (CAD)
  - Make interpretations of PET images easier for doctors.
  - Help radiologists achieve their tasks more effectively.
  - Improve the sensitivity of anomaly detection and reduce the interpretation variation among radiologists.

# Difficulties

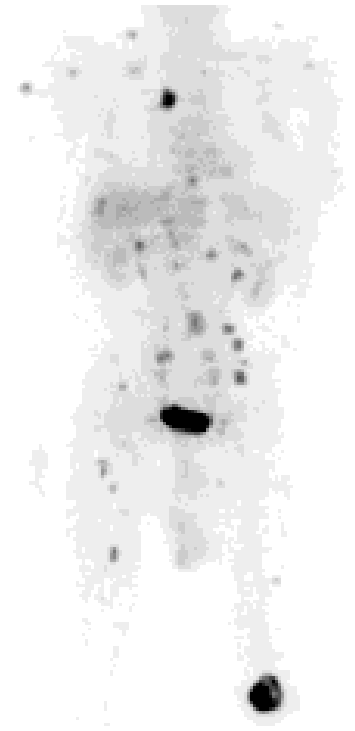


- Clinical perspective

- Normal tissues also uptake different levels of FDG.
- Different body parts uptake different levels of FDG.
- The shape, size, location of the hot spots are unpredictable.

# Difficulties (cont.)

- Image processing perspective
  - Low resolution 5-10mm
  - Image intensity changes dramatically
    - applied radiopharmaceutical
    - injection dose and time
    - patients factors, such as body weight and the tissue uptake



An example of PET <sup>1</sup>

<sup>1</sup><http://www.geocities.com/HotSprings/Villa/8162/mypet.html>

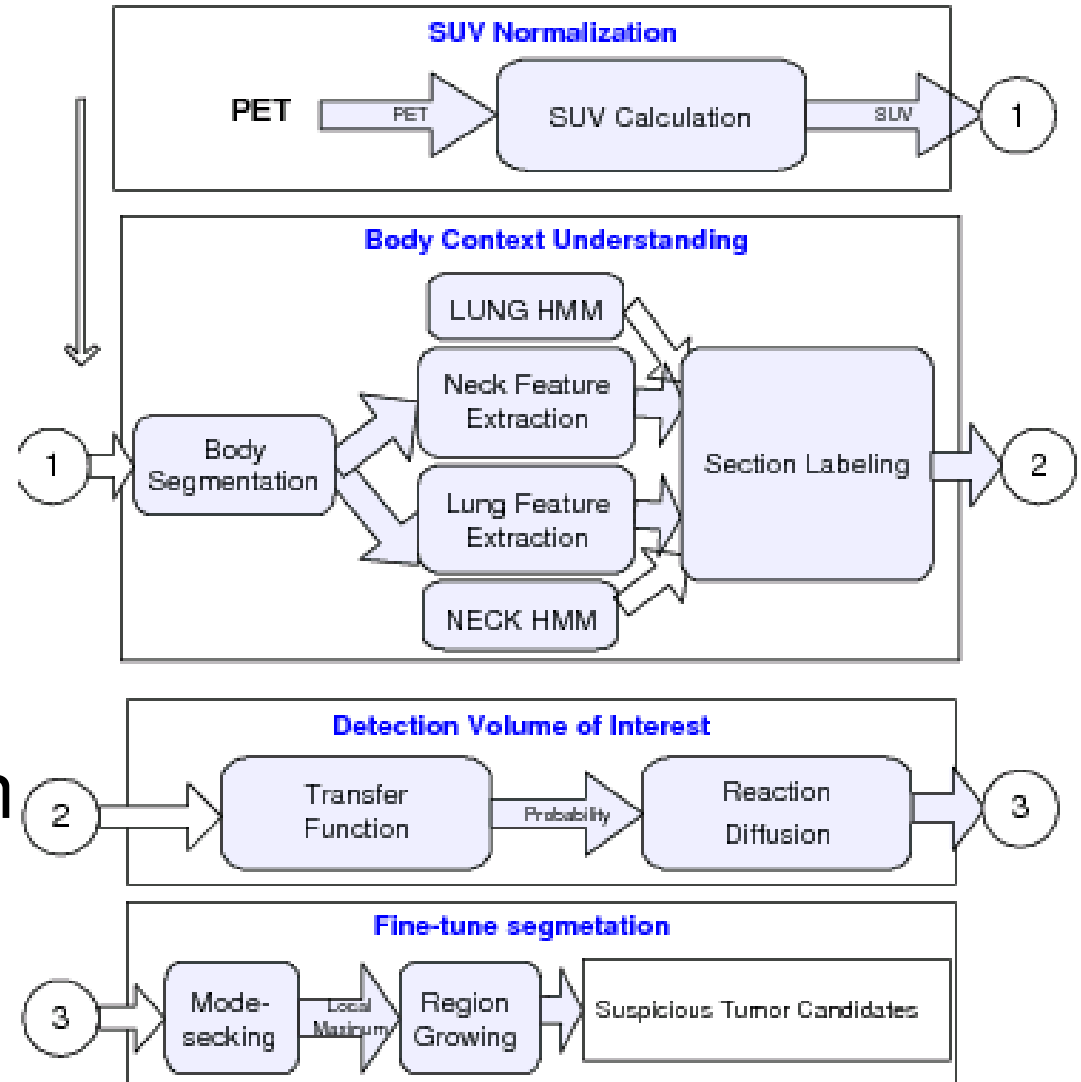
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# Contributions

