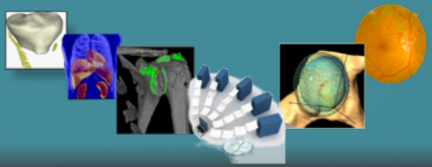


# 10 ans de développements d’approches de segmentation d’images TEP/TDM : le chemin parcouru, ce qu’il reste à explorer

**Mathieu Hatt**

Laboratoire du Traitement de l’Information Médicale

LaTIM, UMR INSERM-UBO 1101, Brest

**EPU Traitements d’images en physique médicale**

**Les Sables-d’Olonne, Octobre 2015**

Instituts thématiques Inserm
Institut national de la santé et de la recherche médicale

UBO université de bretagne occidentale

CHRU BREST Centre Hospitalier Régional Universitaire

# Introduction

## PET/CT mutimodal imaging

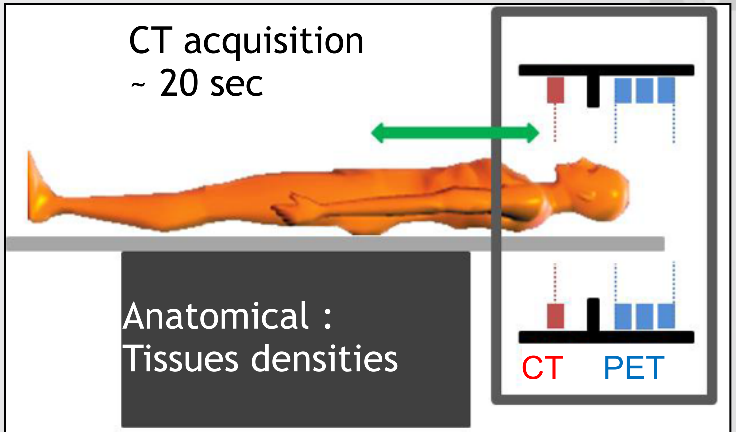
Ron Nutt & David Townsend
2000

Beyer T, *et al*. A combined PET/CT scanner for clinical oncology. *J Nucl Med*. 2000

# Introduction

## PET/CT mutimodal imaging

Ron Nutt & David Townsend
2000




Multimodal PET/CT scanner

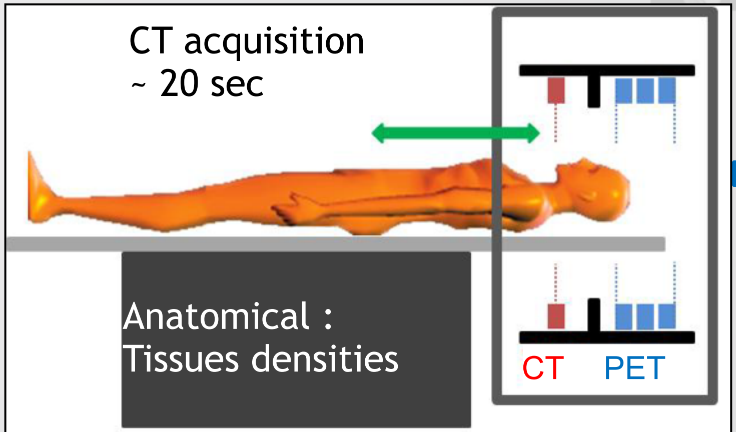
Beyer T, *et al*. A combined PET/CT scanner for clinical oncology. *J Nucl Med*. 2000

# Introduction

## PET/CT mutimodal imaging



Ron Nutt & David Townsend
2000



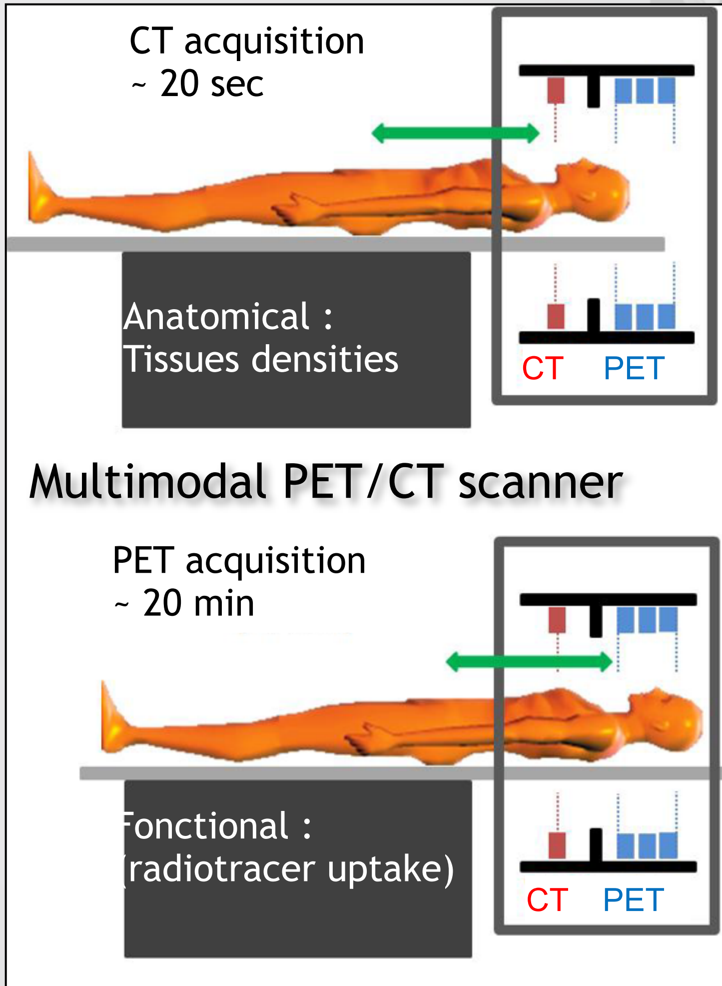

Multimodal PET/CT scanner

Beyer T, *et al*. A combined PET/CT scanner for clinical oncology. *J Nucl Med*. 2000

# Introduction

## PET/CT mutimodal imaging

Ron Nutt & David Townsend
2000



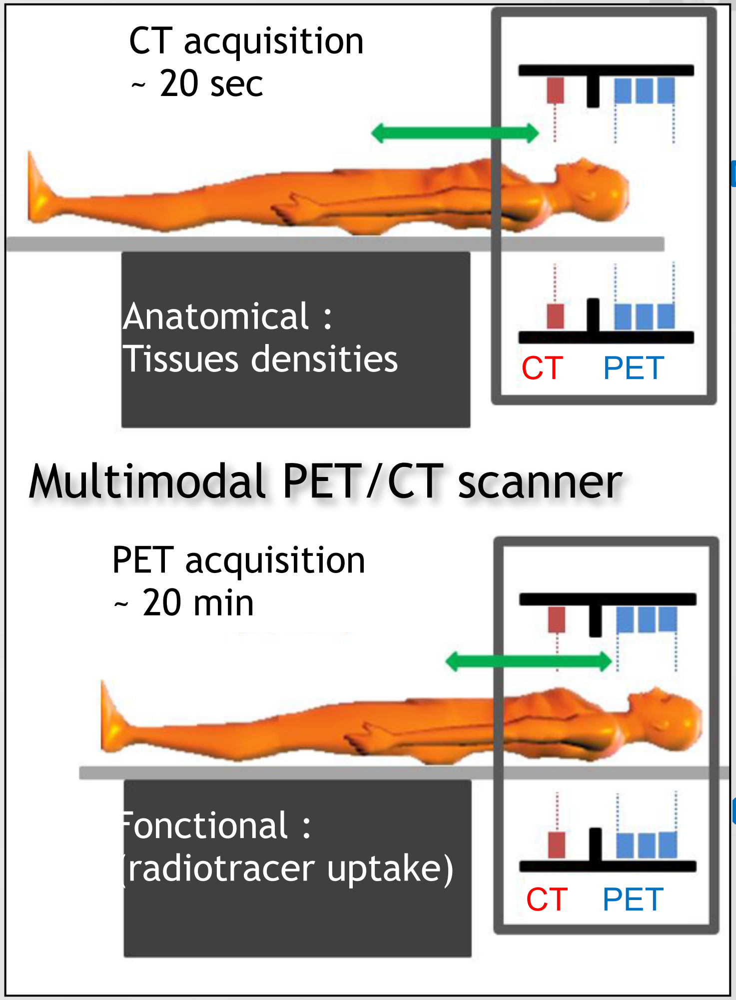

Beyer T, *et al*. A combined PET/CT scanner for clinical oncology. *J Nucl Med*. 2000

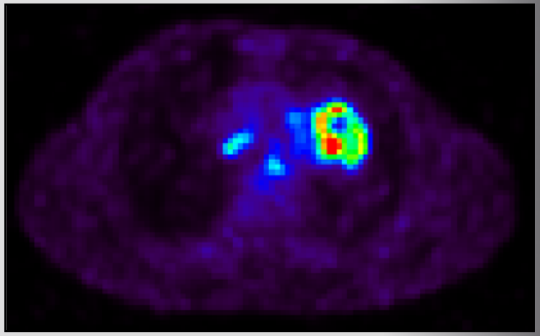
# Introduction

## PET/CT mutimodal imaging



Ron Nutt & David Townsend
2000



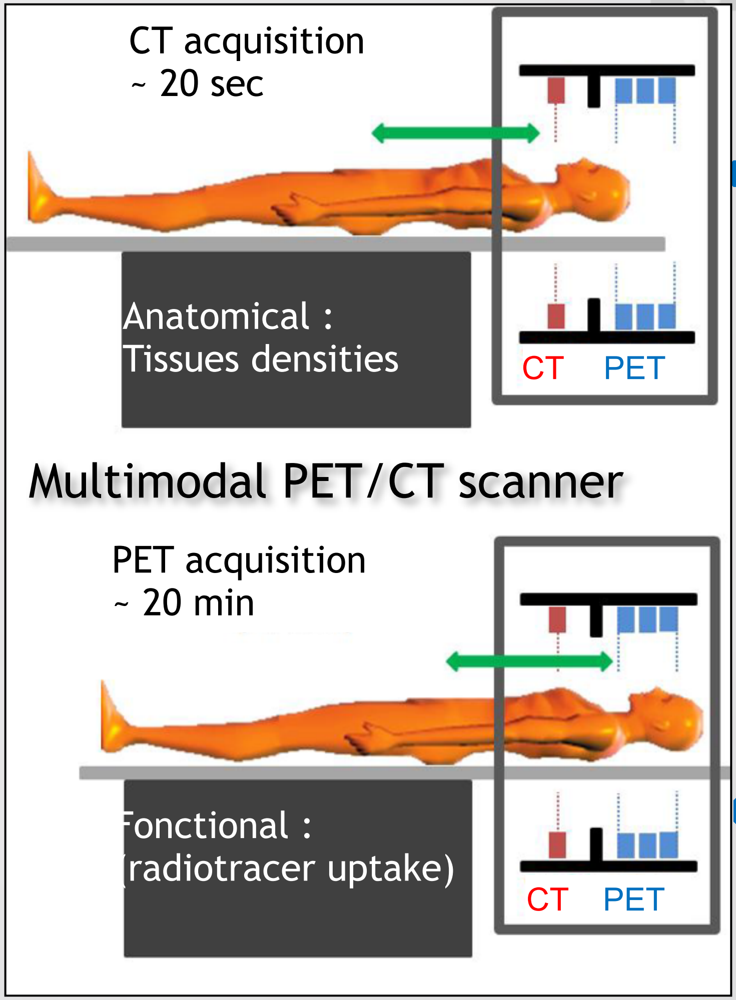



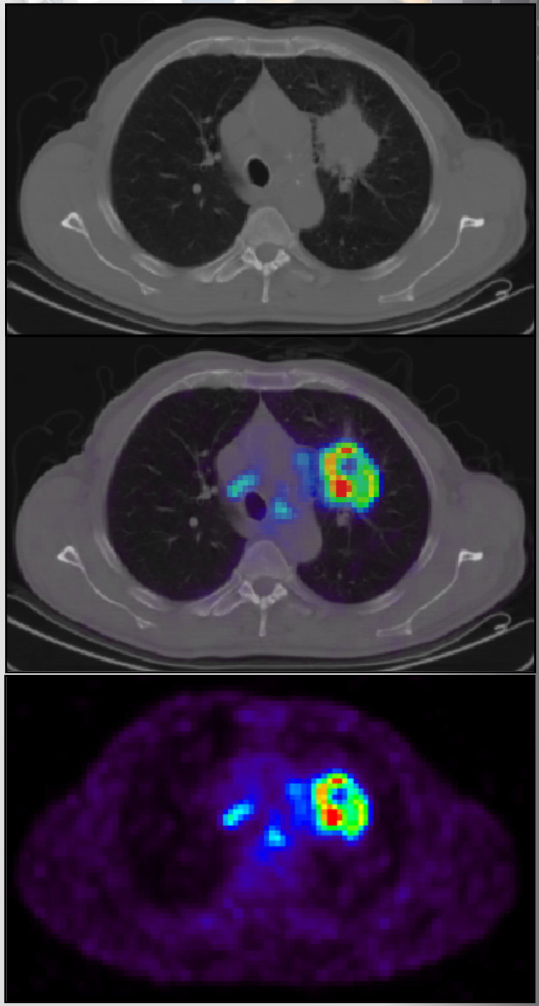
Beyer T, *et al*. A combined PET/CT scanner for clinical oncology. *J Nucl Med*. 2000

# Introduction

## PET/CT mutimodal imaging

Ron Nutt & David Townsend
2000



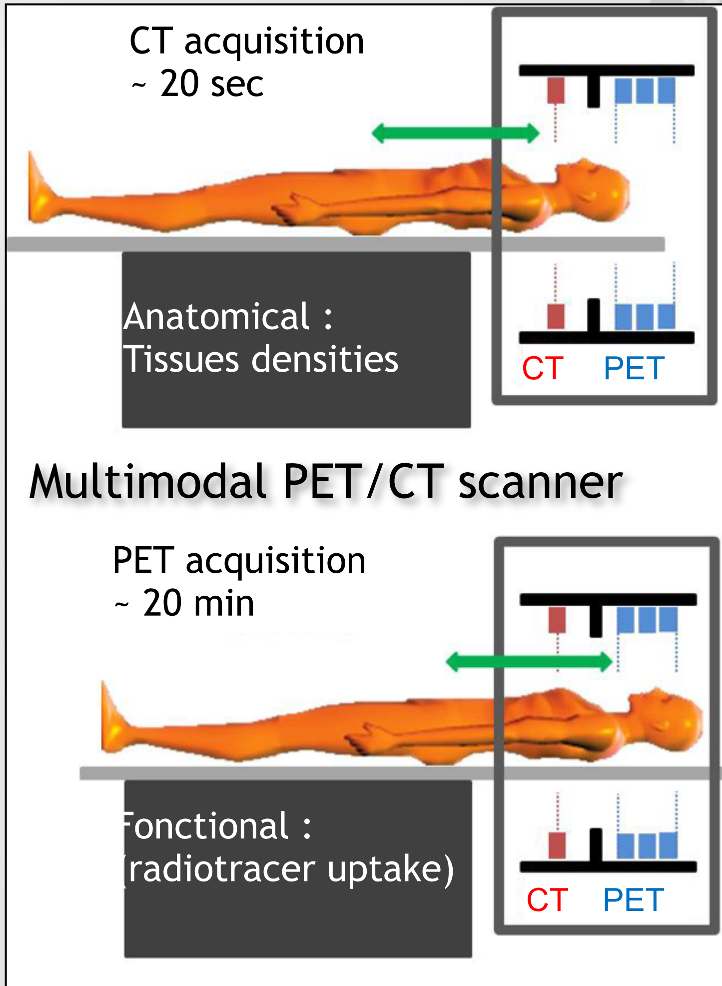



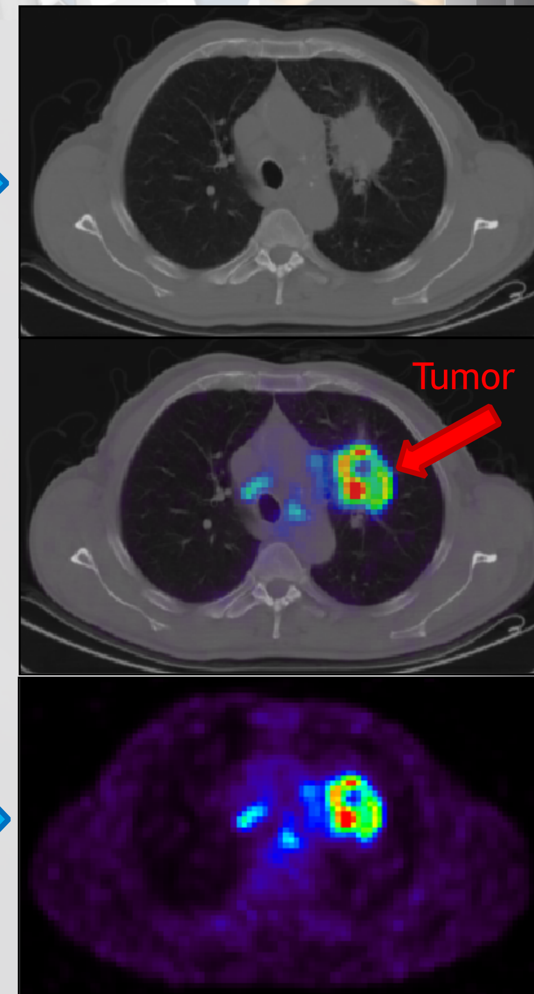
Beyer T, *et al*. A combined PET/CT scanner for clinical oncology. *J Nucl Med*. 2000

# Introduction

## PET/CT mutimodal imaging

Ron Nutt & David Townsend
2000



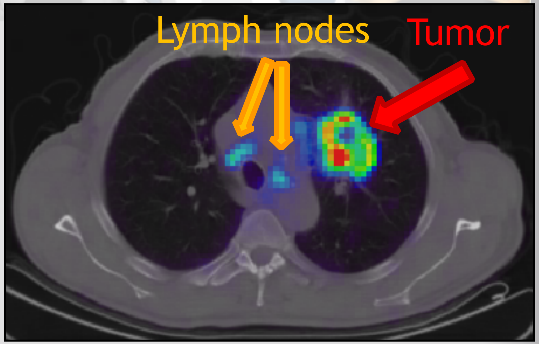




Beyer T, *et al*. A combined PET/CT scanner for clinical oncology. *J Nucl Med*. 2000

# Introduction

## Clinical exploitation of PET/CT images

- Clinical routine:
  - Diagnosis, staging
    - Visual detection
    - Tumor, lymph nodes, metastases

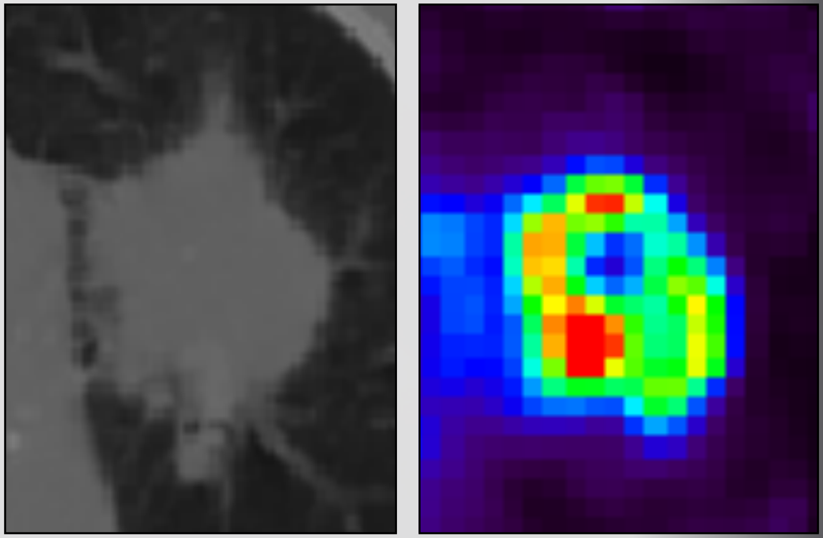



Fused PET/CT

# Introduction

## Clinical exploitation of PET/CT images

- Clinical routine:
  - Diagnosis, staging
    - Visual detection
    - Tumor, lymph nodes, metastases
  - Monitoring treatment
    - Manual / visual
    - Simple metrics
      - Longest axes (CT)
      - $SUV^{*}_{max}$, $SUV_{peak}$ (PET)



CT FDG PET

*SUV = standardized uptake value

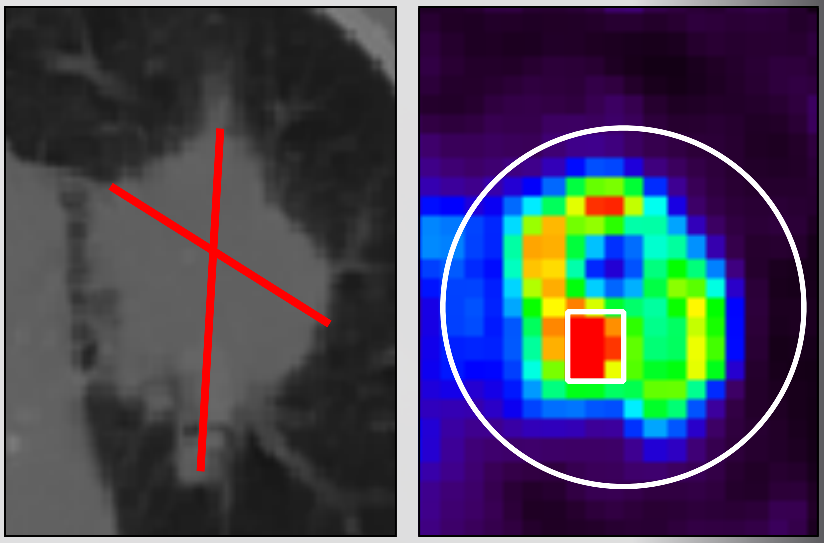
# Introduction

## Clinical exploitation of PET/CT images



### Clinical routine:

- Diagnosis, staging
  - Visual detection
  - Tumor, lymph nodes, metastases
- Monitoring treatment
  - Manual / visual
  - Simple metrics
    - Longest axes (CT)
    - $SUV^{*}_{max}$, $SUV_{peak}$ (PET)



CT FDG PET

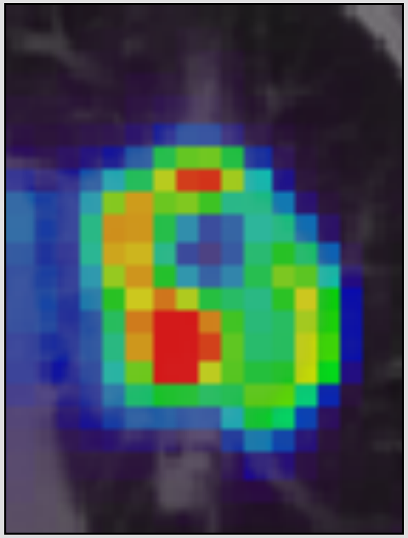
*SUV = standardized uptake value

# Introduction

## Clinical exploitation of PET/CT images

### Clinical routine:

- Diagnosis, staging
  - Visual detection
  - Tumor, lymph nodes, metastases
- Monitoring treatment
  - Manual / visual
  - Simple metrics
    - Longest axes (CT)
    - $SUV^{*}_{max}$, $SUV_{peak}$ (PET)
- Radiotherapy
  - Manual delineation



Fused PET/CT

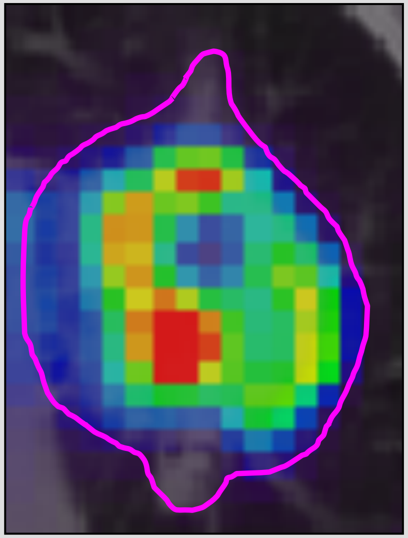
*SUV = standardized uptake value

# Introduction

## Clinical exploitation of PET/CT images



- Clinical routine:
  - Diagnosis, staging
    - Visual detection
    - Tumor, lymph nodes, metastases
  - Monitoring treatment
    - Manual / visual
    - Simple metrics
      - Longest axes (CT)
      - $SUV^*_{max}$, $SUV_{peak}$ (PET)
  - Radiotherapy
    - Manual delineation



Fused PET/CT

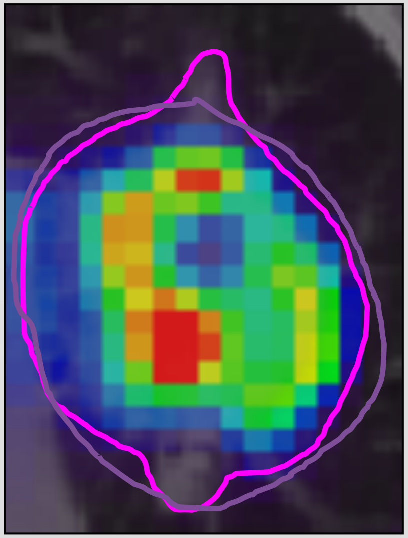
*SUV = standardized uptake value

# Introduction

Clinical exploitation of PET/CT images

## Clinical routine:

- Diagnosis, staging
  - Visual detection
  - Tumor, lymph nodes, metastases
- Monitoring treatment
  - Manual / visual
  - Simple metrics
    - Longest axes (CT)
    - SUV*$_{max}$, SUV$_{peak}$ (PET)
- Radiotherapy
  - Manual delineation



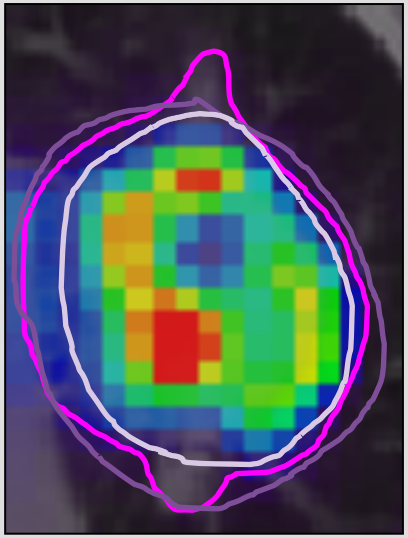
Fused PET/CT

*SUV = standardized uptake value

# Introduction

## Clinical exploitation of PET/CT images

- Clinical routine:
  - Diagnosis, staging
    - Visual detection
    - Tumor, lymph nodes, metastases
  - Monitoring treatment
    - Manual / visual
    - Simple metrics
      - Longest axes (CT)
      - $SUV^*_{max}$, $SUV_{peak}$ (PET)
  - Radiotherapy
    - Manual delineation



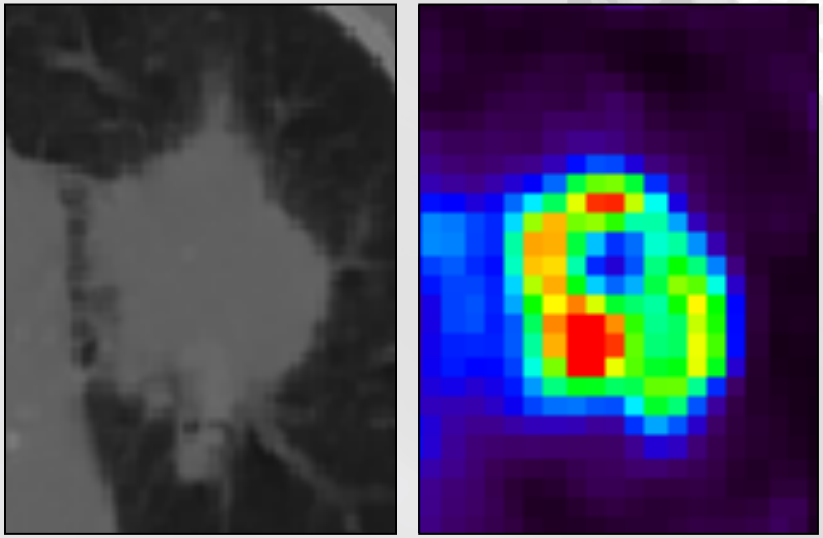
Fused PET/CT

*SUV = standardized uptake value

# Introduction

## Characterization of tumors in oncology: rationale

- Research:

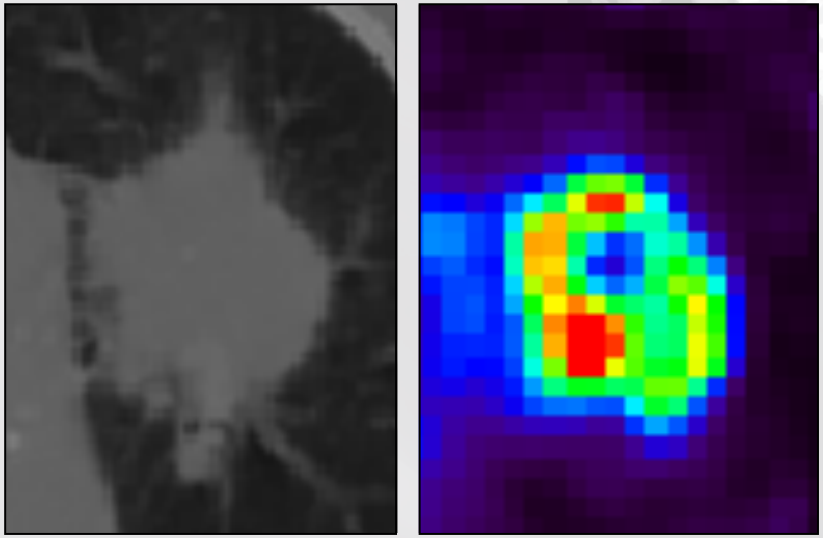


CT FDG PET

# Introduction

Characterization of tumors in oncology: rationale

## Research:



CT

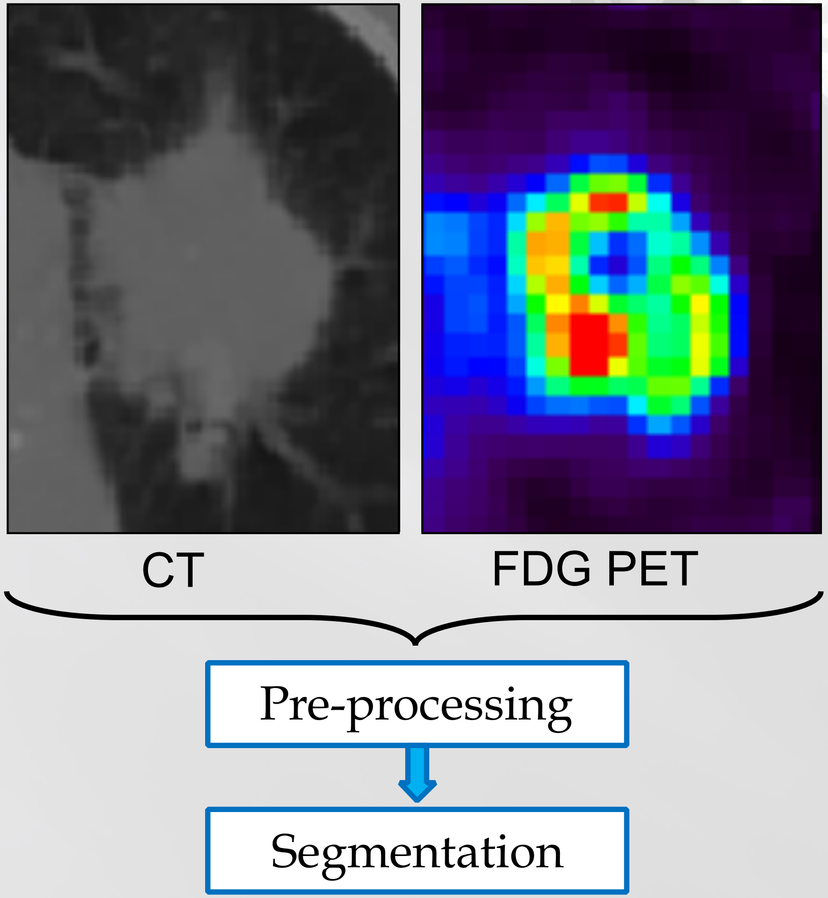
FDG PET

$\boxed{\text{Pre-processing}}$

# Introduction

## Characterization of tumors in oncology: rationale

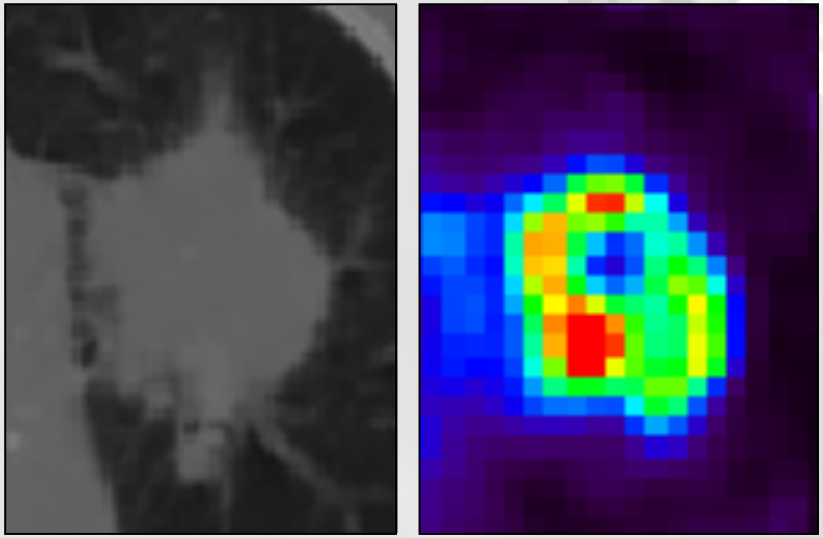
- Research:



# Introduction

## Characterization of tumors in oncology: rationale

- Research:



CT FDG PET

Pre-processing

↓

Segmentation

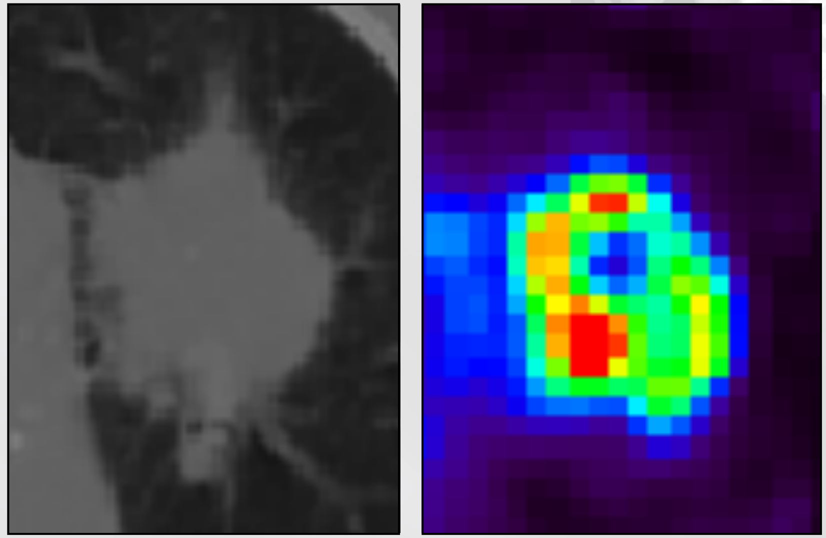
↓

Characterization

# Introduction

## Characterization of tumors in oncology: rationale

### Research:



CT FDG PET

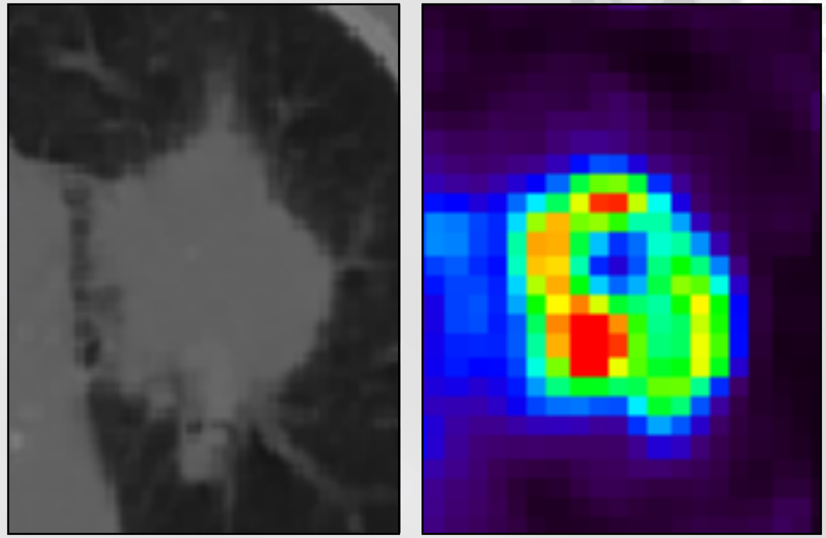
- ❑ (Semi)Automatic
- ❑ Robust
- ❑ Reproducible
- ❑ Quantitative
- ❑ Prognostic / predictive

Pre-processing
↓
Segmentation
↓
Characterization

# Introduction

## Characterization of tumors in oncology: rationale

### Research:



CT

FDG PET

- ❑ (Semi)Automatic
- ❑ Robust
- ❑ Reproducible
- ❑ Quantitative
- ❑ Prognostic / predictive

Pre-processing

↓

Segmentation

↓

Characterization → Imaging signature Clinical value?