- A PET-CAD system for hot spots detection
  - Detection is based on clinical study claims.
  - The hot spot segmentation results are clinically meaningful.
  - 30 cases with different cancers are tested, the segmentation process is completely automatic and the results are reproducible.

# System Overview

- Image normalization
  - SUV
- Body Segmentation
  - HMM
- Image Segmentation
  - Competition Diffusion
- Fine-tune Seg.



System Overview

# Image normalization

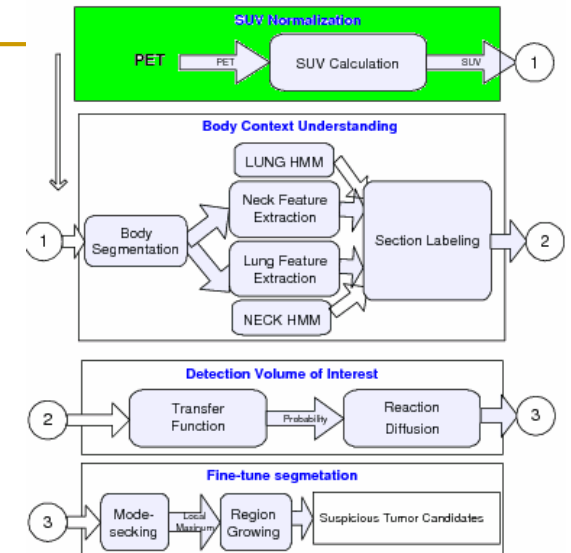
## ■ Purpose:

- ❑ Normalization based only on voxel intensity is not effective
- ❑ The intensity heavily depends on clinical and patient factors