# Image segmentation:

- Partitionning the image (2D, pixels) or volume (3D, voxels) into homogeneous regions

# Image segmentation:

- Partitionning the image (2D, pixels) or volume (3D, voxels) into homogeneous regions
- According to one or several criteria
  - Intensities
  - Shapes, positions
  - Textures
  - …

## Image segmentation:

http://www.cs.cmu.edu/~chuck/lennapg/

## Image segmentation:

http://www.cs.cmu.edu/~chuck/lennapg/

# Introduction
## Image segmentation



- 1973, Alexander Sawchuk, USC Signal and Image Processing Institute
- Looking for an image for conference proceedings:
  - A human face
  - High dynamic range
  - Textures and details as well as large homogeneous regions, etc.



http://www.cs.cmu.edu/~chuck/lennapg/

# Introduction
Image segmentation

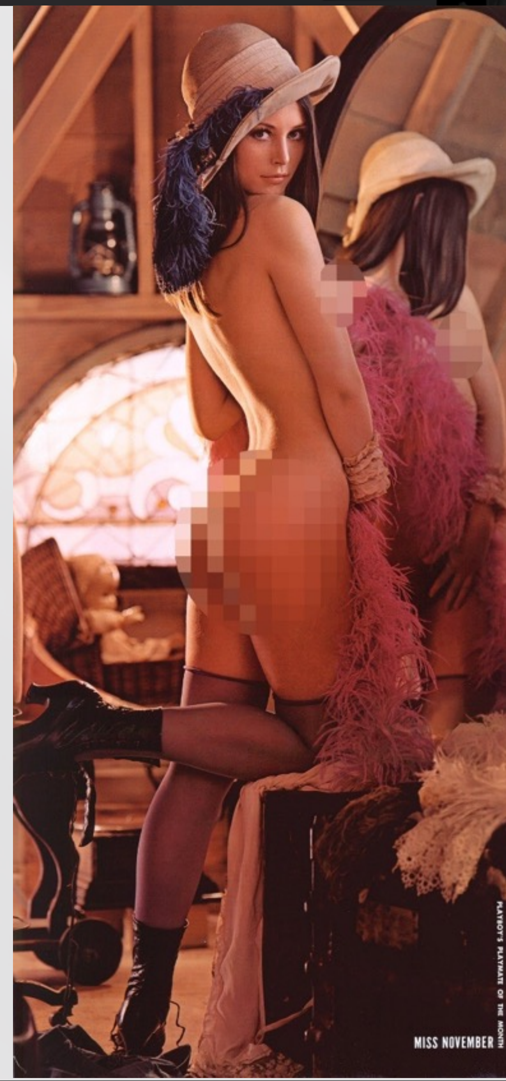
http://www.cs.cmu.edu/~chuck/lennapg/

# Introduction

## Image segmentation

PLAYBOY

Lenna Soderberg
Miss November ‘72

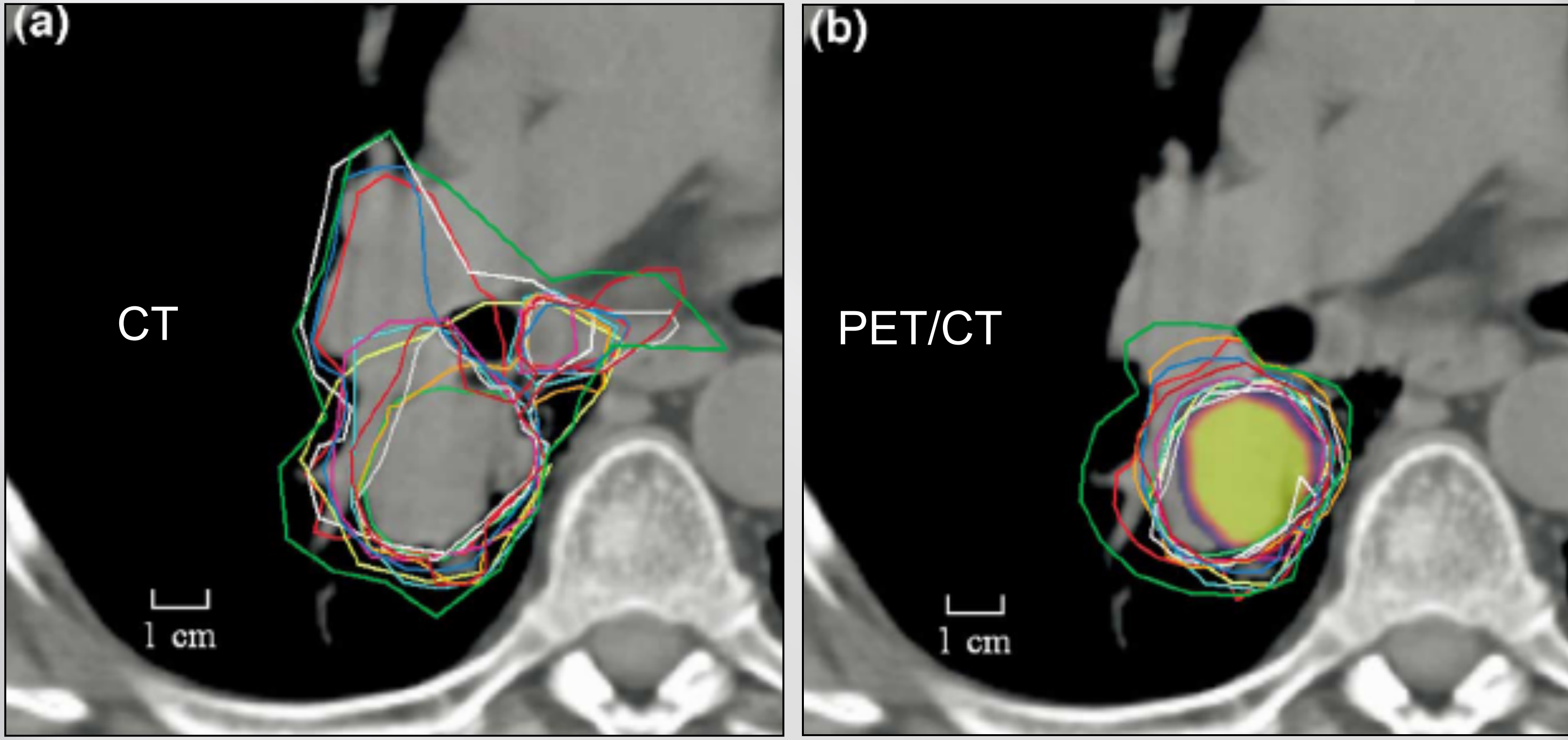



http://www.cs.cmu.edu/~chuck/lennapg/

# Introduction

## PET segmentation: motivations

- PET/CT: target definition, treatment planning



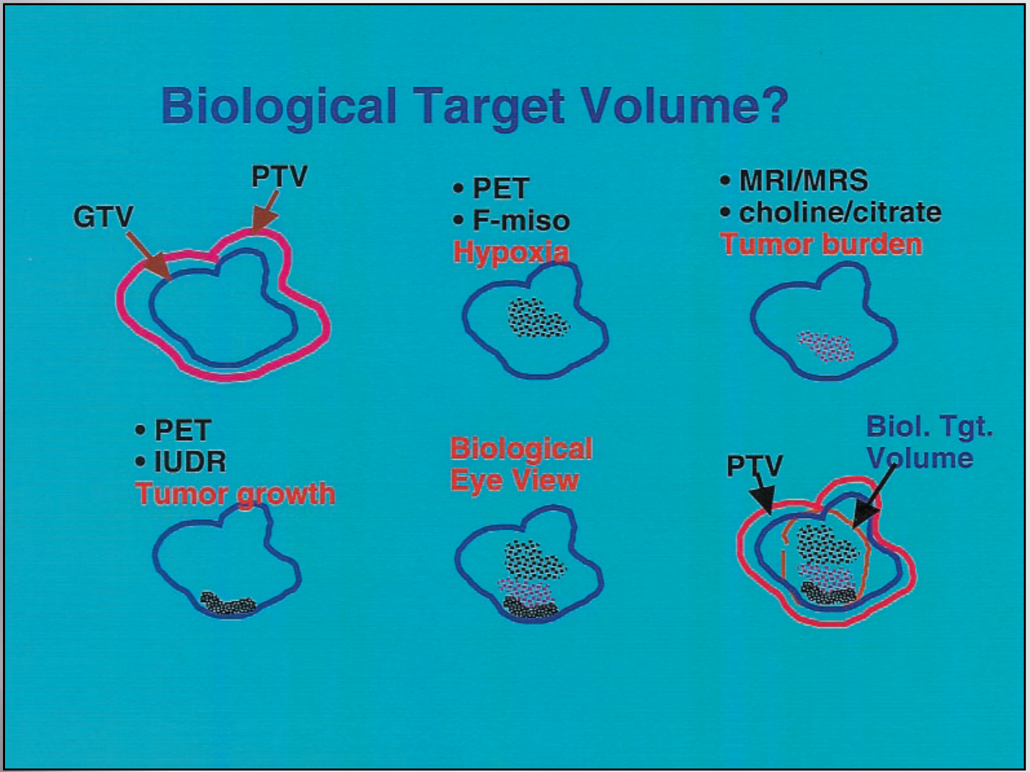

11 radiation oncologists:

Reduced inter observer variability
Faster delineation

# Introduction

## PET segmentation: motivations

- PET/CT: target definition, treatment planning

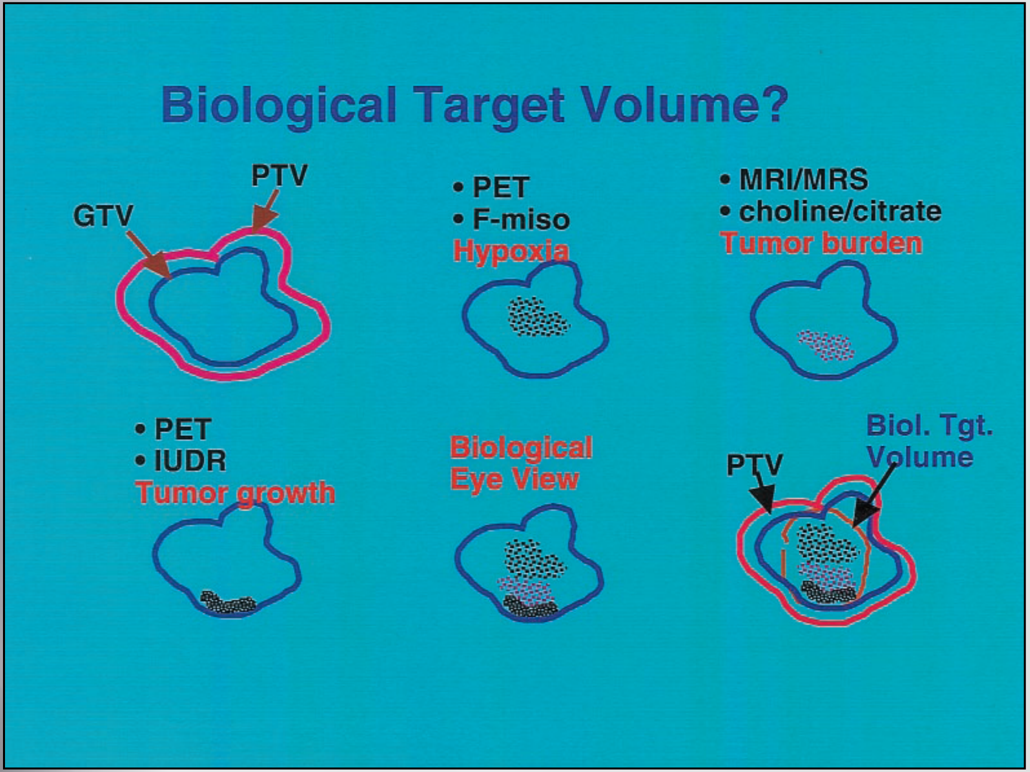


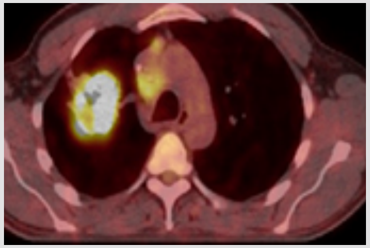

CC. Ling, *et al*. Towards multidimensional radiotherapy (MD-CRT): biological imaging and biological conformality. *Int J Radiat Oncol Biol Phys*. 2000

# Introduction

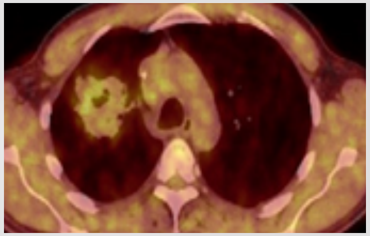
## PET segmentation: motivations

- PET/CT: target definition, treatment planning

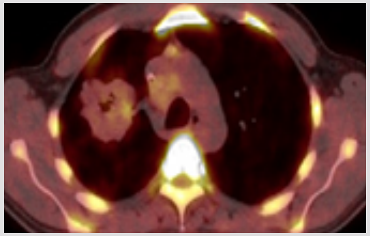


FDG (metabolism)



FMISO (hypoxia)



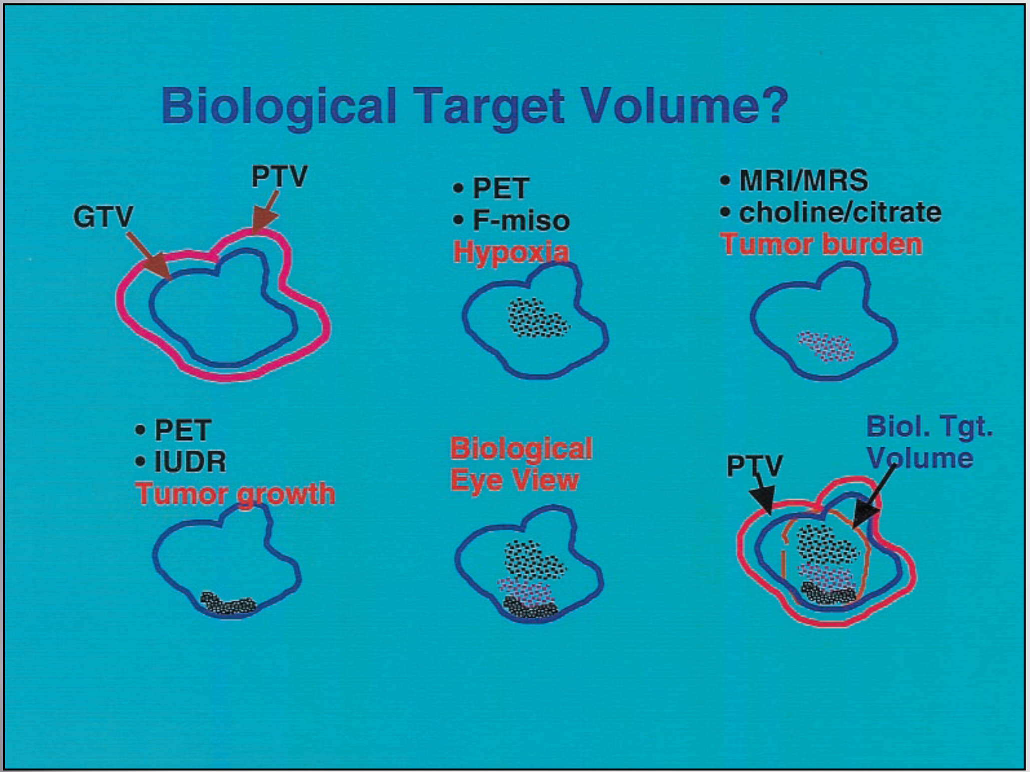
FLT (cellular proliferation )

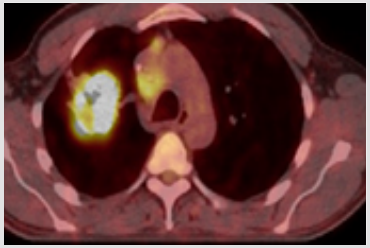
Vera P., *et al*. Simultaneous PET assessment of metabolism with FDG, proliferation with FLT, and hypoxia with F-miso before and during radiotherapy in patients with non-small-cell lung cancer (NSCLC): a pilot study. *Radiother Oncol*. 2011

# Introduction
PET segmentation: motivations

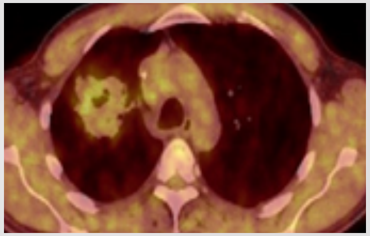


## PET/CT: target definition, treatment planning

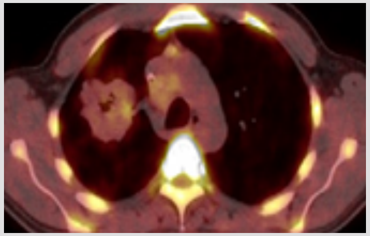


FDG (metabolism)



FMISO (hypoxia)



FLT (cellular proliferation )

Issues:

1. How to define these volumes/sub volumes?
2. How to subsequently use them?

Instituts thématiques Inserm Institut national de la santé et de la recherche médicale

Vera P., *et al*. Simultaneous PET assessment of metabolism with FDG, proliferation with FLT, and hypoxia with F-miso before and during radiotherapy in patients with non-small-cell lung cancer (NSCLC): a pilot study. *Radiother Oncol*. 2011

## PET/CT: target definition, treatment planning

Anatomical/morphological tumor volume

\#

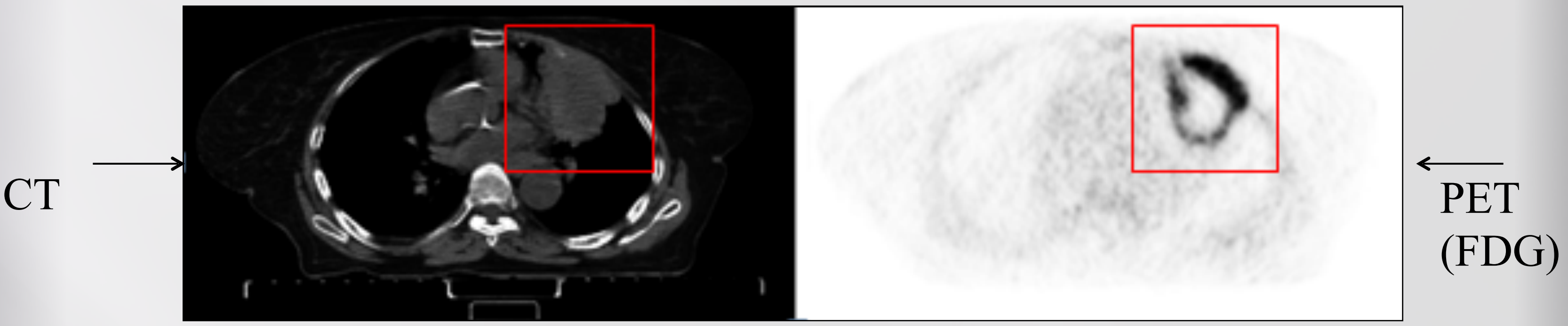
functional (metabolic/hypoxic/proliferative) tumor volume

# Introduction

## PET segmentation: motivations

- PET/CT: target definition, treatment planning

Anatomical/morphological tumor volume
#
functional (metabolic/hypoxic/proliferative) tumor volume



# Introduction

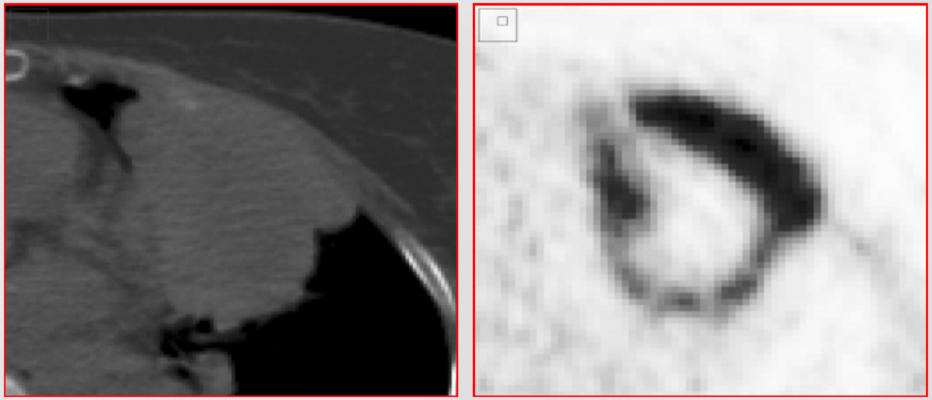
## PET segmentation: motivations

### PET/CT: target definition, treatment planning

Anatomical/morphological tumor volume

#

functional (metabolic/hypoxic/proliferative) tumor volume



# Introduction

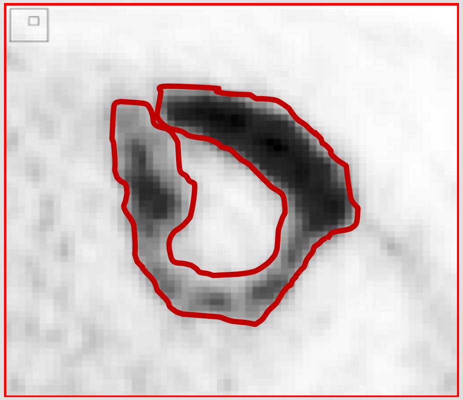
## PET segmentation: motivations

### PET/CT: target definition, treatment planning

Anatomical/morphological tumor volume

#

functional (metabolic/hypoxic/proliferative) tumor volume

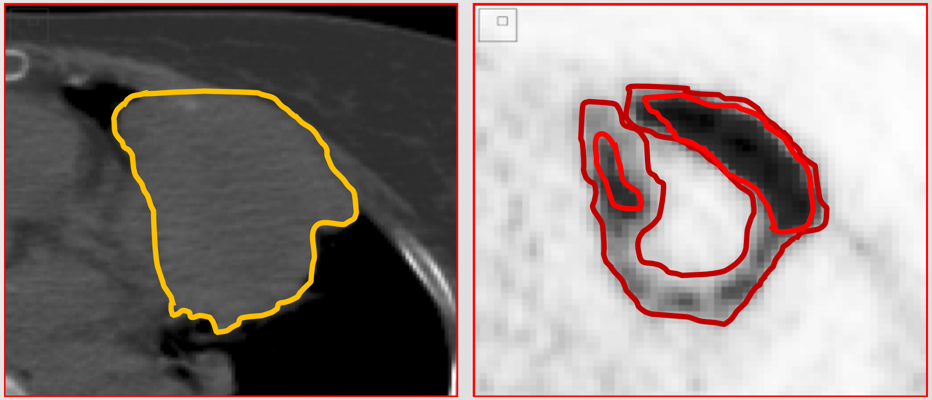


## PET/CT: target definition, treatment planning

Anatomical/morphological tumor volume

#

functional (metabolic/hypoxic/proliferative) tumor volume



# Introduction

## PET segmentation: motivations

- PET/CT: target definition, treatment planning

Anatomical/morphological tumor volume
#
functional (metabolic/hypoxic/proliferative) tumor volume

# Introduction

## PET segmentation: motivations

### PET/CT: target definition, treatment planning

Anatomical/morphological tumor volume

#

functional (metabolic/hypoxic/proliferative) tumor volume

Complementary information + dosimetry optimization

# Introduction

PET segmentation: motivations

## PET/CT: target definition, treatment planning

Anatomical/morphological tumor volume
#
functional (metabolic/hypoxic/proliferative) tumor volume

Complementary information + dosimetry optimization

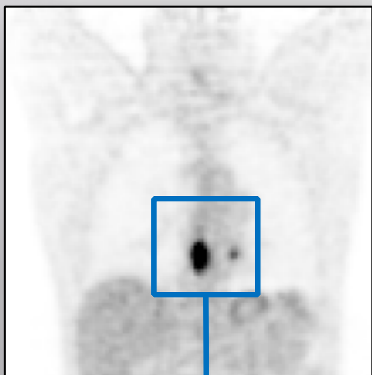
# Introduction

## PET segmentation: motivations

- PET/CT: from assessment to monitoring/predicting response to therapy

Treatment

Pre treatment
(« baseline »)



Prediction

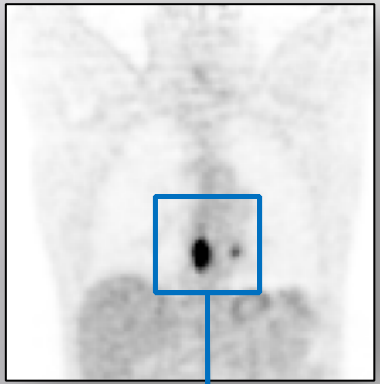
# Introduction

## PET segmentation: motivations

- PET/CT: from assessment to monitoring/predicting response to therapy

Treatment

Pre treatment
(« baseline »)



Prediction

Post treatment

Late assessment
(RECIST → PERCIST)

- ❑ response, relapse, overall/disease-free survival, toxicity
- ❑ goal: improve patient management, personalized treatment

Instituts thématiques Inserm
Institut national de la santé et de la recherche médicale

Wahl, *et al*. From RECIST to PERCIST: evolving considerations for PET response criteria in solid tumors. *J Nucl Med* 2009

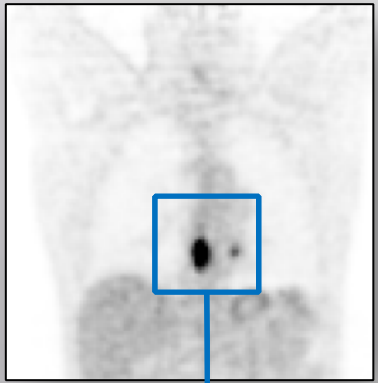
# Introduction

## PET segmentation: motivations

- PET/CT: from assessment to monitoring/predicting response to therapy

Treatment

Pre treatment
(« baseline »)

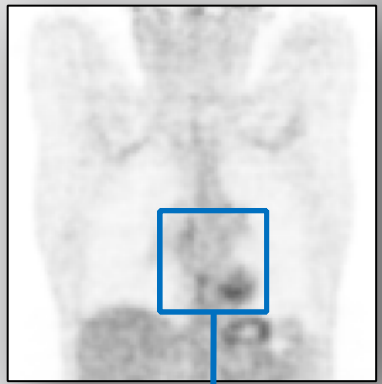


Prediction

During treatment
(1, 2 weeks /cycles)

Prediction /early evaluation

Post treatment



Late assessment
(RECIST → PERCIST)

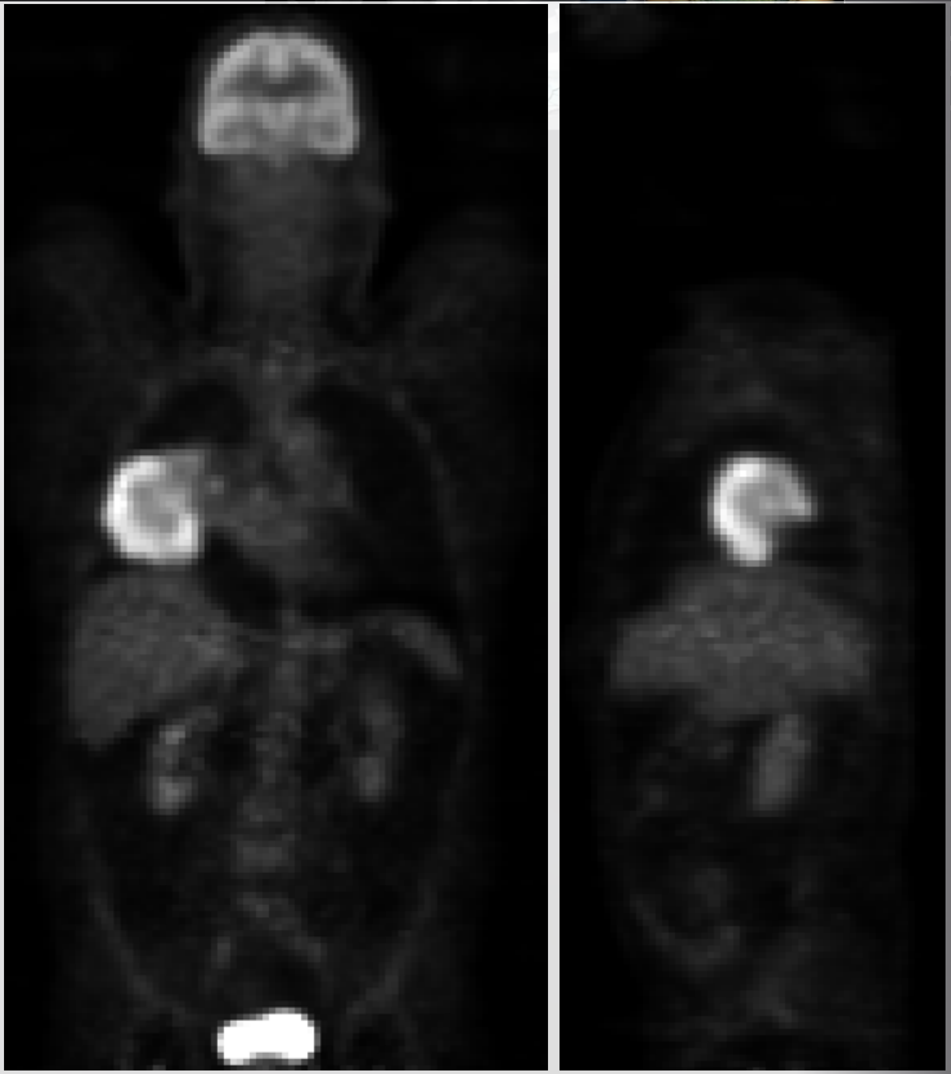
- ❑ response, relapse, overall/disease-free survival, toxicity
- ❑ goal: improve patient management, personalized treatment

Wahl, *et al*. From RECIST to PERCIST: evolving considerations for PET response criteria in solid tumors. *J Nucl Med* 2009

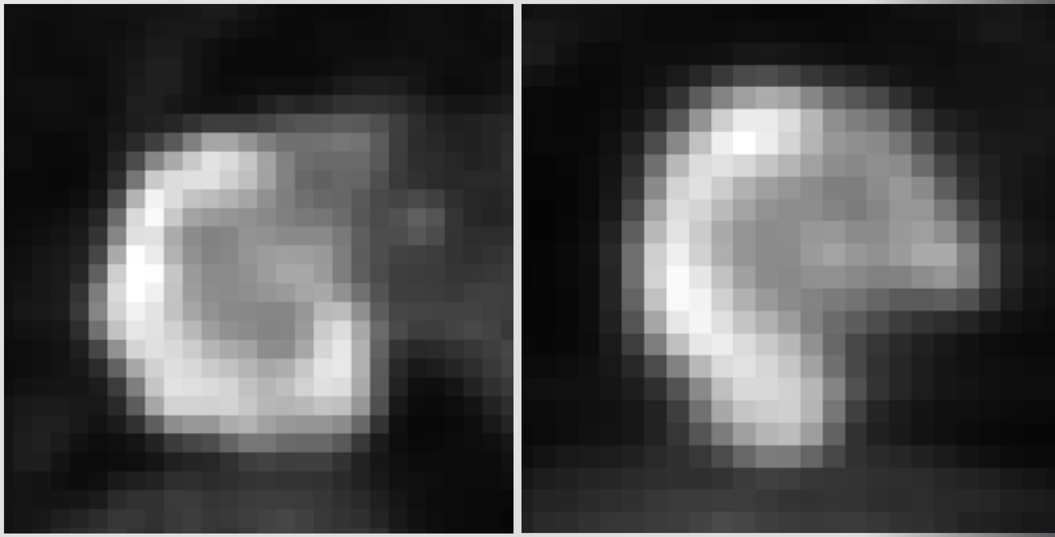
# Introduction

## PET segmentation: challenges

- Challenges in PET

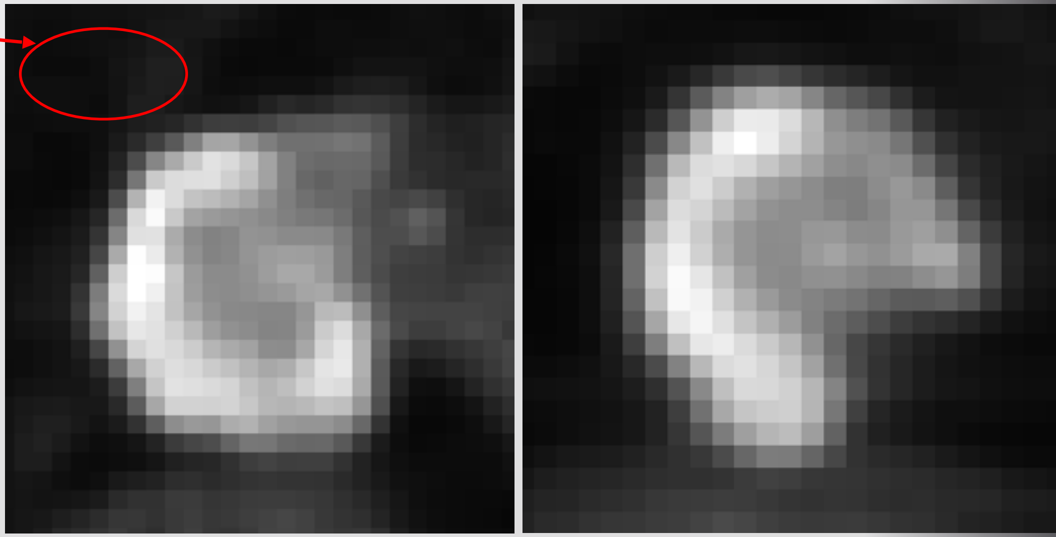


## Challenges in PET



## Challenges in PET

- ✓ Limited signal to noise ratio (sensitivity, acq. duration…)



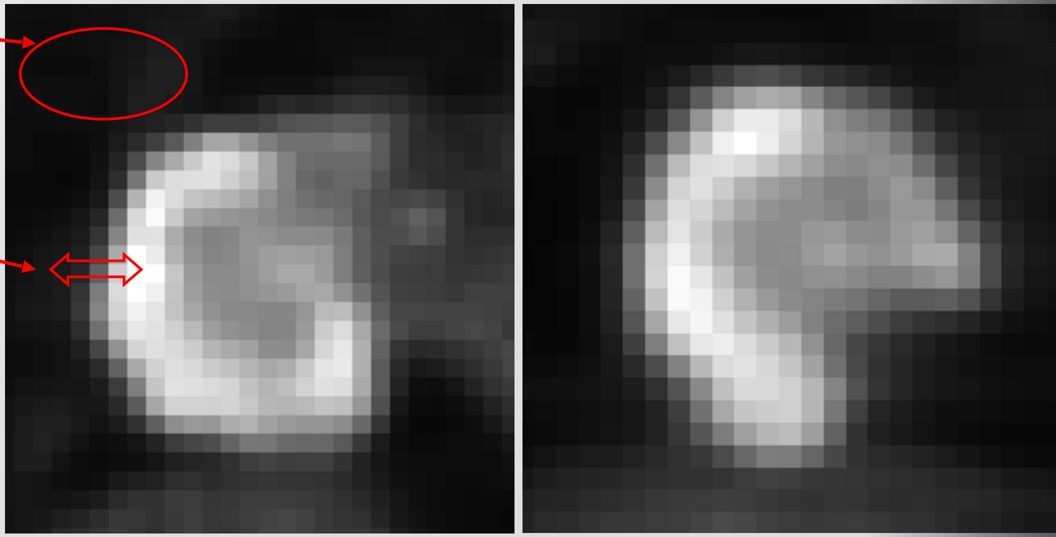
## Challenges in PET

✓ Limited signal to noise ratio

(sensitivity, acq. duration…)

✓ Partial volume effects

(limited spatial resolution)



## Challenges in PET

- ✓ Limited signal to noise ratio

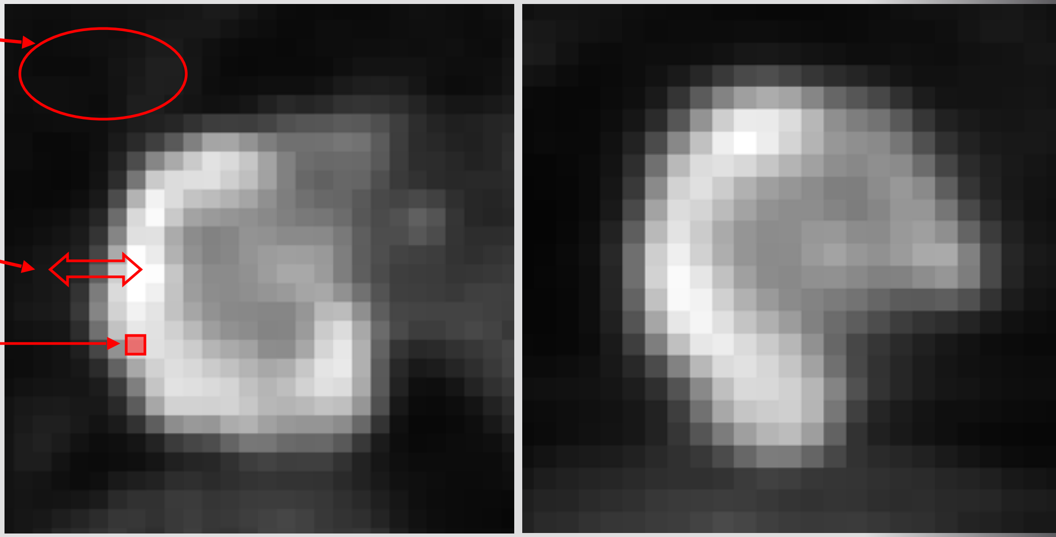
  (sensitivity, acq. duration…)

- ✓ Partial volume effects

  (limited spatial resolution)

- ✓ Spatial sampling

  (voxel size, grid matrix)

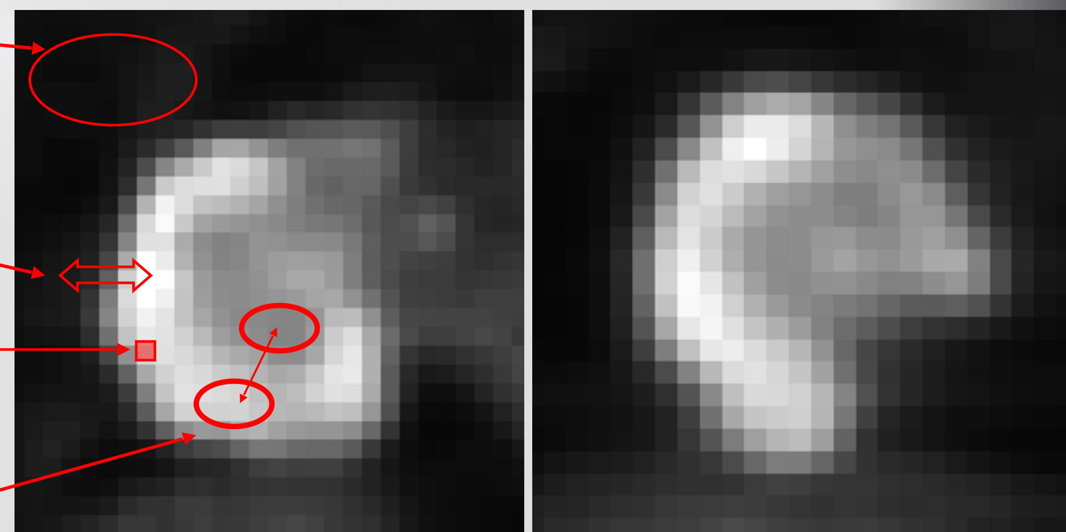


# Introduction

PET segmentation: challenges

## Challenges in PET

- ✓ Limited signal to noise ratio (sensitivity, acq. duration…)
- ✓ Partial volume effects (limited spatial resolution)
- ✓ Spatial sampling (voxel size, grid matrix)
- ✓ Uptake heterogeneity
- ✓ Complex shapes



# PET segmentation

The era of thresholding

- 1997-2007
  - One of the first papers (conference)
    - Suggested the use of a fixed threshold of 42% of the max

Sixth Conference on Radioimmunodetection and Radioimmunotherapy of Cancer

*Supplement to **Cancer***

## Segmentation of Lung Lesion Volume by Adaptive Positron Emission Tomography Image Thresholding

Yusuf E. Erdi, D.Sc.[1]
O. Mawlawi, M.Sc.[2]
Steven M. Larson, M.D.[2]
M. Imbriaco, M.D.[2]
H. Yeung, M.D.[2]
R. Finn, Ph.D.[1]
John L. Humm, Ph.D.[1]

**BACKGROUND.** It is common protocol in radionuclide therapies to administer a tracer dose of a radiopharmaceutical, determine its lesion uptake and biodistribution by gamma imaging, and then use this information to determine the most effective therapeutic dose. This treatment planning approach can be used to quantitate accurately the activity and volume of lesions and organs with positron emission tomography (PET). In this article, the authors focus on the specification of appropriate volumes of interest (VoI) using PET in association with computed tomography (CT).