## ■ SUV

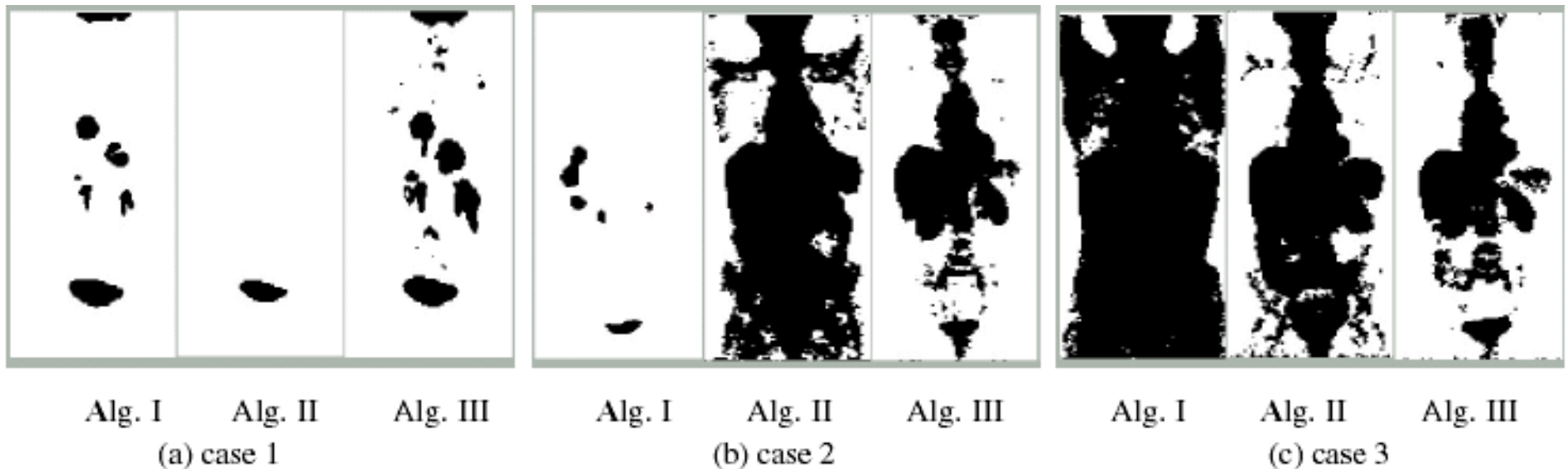
- ❑ Widely used by radiologists
- ❑ It normalizes the FDG concentration by decay-corrected injection dose per gram body-mass.

$$\mathbf{v}_{suv} = A_s \mathbf{v}_{pet} WD^{-1} e^{-\log(2)T / \Delta T}$$



# Image normalization (cont.)

- Alg. I - fixed thresholding on raw PET values
  - Alg. II - adaptive thresholding on raw PET values
  - Alg. III - fixed thresholding on SUV values
- the benefit of SUV: consistent



SUV illustration

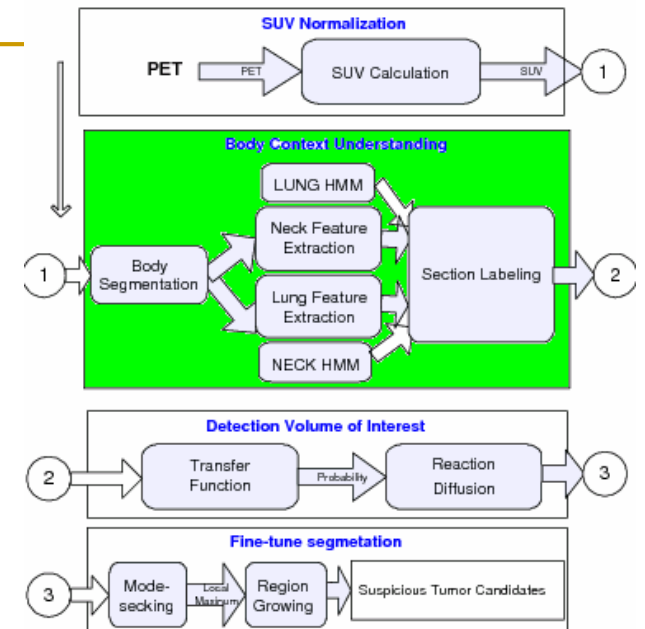
# Body Segmentation

## ■ Purpose:

- ❑ Different organs exhibit different levels of FDG uptake.
- ❑ A rough anatomical interpretation is necessary for accurate detection