# PET segmentation

The era of thresholding

## 1997-2007

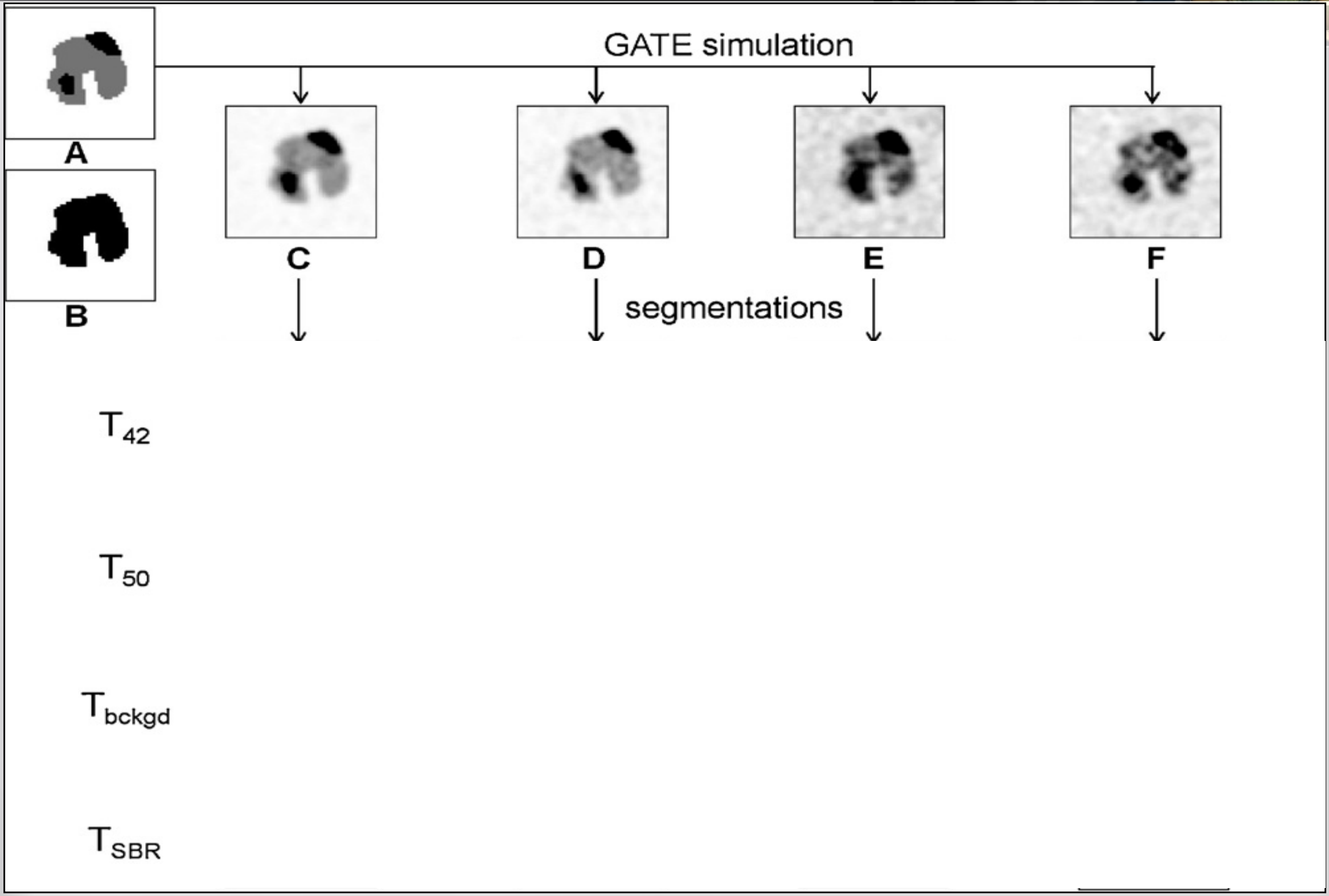
- One of the first papers (conference)
  - Suggested the use of a fixed threshold of 42% of the max
- Numerous subsequent papers for thresholding[1]
  - Suggested other fixed threshold values (between 30 and 80% of SUVmax / SUVpeak …, or >SUV 2.5, 2.0 …)
  - Extended the paradigm to adaptive thresholding
    - Iterative approaches
    - Taking into account the background value and/or contrast
    - Optimization using phantom acquisitions…



1. A.-S. Dewalle-Vignion, *et al*. Les méthodes de seuillage en TEP : un état de l'art. *Médecine Nucléaire* 2010

# PET segmentation

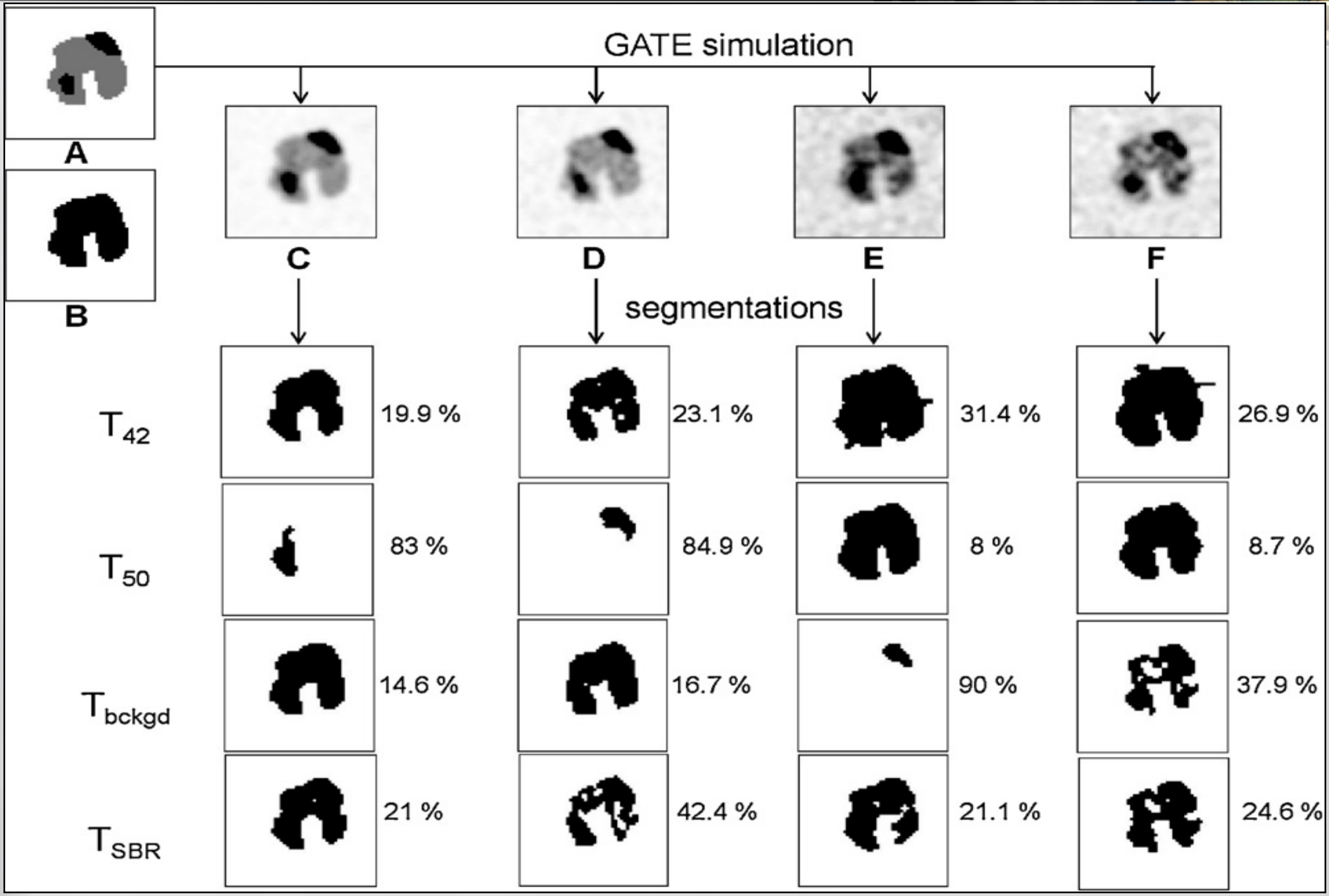
The era of thresholding




M. Hatt. Automatic determination of functional volumes for oncology applications. *PhD*, 2008.

# PET segmentation

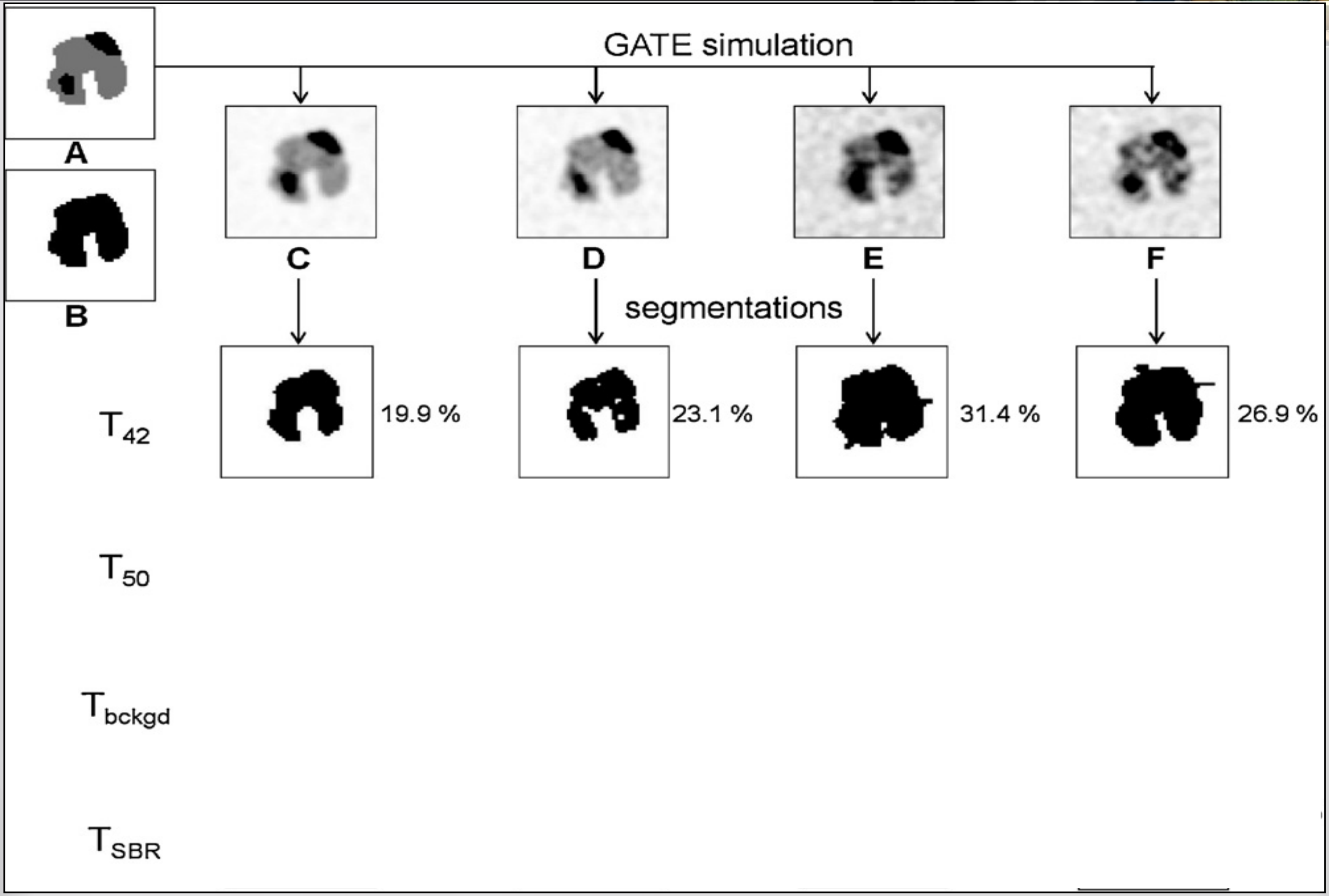
The era of thresholding




M. Hatt. Automatic determination of functional volumes for oncology applications. *PhD*, 2008.

# PET segmentation

The era of thresholding

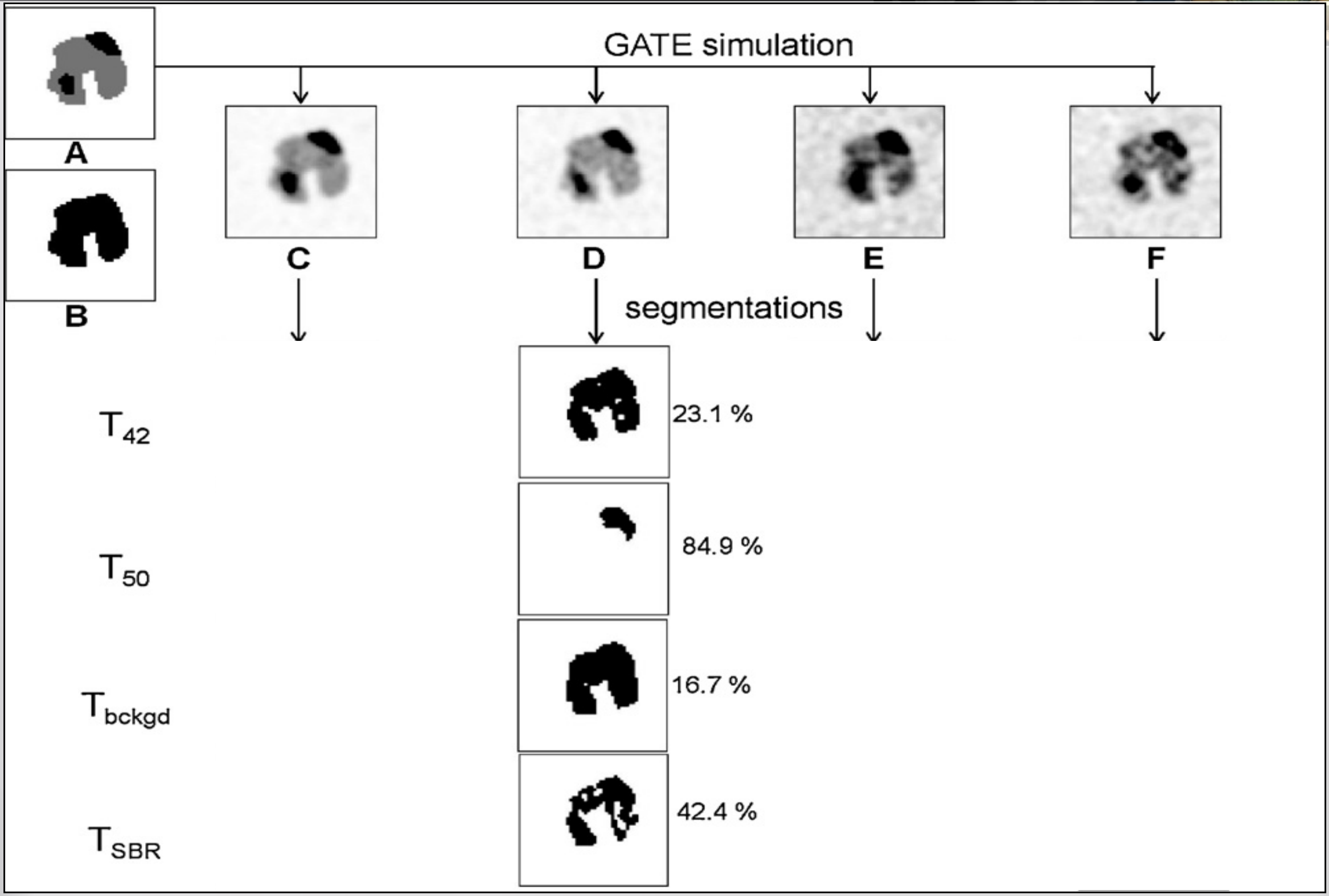



Instituts thématiques Inserm
Institut national de la santé et de la recherche médicale

M. Hatt. Automatic determination of functional volumes for oncology applications. *PhD*, 2008.

# PET segmentation

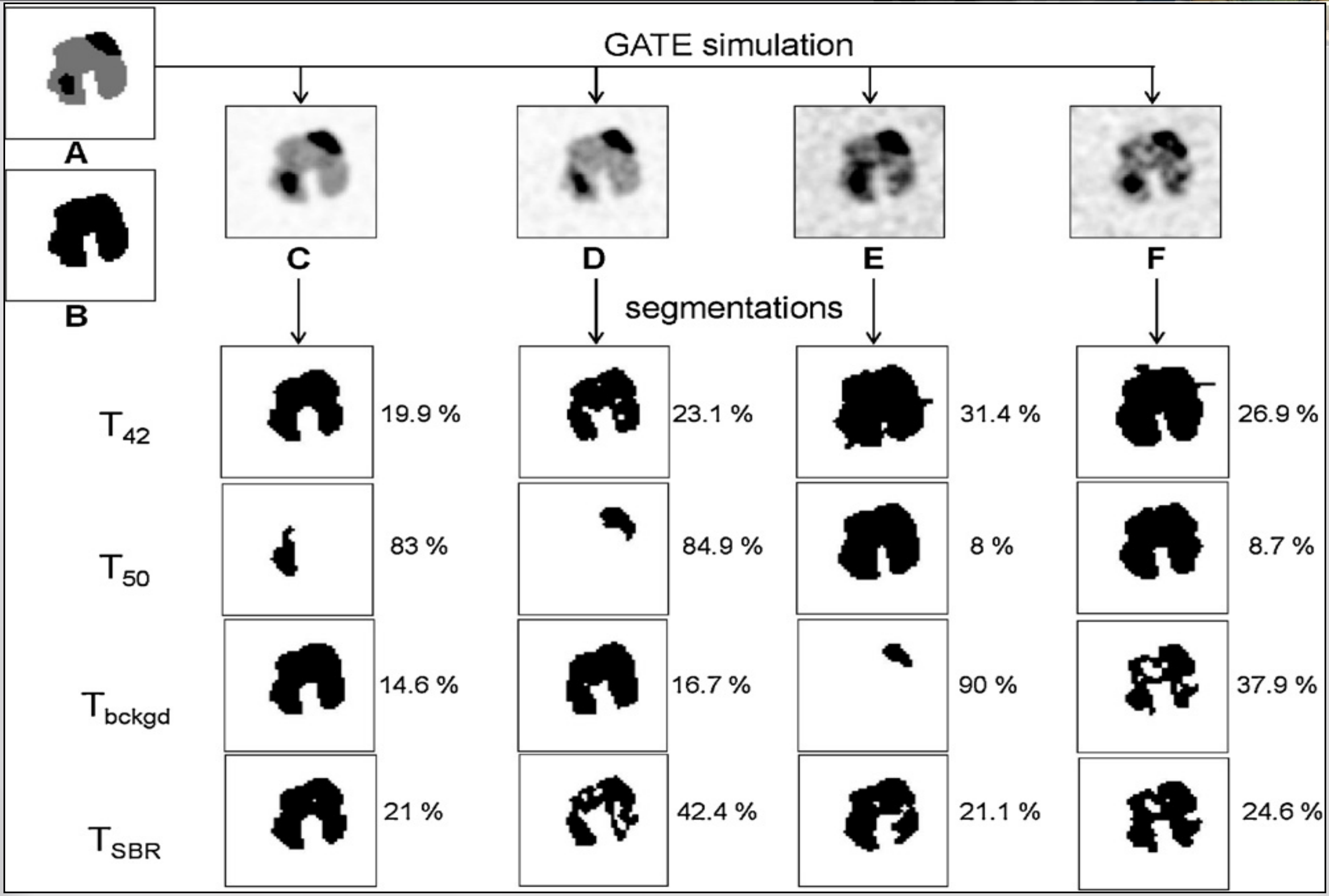
The era of thresholding




M. Hatt. Automatic determination of functional volumes for oncology applications. *PhD*, 2008.

# PET segmentation

The era of thresholding




M. Hatt. Automatic determination of functional volumes for oncology applications. *PhD*, 2008.

# PET segmentation

The era of thresholding

## 1997-2007

- MATV delineation directly on PET
  - Fixed threshold (either absolute SUV or % of the max)
    - **Not accurate, not robust and should not be used!**

      → even manual delineation is preferable! [1]

1. Hatt, *et al*. Regarding Autocontouring and Manual Contouring: Which Is the Better Method for Target Delineation Using 18F-FDG PET/CT in Non–Small Cell Lung Cancer? *J Nucl Med* 2011
2. Hatt, *et al*. Reproducibility of 18F-FDG and 3'-Deoxy-3'-18F-Fluorothymidine PET Tumor Volume Measurements, *J Nucl Med* 2010

# PET segmentation

The era of thresholding

## 1997-2007

- MATV delineation directly on PET
  - Fixed threshold (either absolute SUV or % of the max)
    - **Not accurate, not robust and should not be used!**

      → even manual delineation is preferable! [1]
  - Manual delineation
    - high inter and intra observer variability [2]

      → use consensus of several observers
    - time consuming

1. Hatt, *et al*. Regarding Autocontouring and Manual Contouring: Which Is the Better Method for Target Delineation Using 18F-FDG PET/CT in Non–Small Cell Lung Cancer? *J Nucl Med* 2011
2. Hatt, *et al*. Reproducibility of 18F-FDG and 3'-Deoxy-3'-18F-Fluorothymidine PET Tumor Volume Measurements, *J Nucl Med* 2010

# PET segmentation

The era of thresholding

## 1997-2007

- MATV delineation directly on PET
  - Fixed threshold (either absolute SUV or % of the max)
    - **Not accurate, not robust and should not be used!**

      → even manual delineation is preferable! [1]
  - Manual delineation
    - high inter and intra observer variability [2]

      → use consensus of several observers
    - time consuming
  - Adaptive threshold
    - can provide good results for homogeneous uptake within MATV and sufficient tumor-to-background contrast
    - requires center-specific optimization, user interaction
    - not robust versus heterogeneous uptake and/or low T-B contrast



1. Hatt, *et al*. Regarding Autocontouring and Manual Contouring: Which Is the Better Method for Target Delineation Using 18F-FDG PET/CT in Non–Small Cell Lung Cancer? *J Nucl Med* 2011
2. Hatt, *et al*. Reproducibility of 18F-FDG and 3'-Deoxy-3'-18F-Fluorothymidine PET Tumor Volume Measurements, *J Nucl Med* 2010

# PET segmentation

Improving over thresholding using adaptive region growing

## ROVER method

- Principle: region growing with locally adaptive thresholding (in order to adapt to heterogeneous lesions)
- No pre processing but optimization on phantom images (parameter = 39%)
- Validated on simulated images and clinical with respect to expert contours
- Implemented in the ROVER™ software (http://www.abx.de/rover)



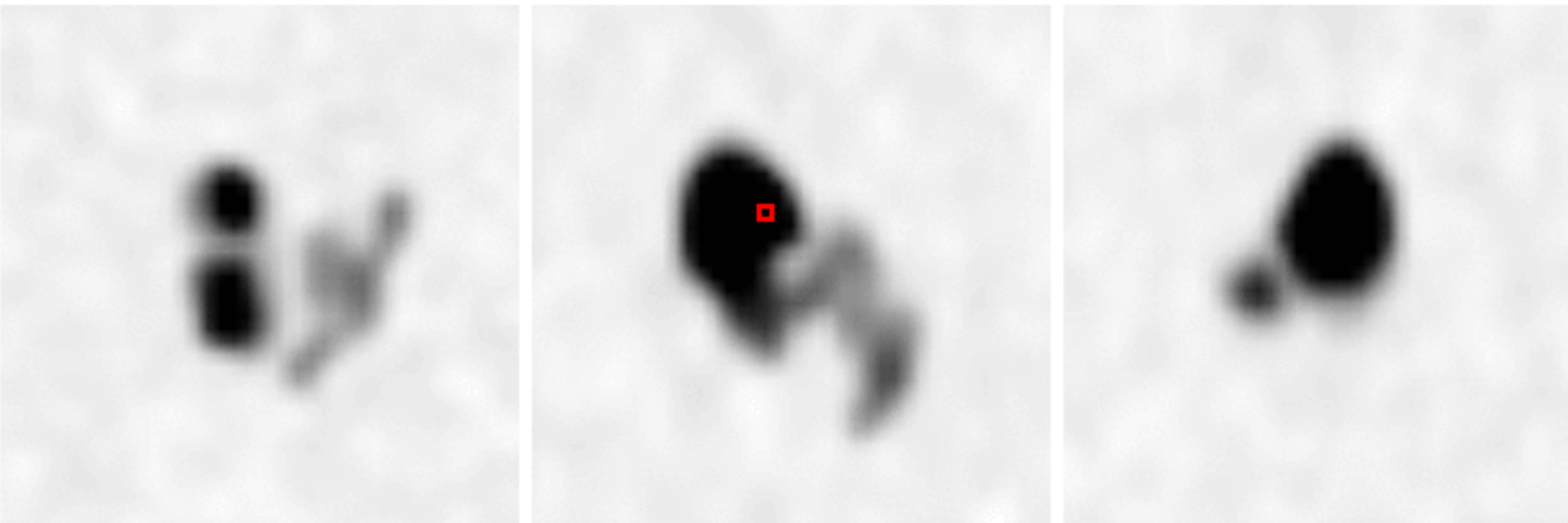
Hofheinz, *et al*. An automatic method for accurate volume delineation of heterogeneous tumors in PET. *Med Phys* 2013

# PET segmentation

Improving over thresholding using adaptive region growing

## ROVER method

- Principle: region growing with locally adaptive thresholding (in order to adapt to heterogeneous lesions)



Institut thématiques Inserm

Institut national de la santé et de la recherche médicale

Hofheinz, *et al*. An automatic method for accurate volume delineation of heterogeneous tumors in PET. *Med Phys* 2013

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## 2007-2010

- Two important papers in 2007

Eur J Nucl Med Mol Imaging (2007) 34:1427–1438
DOI 10.1007/s00259-006-0363-4

ORIGINAL ARTICLE

**A gradient-based method for segmenting FDG-PET images: methodology and validation**

Xavier Geets • John A. Lee • Anne Bol • Max Lonneux • Vincent Grégoire

IOP PUBLISHING — PHYSICS IN MEDICINE AND BIOLOGY

Phys. Med. Biol. **52** (2007) 3467–3491 doi:10.1088/0031-9155/52/12/010

**Fuzzy hidden Markov chains segmentation for volume determination and quantitation in PET**

M Hatt[1], F Lamare[1], N Boussion[1], A Turzo[1,2], C Collet[3], F Salzenstein[4], C Roux[1,5], P Jarritt[6], K Carson[6], C Cheze-Le Rest[1,2] and D Visvikis[1]

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## 2007-2010

- Two important papers in 2007

Eur J Nucl Med Mol Imaging (2007) 34:1427–1438
DOI 10.1007/s00259-006-0363-4

ORIGINAL ARTICLE

**A gradient-based method for segmenting FDG-PET images: methodology and validation**

**Xavier Geets • John A. Lee • Anne Bol • Max Lonneux • Vincent Grégoire**

Citations ~260

IOP PUBLISHING PHYSICS IN MEDICINE AND BIOLOGY

Phys. Med. Biol. **52** (2007) 3467–3491 doi:10.1088/0031-9155/52/12/010

**Fuzzy hidden Markov chains segmentation for volume determination and quantitation in PET**

**M Hatt[1], F Lamare[1], N Boussion[1], A Turzo[1,2], C Collet[3], F Salzenstein[4], C Roux[1,5], P Jarritt[6], K Carson[6], C Cheze-Le Rest[1,2] and D Visvikis[1]**

Citations ~60

# Gradient-based method

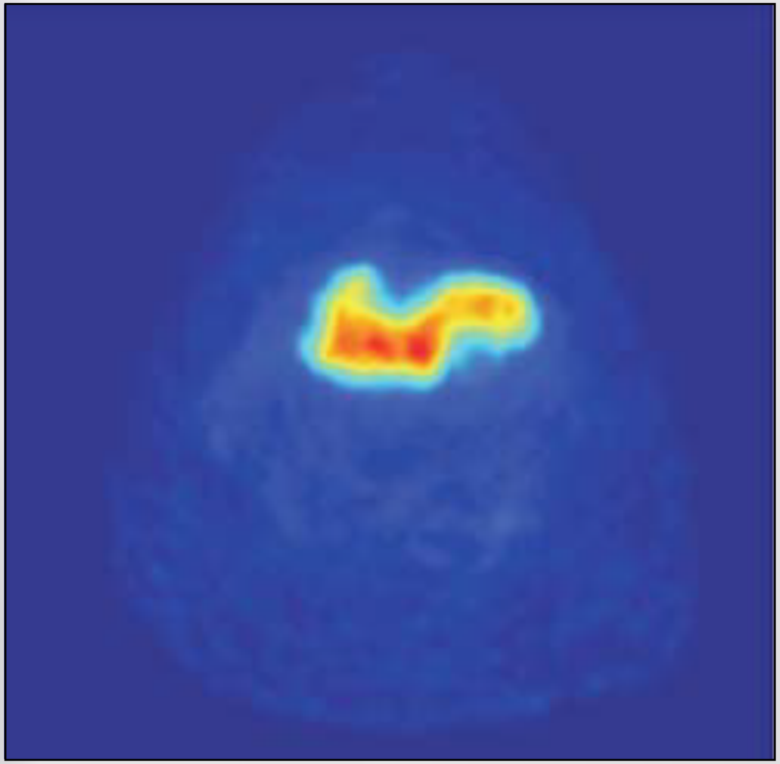
- Principle: determine contours as gradients in the watershed transform of the pre processed image (contour detection is sensitive to noise and blur)
- Requires pre processing (denoising+deblurring), binary segmentation only
- Validated on histopathology and real phantoms (+robustness with multiple scanners)[1,2]
- Implemented in the PETedge[3] software (MIMvista) as a "black box" requiring a manual initialization

1 Geets, *et al*. A gradient-based method for segmenting FDG PET images: methodology and validation. *Eur J Nucl Med Mol Imaging*. 2007
2 Wanet, *et al*. Gradient-based delineation of the primary GTV on FDG-PET in non-small cell lung cancer: a comparison with threshold-based approaches, CT and surgical specimens. *Radiother Oncol*. 2011
3 http://downloads.mimsoftware.com/Tissue_Segmentation_in_PET_image_Volumes.pdf

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

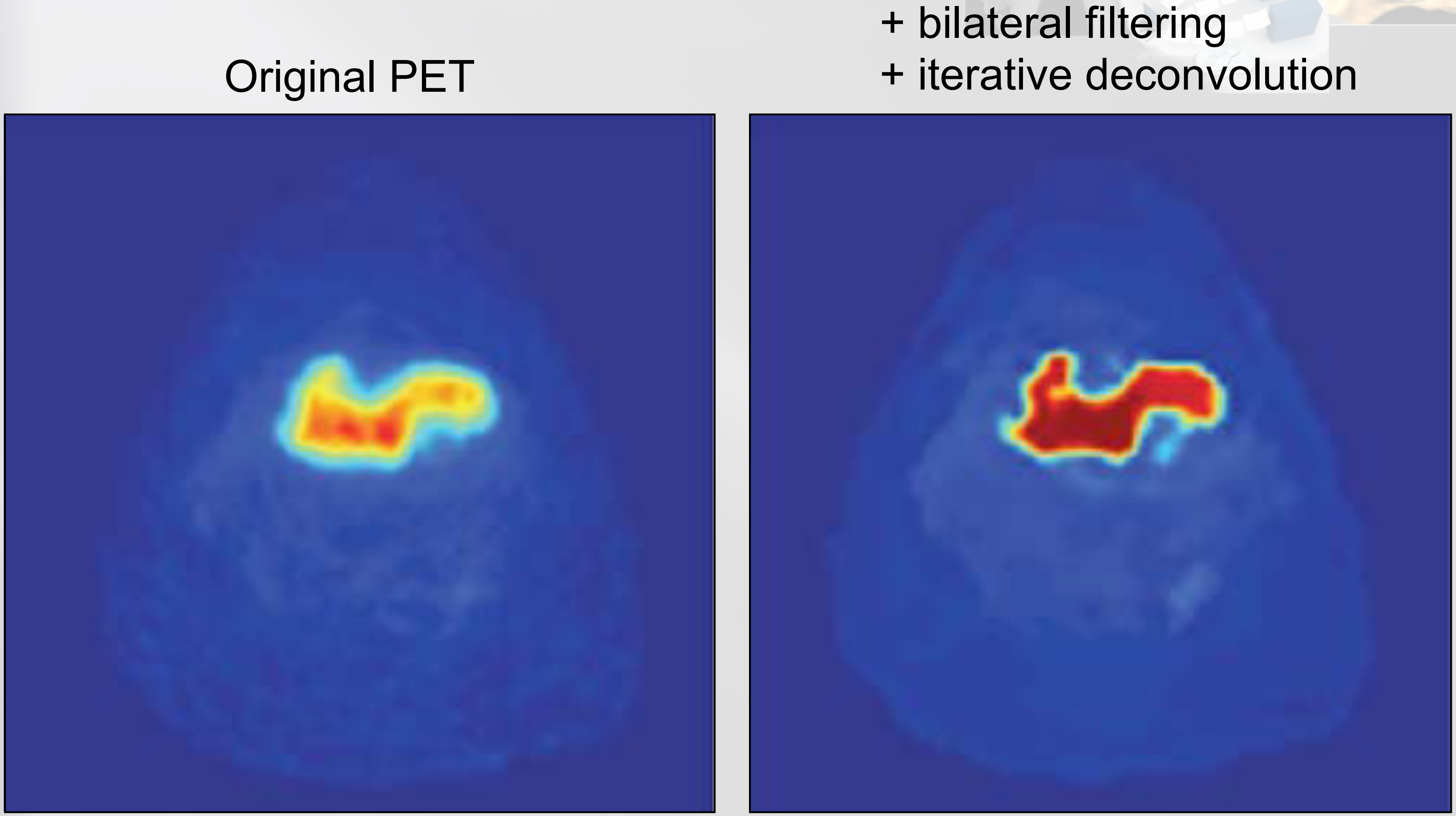
Original PET



Geets, *et al*. A gradient-based method for segmenting FDG PET images: methodology and validation. *Eur J Nucl Med Mol Imaging*. 2007

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

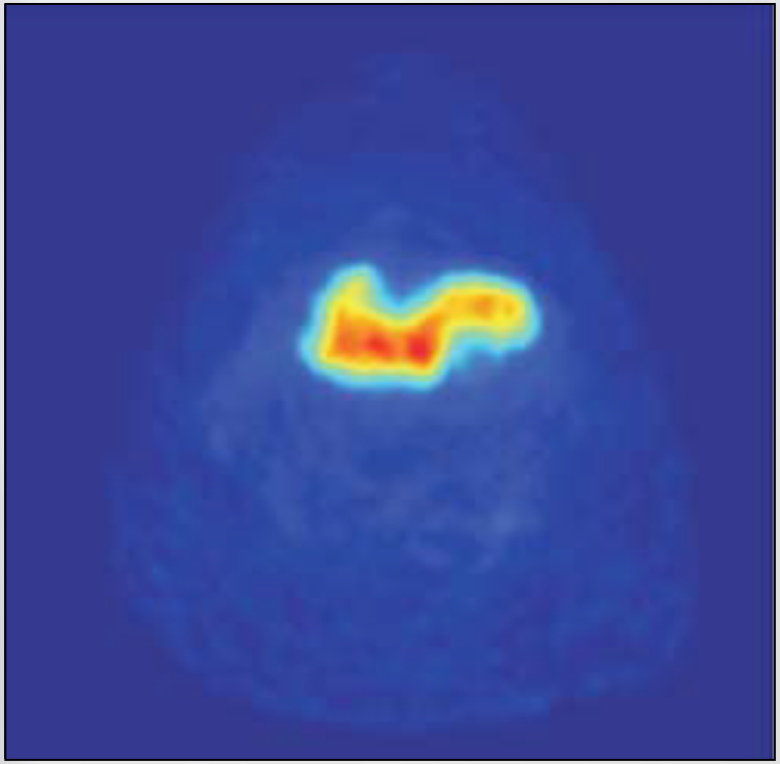



Geets, *et al*. A gradient-based method for segmenting FDG PET images: methodology and validation. *Eur J Nucl Med Mol Imaging*. 2007

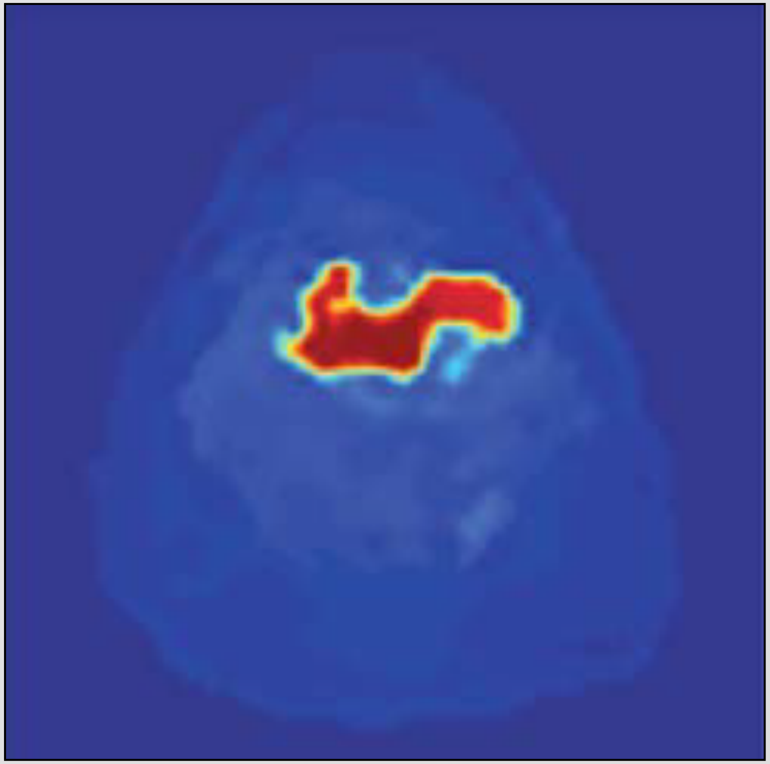
# PET segmentation

## Beyond thresholds: the era of advanced segmentation paradigms

Original PET



+ bilateral filtering
+ iterative deconvolution

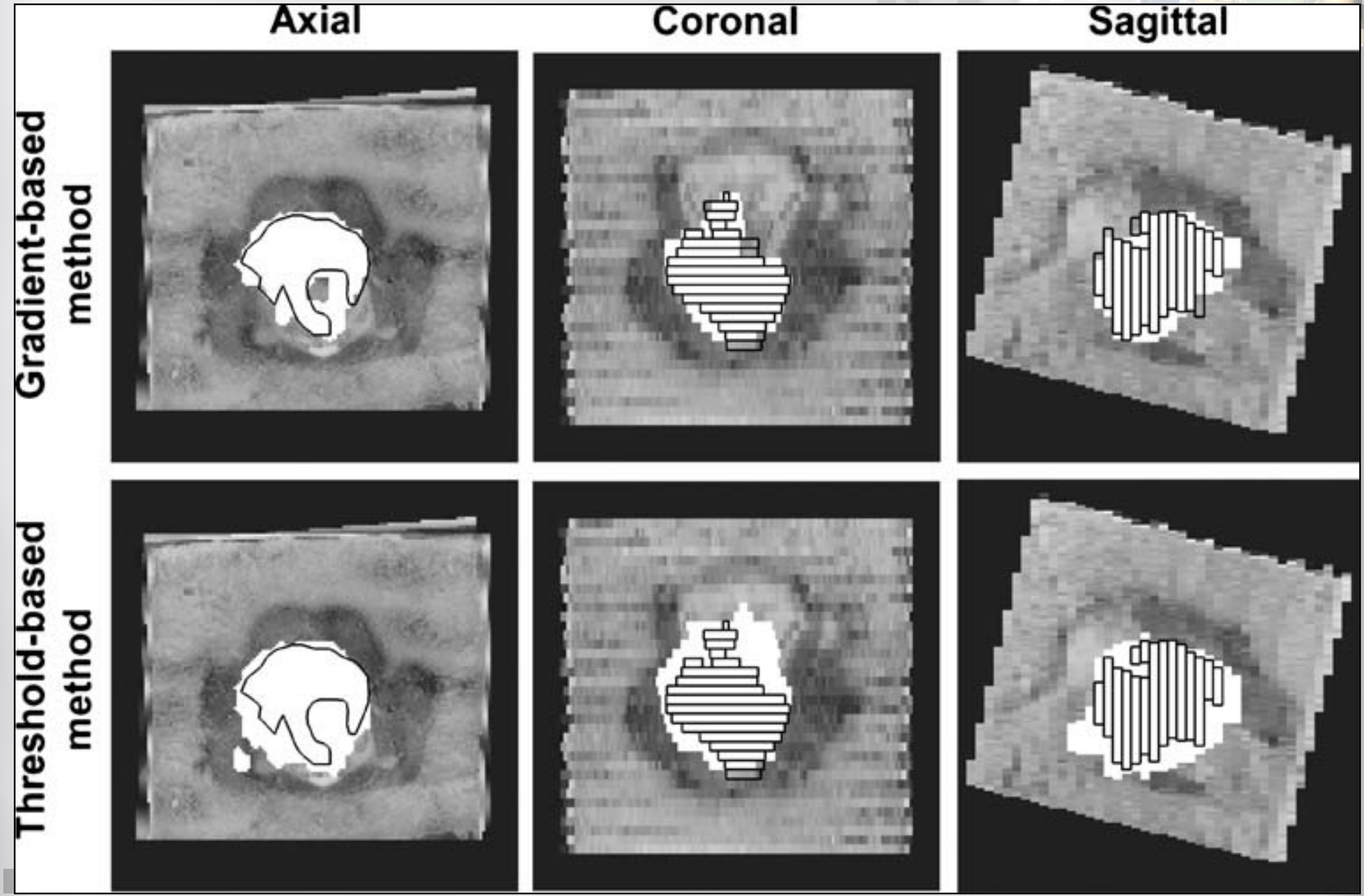


Contours detection

Geets, *et al*. A gradient-based method for segmenting FDG PET images: methodology and validation. *Eur J Nucl Med Mol Imaging*. 2007