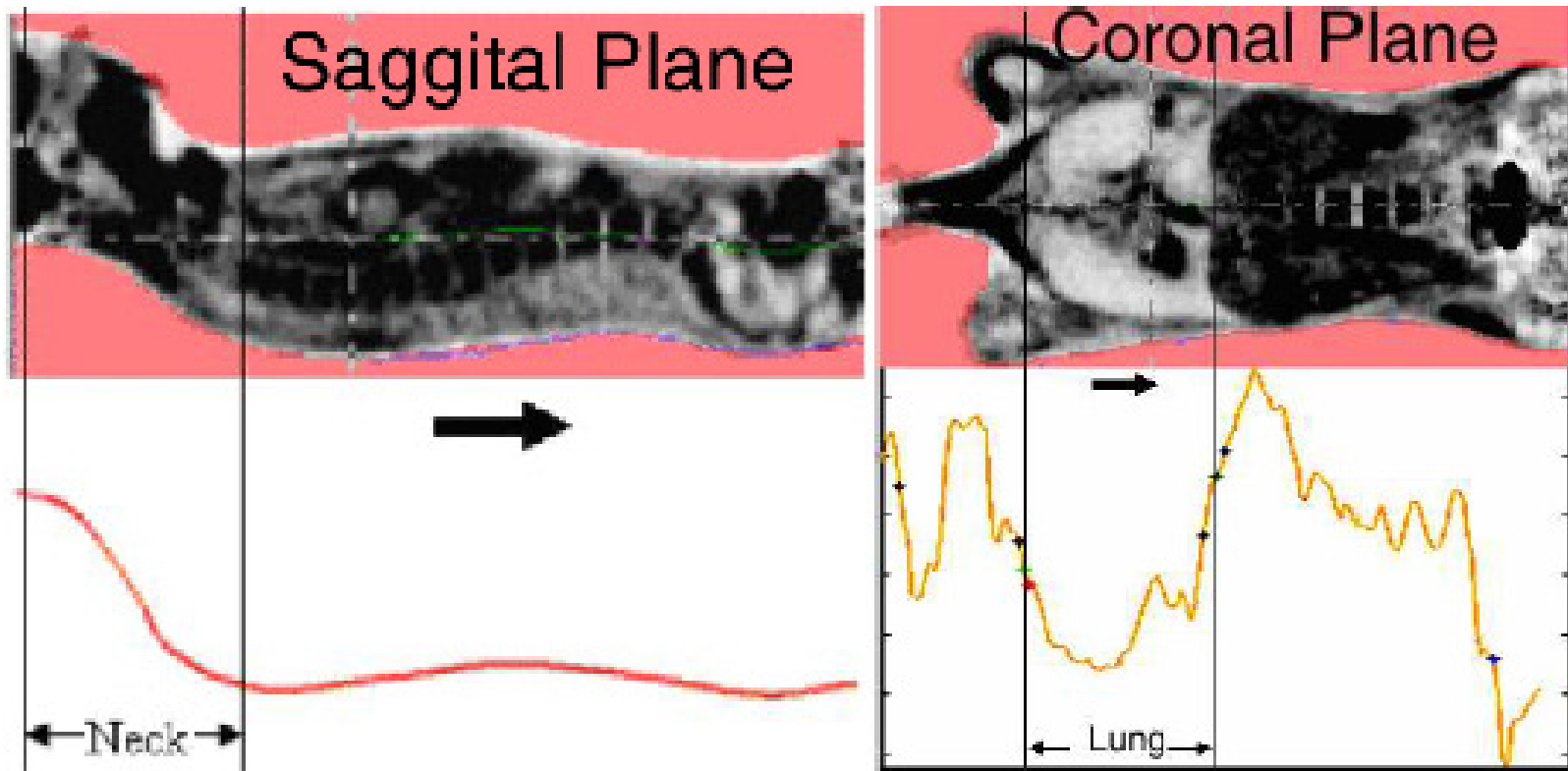
## ■ Objective:

- ❑ Three-section labeling : above lung, lung and below lung



# Body Segmentation (cont.)

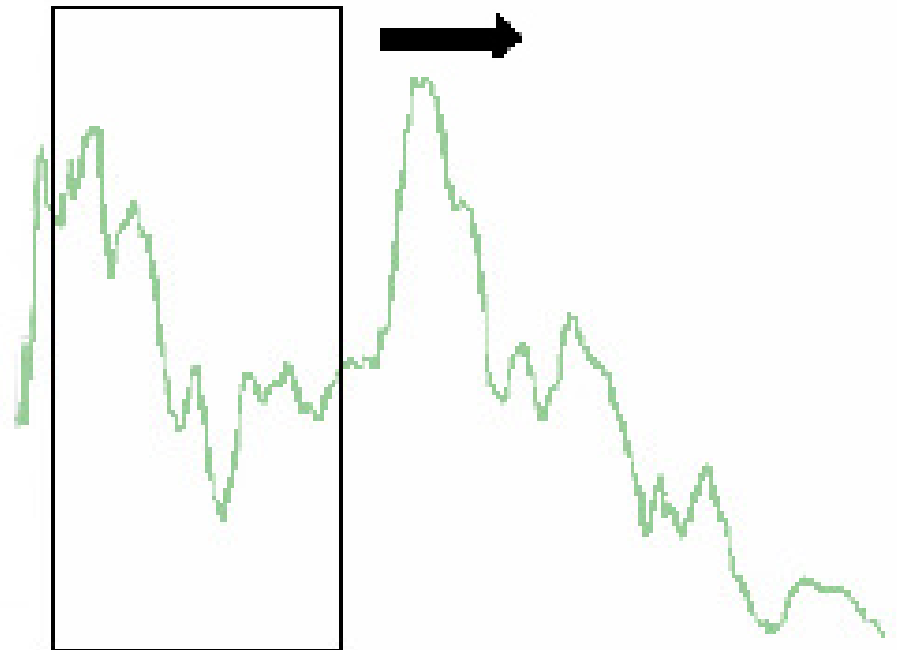
- Observation I: the neck geometric curve pattern
- Observation II: the lung intensity curve pattern



# Body Segmentation (cont.)

## ■ HMM Labeling

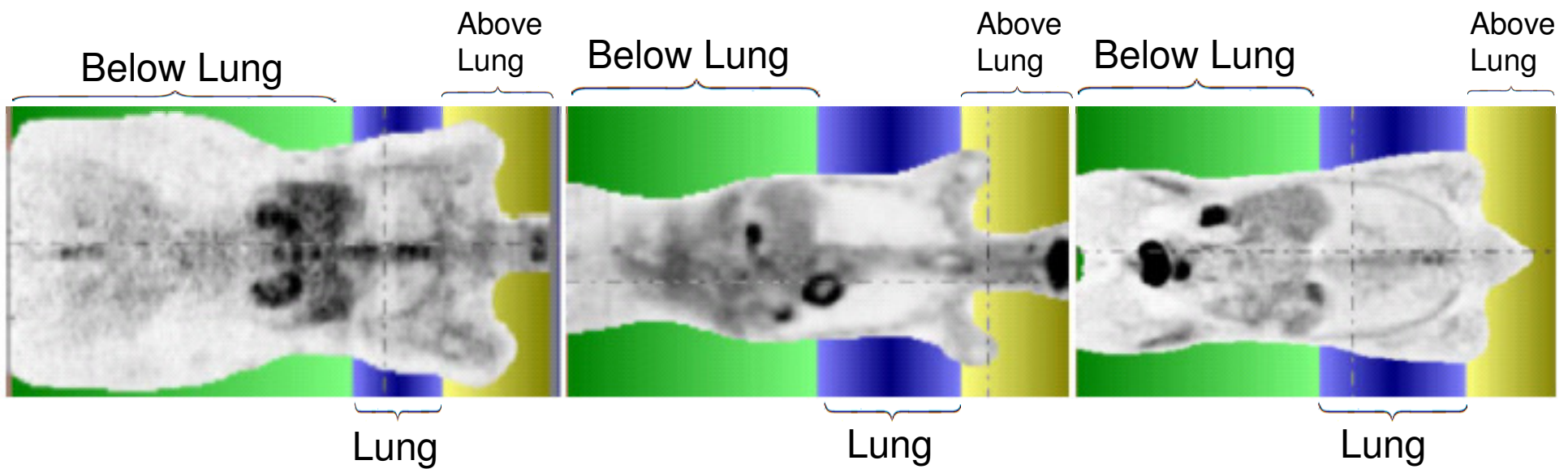
- A spatial discrete HMM along the head to toes direction
- Training the models  
 $\Pr(\text{Observ}/\text{Model})$
- Find the best match by a searching window



(c) Recognition

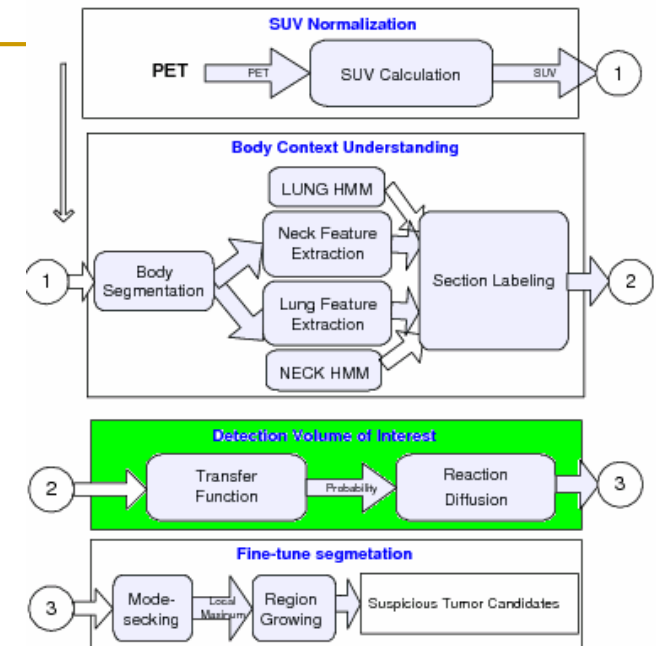
# Body Segmentation (cont.)

- Body segmentation results



# Image Segmentation

- Competition Diffusion (CD)
  - It assigns to each voxel a class label from a set of  $n$  classes
  - Two processes<sup>1</sup>
    - Competition: selects the most fitted label and prevents over smoothing
    - Diffusion: a good spatial coherence



<sup>1</sup>Dynamics Equation  $\dot{x}_i = x_i(f_i - \bar{f}) + \mu \nabla^2 x_i$

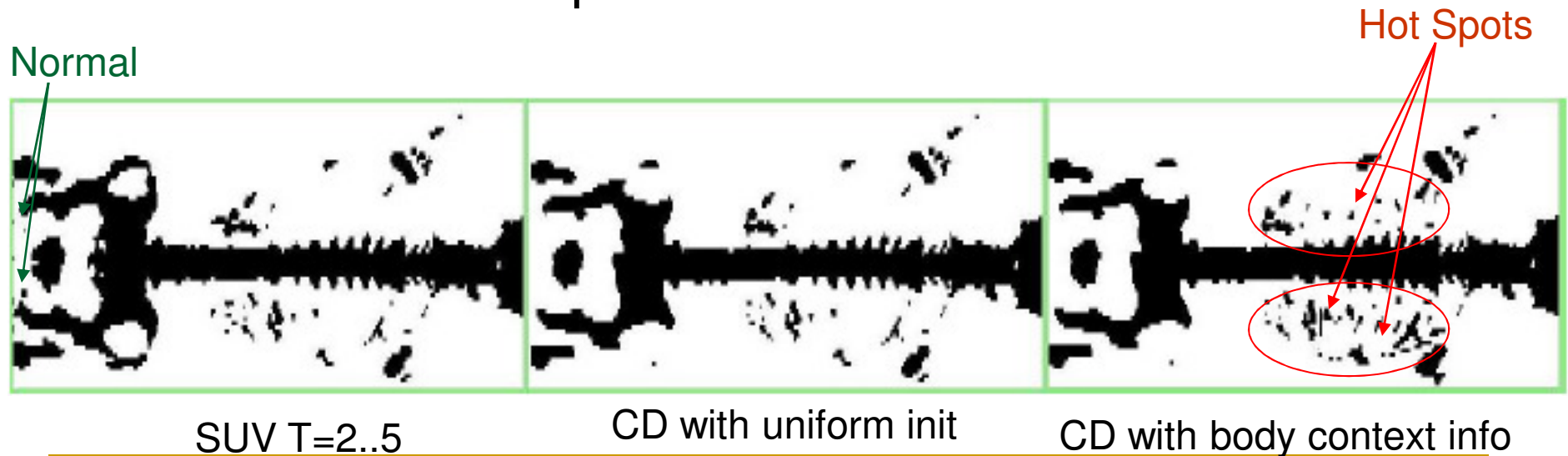
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# Image Segmentation (cont.)

- Different initialization strategies
  - Body segmentation
    - Three sections: above lung, lung, and below lung.
  - Abnormal tissue thresholds:
    - $SUV > 2.5$ , for above lung section
    - $SUV > 2.0$ , for lung section
    - $SUV > 3.0$ , for liver and kidney (below lung section)
  - Different thresholds (or adaptive thresholds) for different body sections

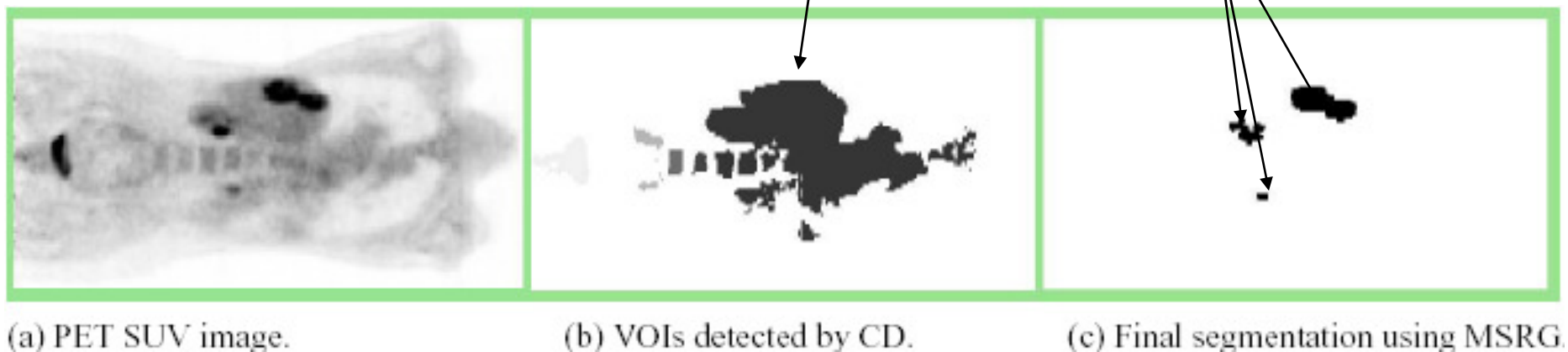
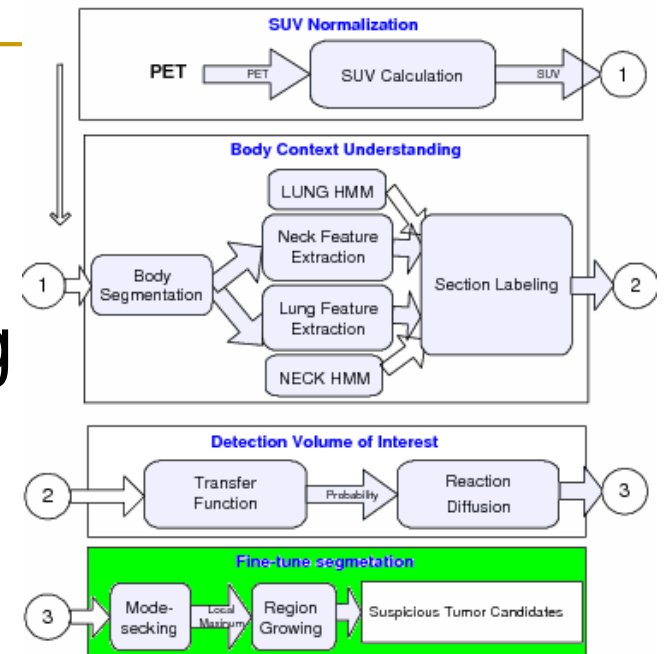
# Image Segmentation (cont.)

- Bone Metastasis detection results
  - CD removed some small clusters whose SUV values are not significantly high
  - the body section dependent initialization revealed additional hot spots in the ribs.



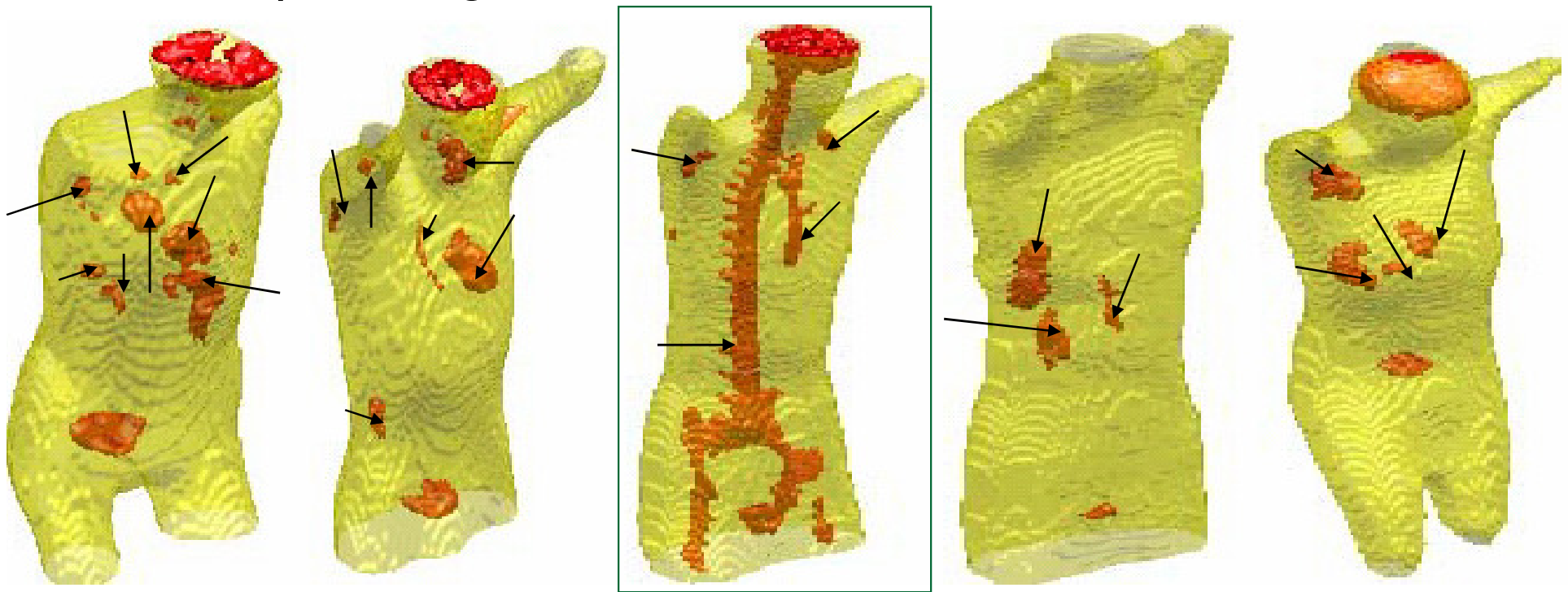
# Fine-Tune Segmentation

- Mode Seeking Region Growing (MSRG)
- SUV local maximums
- 4D Mean-shift
- Region-growing



# Experimental Results

- Data acquisition
  - SIEMENS Biograph LSO PET/CT scanners
  - 11 cases for training, 30 cases for testing
- Hotspots segmentation results



↓  
Bone marrow cancer

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# Conclusions

- PET-CAD system
  - ❑ SUV is clinically meaningful and effective for PET data normalization.
  - ❑ HMM algorithm is robust for lung section detection based on 30 cases testing results.
  - ❑ Competition Diffusion algorithm is effective for noise removal and real hot spots detection.
  - ❑ Mode-seeking region growing algorithm is clinically meaningful and the results are reproducible.