# PET segmentation

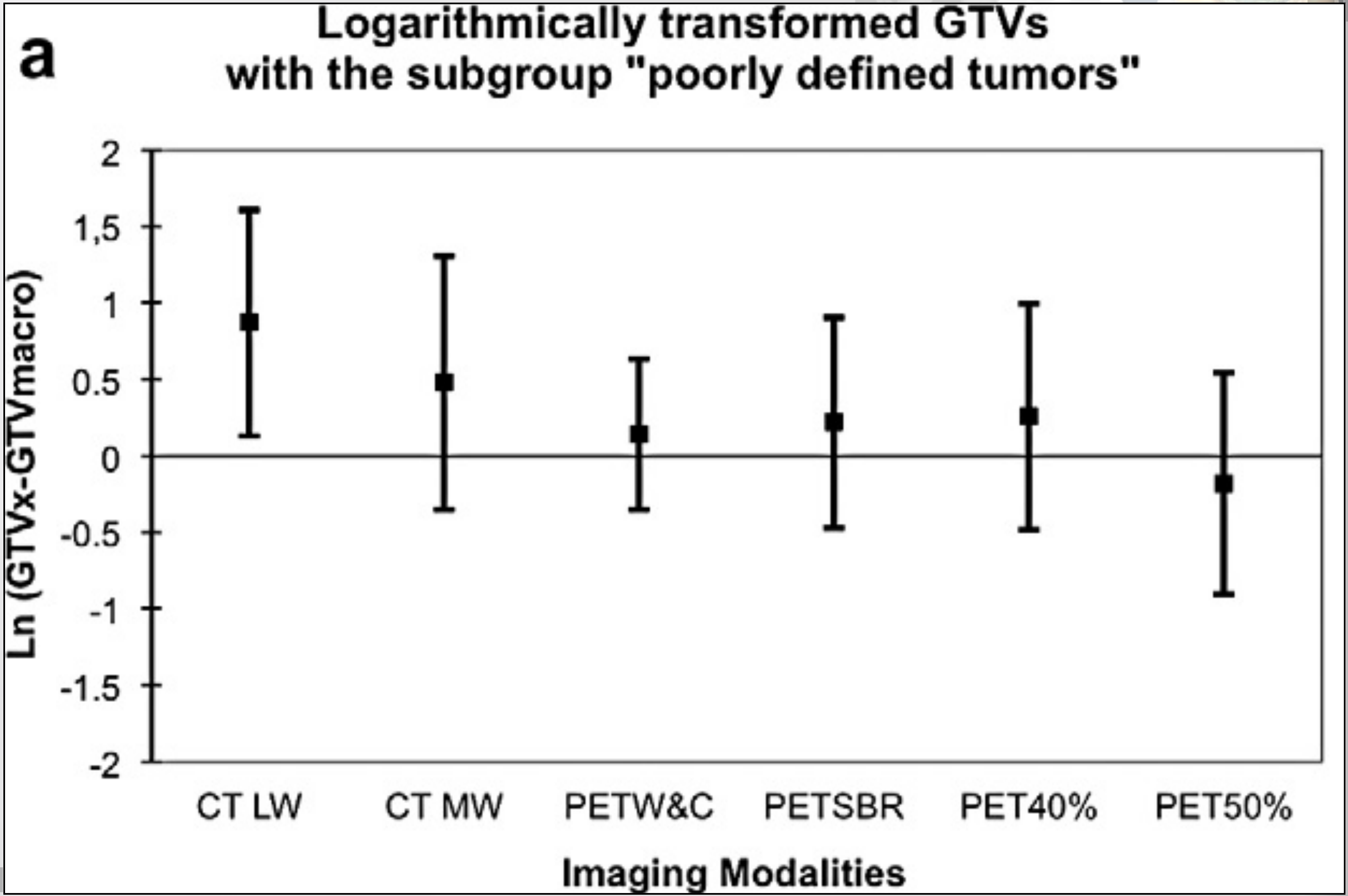
Beyond thresholds: the era of advanced segmentation paradigms




Geets, *et al*. A gradient-based method for segmenting FDG PET images: methodology and validation. *Eur J Nucl Med Mol Imaging*. 2007

# PET segmentation

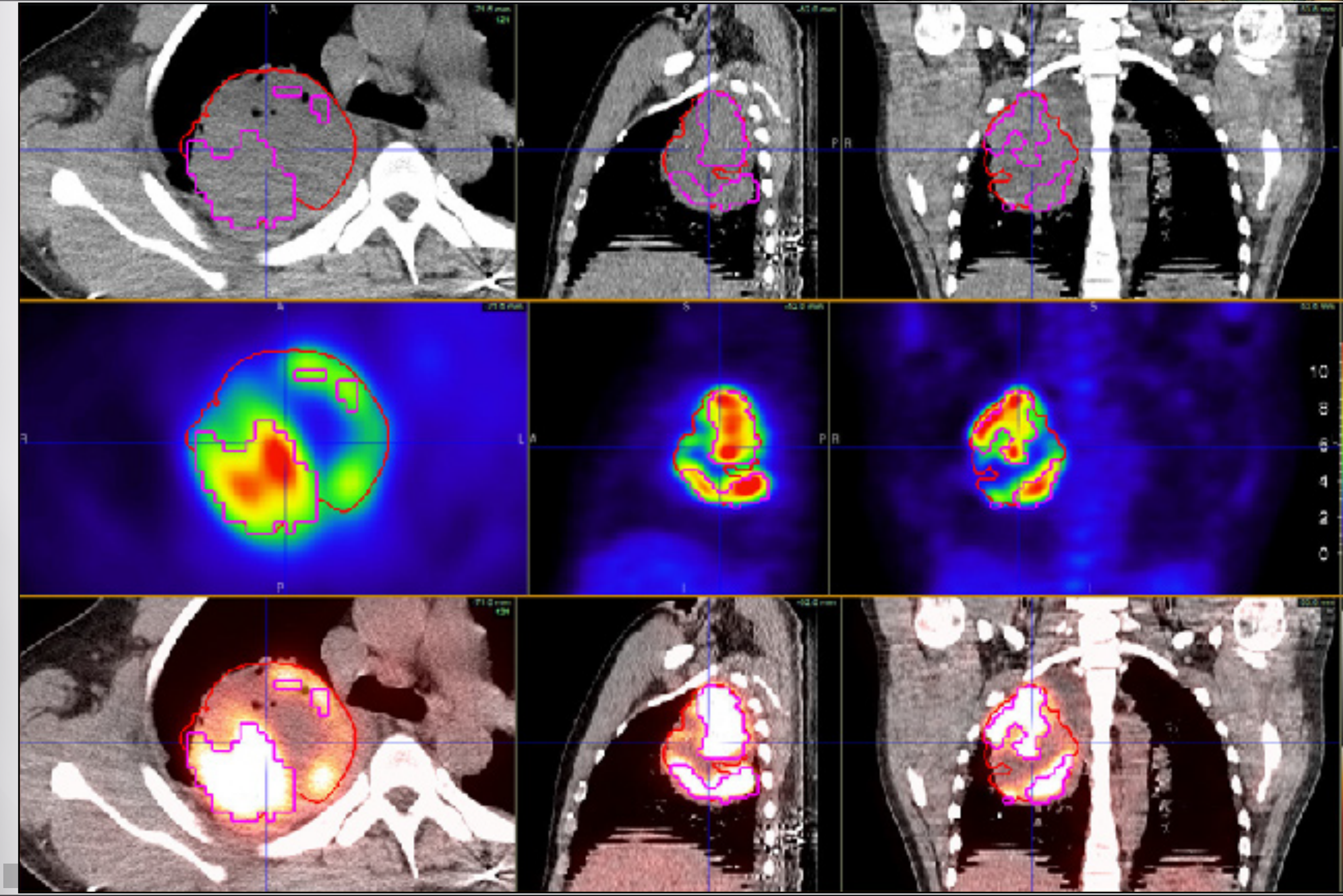
Beyond thresholds: the era of advanced segmentation paradigms




Wanet, *et al*. Gradient-based delineation of the primary GTV on FDG-PET in non-small cell lung cancer: a comparison with threshold-based approaches, CT and surgical specimens. *Radiother Oncol*. 2011

# PET segmentation

## Beyond thresholds: the era of advanced segmentation paradigms

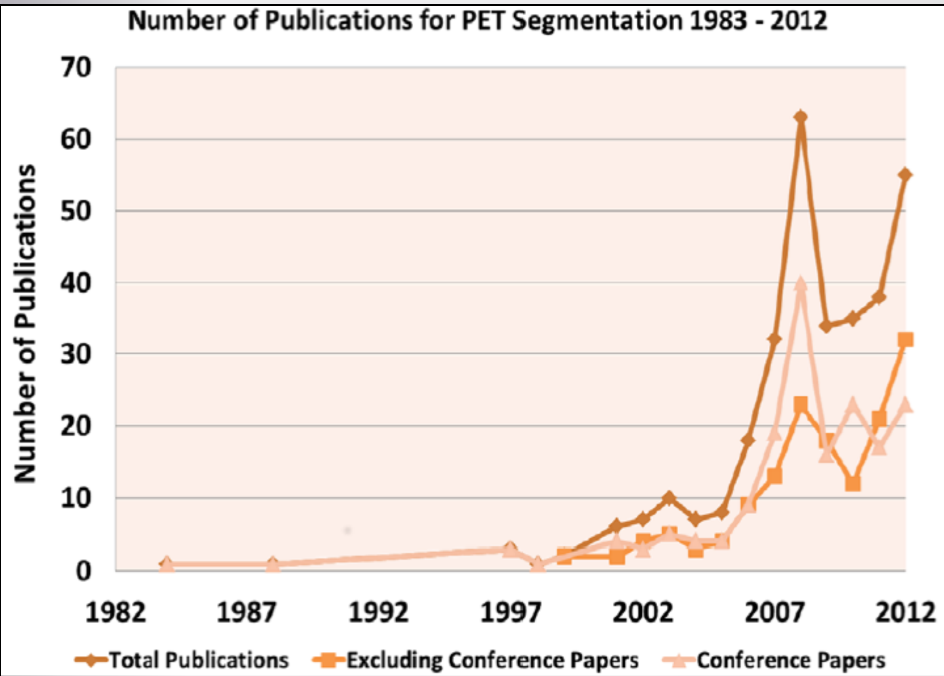



http://downloads.mimsoftware.com/Tissue_Segmentation_in_PET_image_Volumes.pdf

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## After 2007: explosion of publications

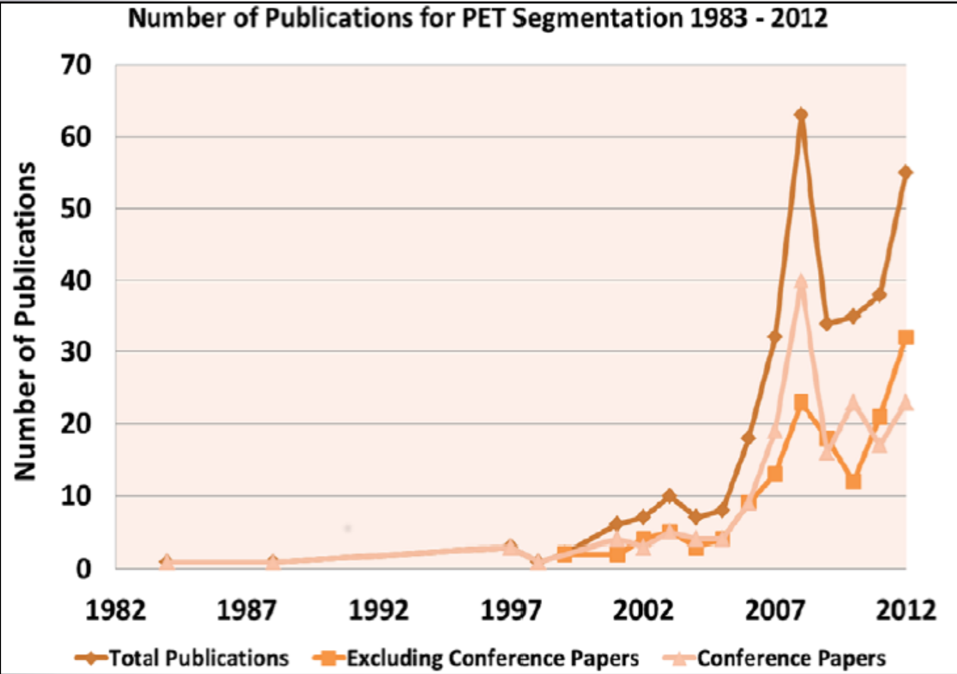


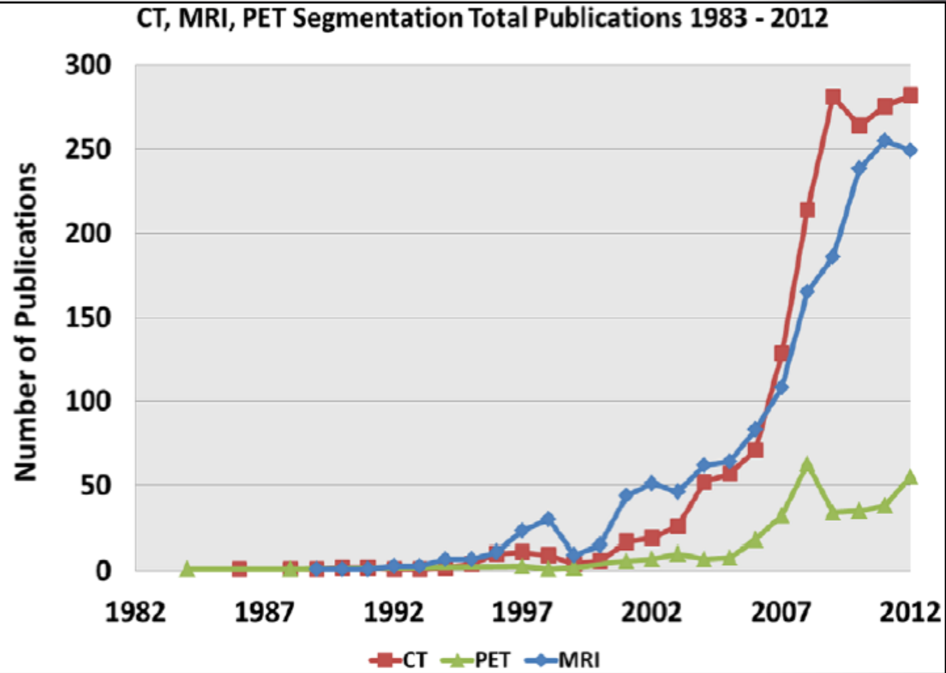

Foster B, *et al*. A review on segmentation of positron emission tomography images. *Comput Biol Med.* 2014

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## After 2007: explosion of publications




Foster B, *et al*. A review on segmentation of positron emission tomography images. *Comput Biol Med.* 2014

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## Other reviews:

Eur J Nucl Med Mol Imaging
DOI 10.1007/s00259-010-1423-3

REVIEW ARTICLE

**PET-guided delineation of radiation therapy treatment volumes: a survey of image segmentation techniques**

**Habib Zaidi · Issam El Naqa**

Cancer/Radiothérapie 16 (2012) 70–81

ELSEVIER MASSON

Disponible en ligne sur
SciVerse ScienceDirect
www.sciencedirect.com

Elsevier Masson France
EM|consulte
www.em-consulte.com

Cancer Radiothérapie

Revue générale

Méthodologies de définition automatique des volumes métaboliquement actifs en TEP : évaluation et perspectives

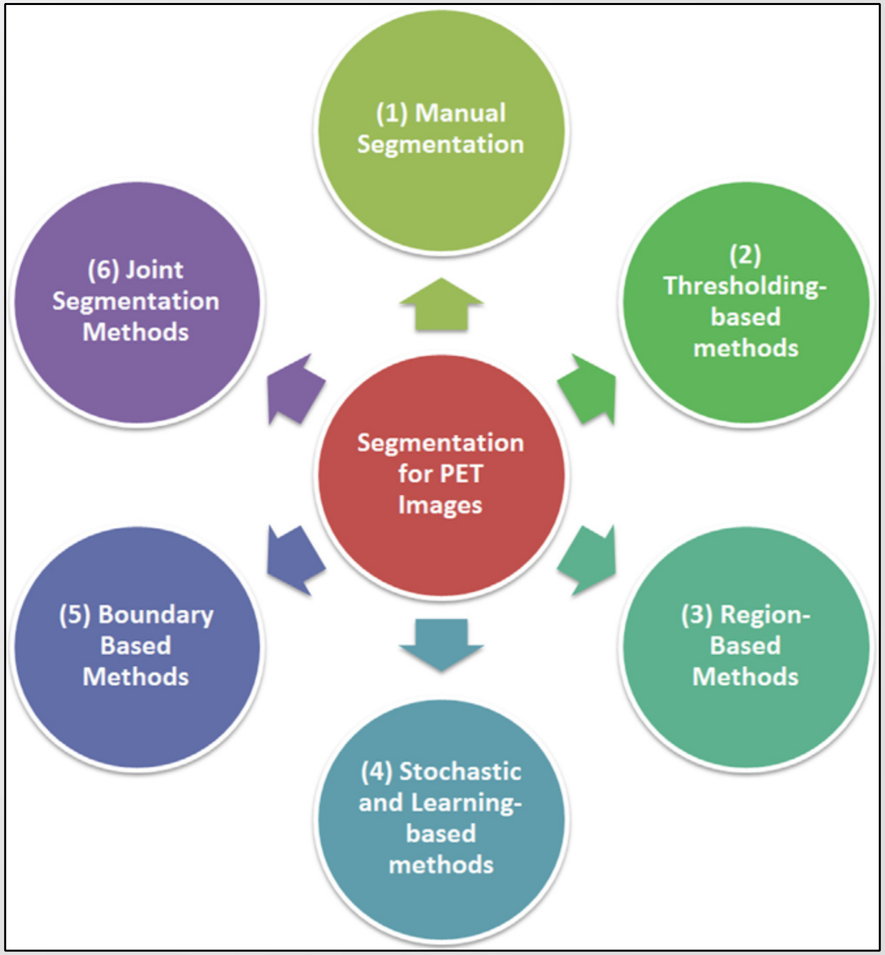
*Metabolically active volumes automatic delineation methodologies in PET imaging: Review and perspectives*

M. Hatt[a,*], N. Boussion[a,b], C. Cheze-Le Rest[a], D. Visvikis[a], O. Pradier[a,b]

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## Review:

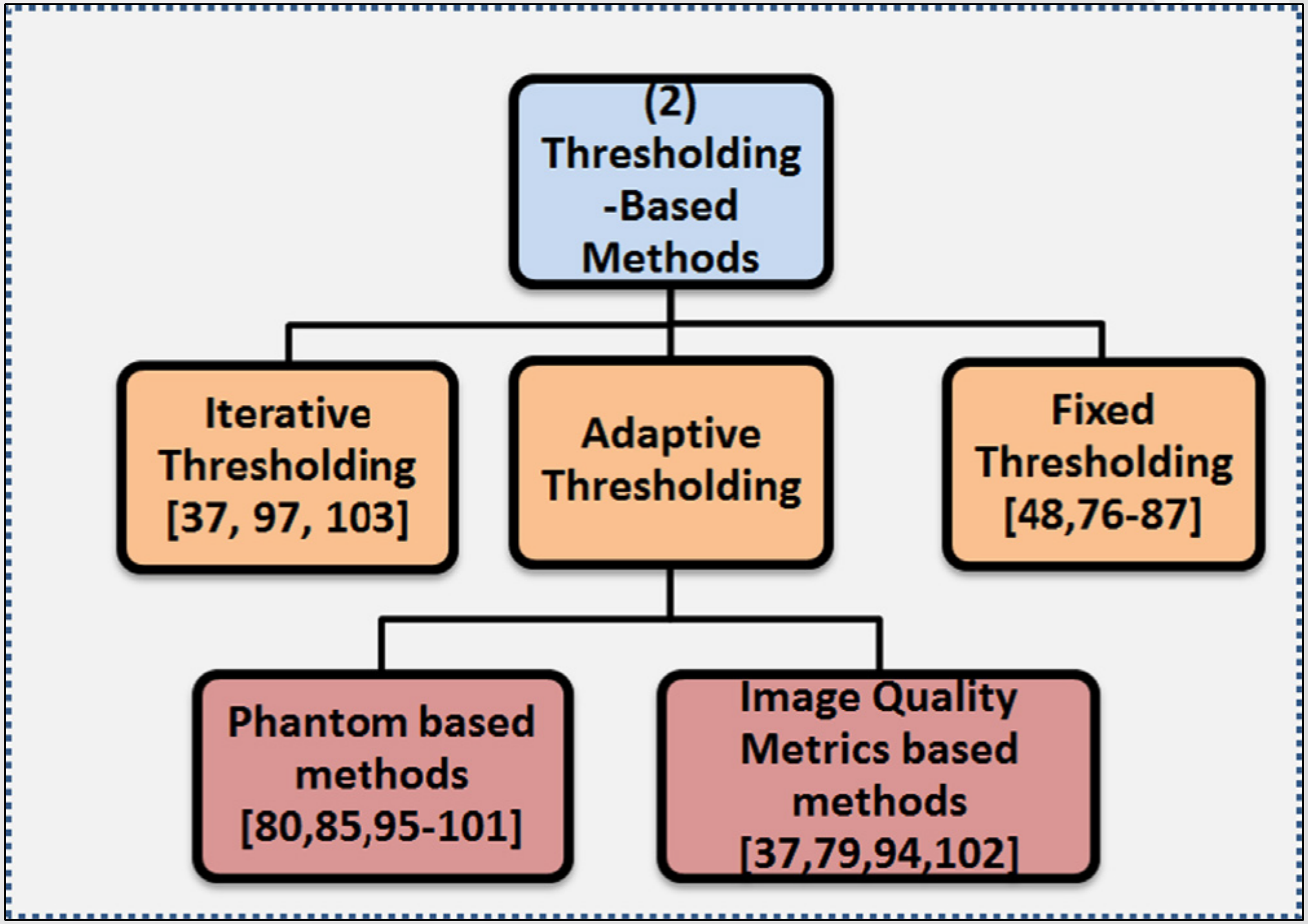



Foster B, *et al*. A review on segmentation of positron emission tomography images. *Comput Biol Med.* 2014

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## Reviews

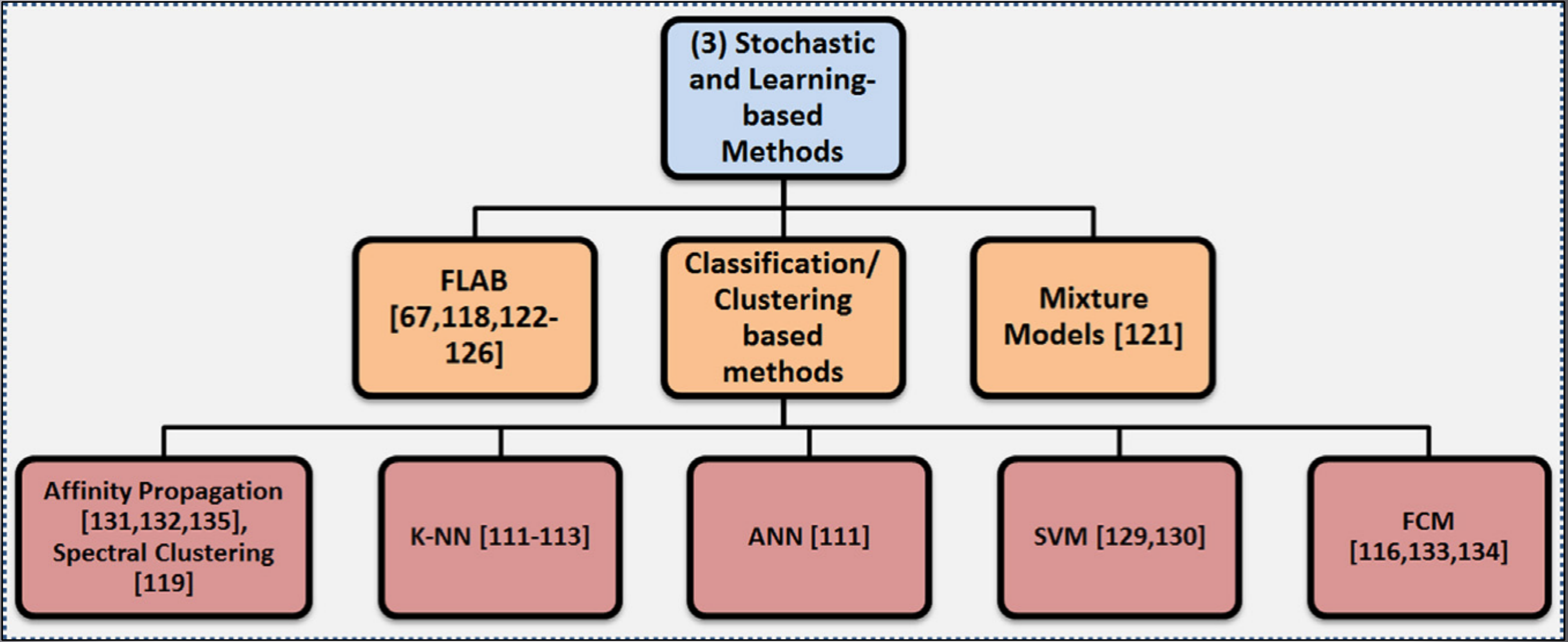



Foster B, *et al*. A review on segmentation of positron emission tomography images. *Comput Biol Med.* 2014

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## Review:

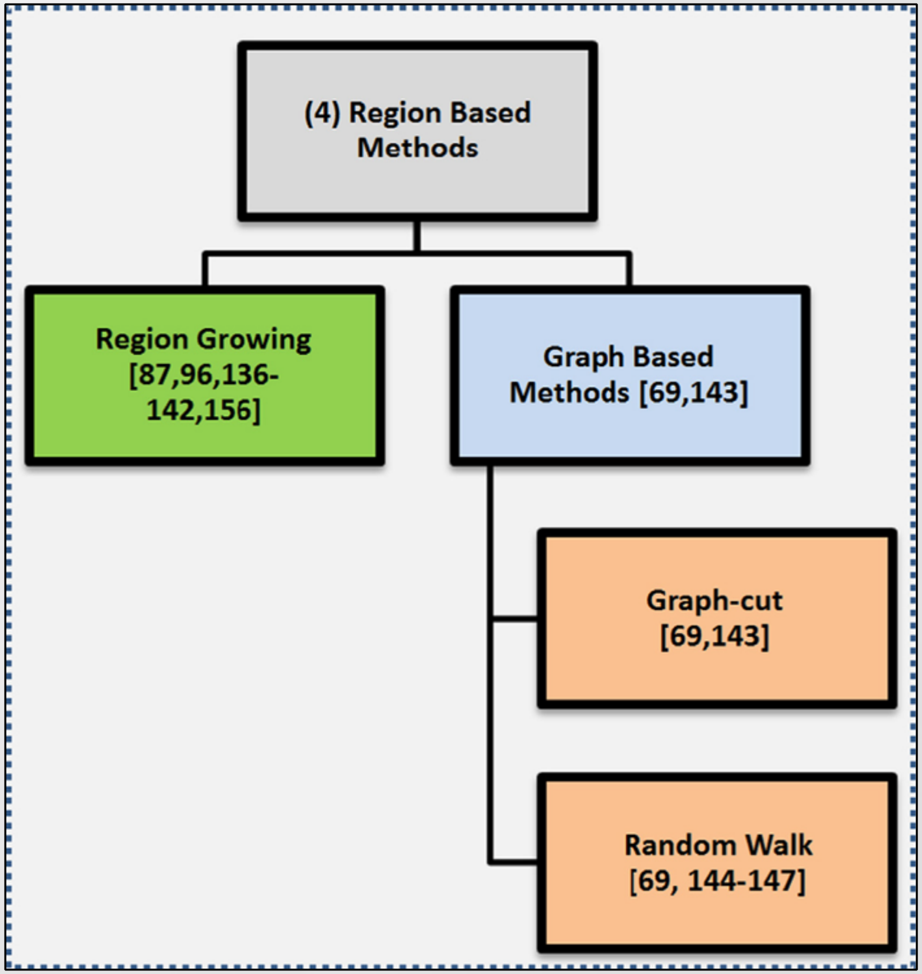



Foster B, *et al*. A review on segmentation of positron emission tomography images. *Comput Biol Med.* 2014

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## Review:

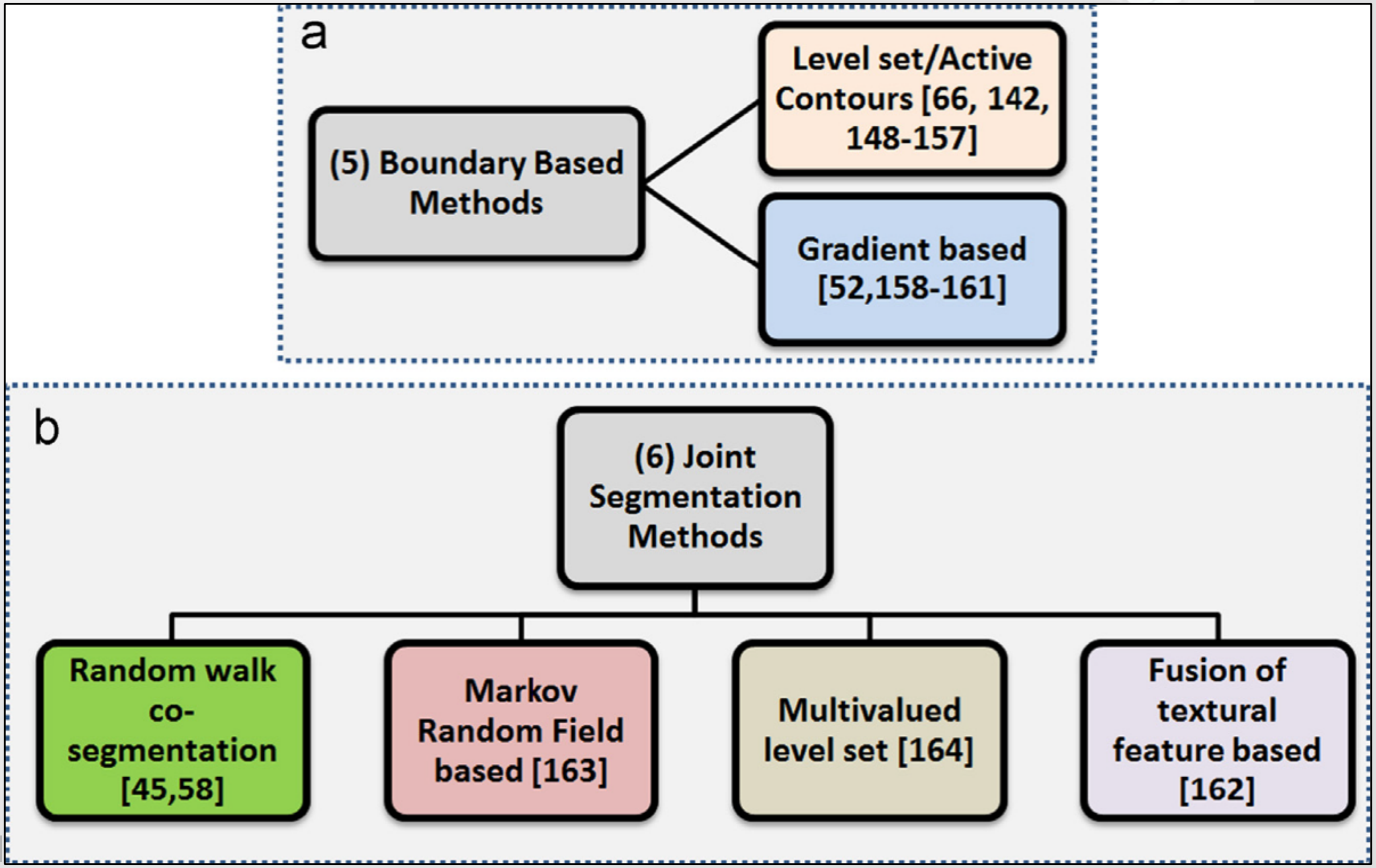



Foster B, *et al*. A review on segmentation of positron emission tomography images. *Comput Biol Med.* 2014

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## Review:




Foster B, *et al*. A review on segmentation of positron emission tomography images. *Comput Biol Med.* 2014

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## 2007-2010

- Two important papers in 2009-2010

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 28, NO. 6, JUNE 2009 881

### A Fuzzy Locally Adaptive Bayesian Segmentation Approach for Volume Determination in PET

Mathieu Hatt*, *Member, IEEE*, Catherine Cheze le Rest, Alexandre Turzo, Christian Roux, *Fellow, IEEE*, and Dimitris Visvikis, *Senior Member, IEEE*

Int. J. Radiation Oncology Biol. Phys., Vol. 77, No. 1, pp. 301–308, 2010

0360-3016/10/$–see front matter

ELSEVIER

doi:10.1016/j.ijrobp.2009.08.018

**PHYSICS CONTRIBUTION**

### ACCURATE AUTOMATIC DELINEATION OF HETEROGENEOUS FUNCTIONAL VOLUMES IN POSITRON EMISSION TOMOGRAPHY FOR ONCOLOGY APPLICATIONS

Mathieu Hatt, Ph.D.,[*] Catherine Cheze le Rest, Ph.D., M.D.,[*†] Patrice Descourt, Ph.D.,[*] André Dekker, Ph.D.,[‡] Dirk De Ruysscher, Ph.D., M.D.,[‡] Michel Oellers, Ph.D.,[‡] Philippe Lambin, Ph.D., M.D.,[‡] Olivier Pradier, Ph.D., M.D.,[*§] and Dimitris Visvikis, Ph.D.[*]

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## 2007-2010

- Two important papers in 2009-2010

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 28, NO. 6, JUNE 2009 881

### A Fuzzy Locally Adaptive Bayesian Segmentation Approach for Volume Determination in PET

Mathieu Hatt*, *Member, IEEE*, Catherine Cheze le Rest, Alexandre Turzo, Christian Roux, *Fellow, IEEE*, and Dimitris Visvikis, *Senior Member, IEEE*

Citations ~280

Int. J. Radiation Oncology Biol. Phys., Vol. 77, No. 1, pp. 301–308, 2010

0360-3016/10/$–see front matter

ELSEVIER

doi:10.1016/j.ijrobp.2009.08.018

**PHYSICS CONTRIBUTION**

### ACCURATE AUTOMATIC DELINEATION OF HETEROGENEOUS FUNCTIONAL VOLUMES IN POSITRON EMISSION TOMOGRAPHY FOR ONCOLOGY APPLICATIONS

Mathieu Hatt, Ph.D.,[*] Catherine Cheze le Rest, Ph.D., M.D.,[*†] Patrice Descourt, Ph.D.,[*] André Dekker, Ph.D.,[‡] Dirk De Ruysscher, Ph.D., M.D.,[‡] Michel Oellers, Ph.D.,[‡] Philippe Lambin, Ph.D., M.D.,[‡] Olivier Pradier, Ph.D., M.D.,[*§] and Dimitris Visvikis, Ph.D.[*]

# PET segmentation

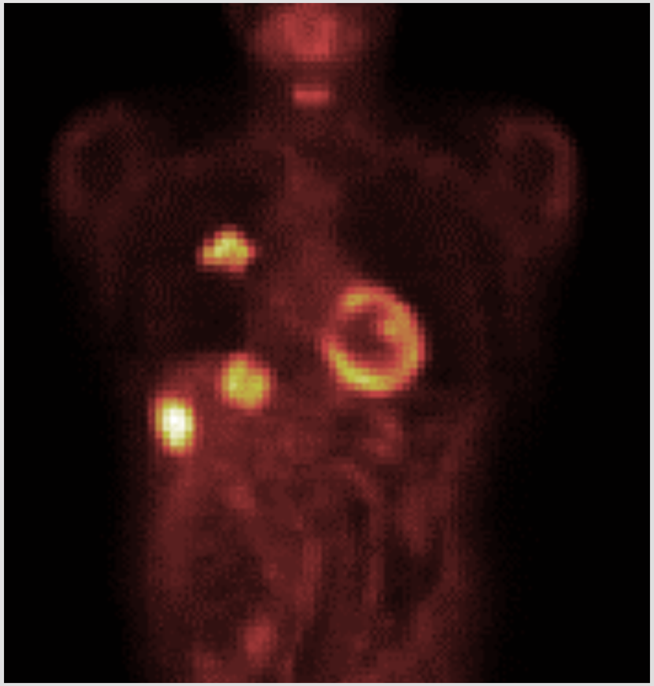
Beyond thresholds: the era of advanced segmentation paradigms

- FLAB is inspired by astronomical imaging



F. Salzenstein, C. Collet, S. Lecam, M. Hatt. Non-stationary fuzzy Markov chain. *Pattern Recognition Letters* 2007.

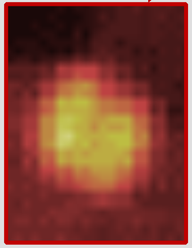
- FLAB is inspired by astronomical imaging



Nebula

$^{18}$F-FDG PET

## FLAB is inspired by astronomical imaging



Nebula

$^{18}$F-FDG PET

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

## Fuzzy Locally Adaptive Bayesian (FLAB)

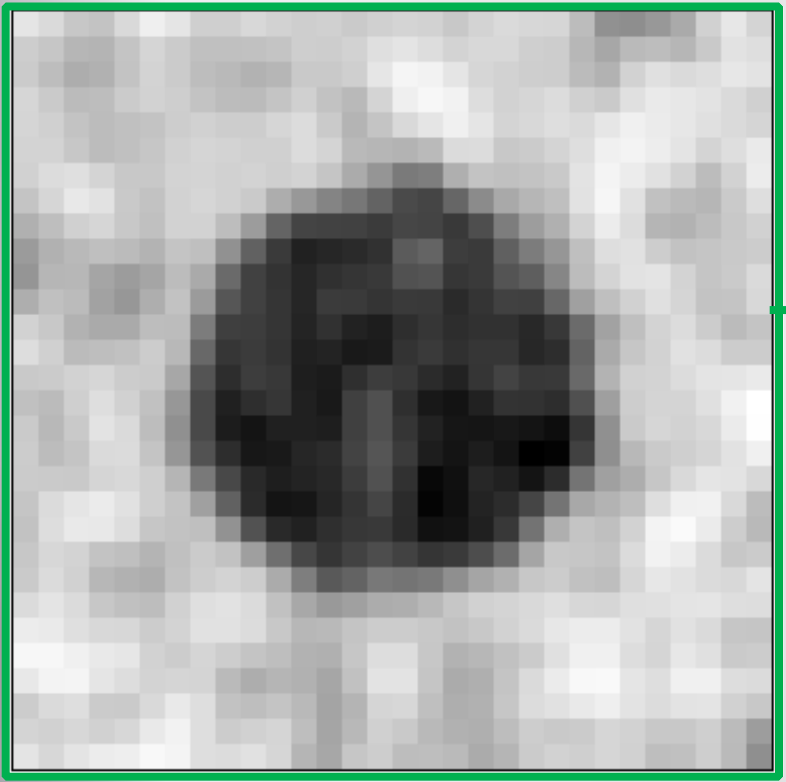
- Principle: models blur (partial volume effects) and noise specific to PET imaging thanks to fuzzy measure and statistical bayesian modeling
- Takes into account spatial correlation using locally adaptive neighborhood
- Iterative estimation of parameters using a stochastic expectation maximization (SEM) algorithm
- Probability for each voxel to belong to a given class: non binary (up to 3 classes): robust versus highly heterogeneous tumors
- Validated against simulated images, clinical images with histopathology, for robustness (four # scanners) and reproducibility (on double baseline scans)

Hatt, *et al*. A fuzzy locally adaptive Bayesian segmentation approach for volume determination in PET. *IEEE Trans Med Imaging*. 2009

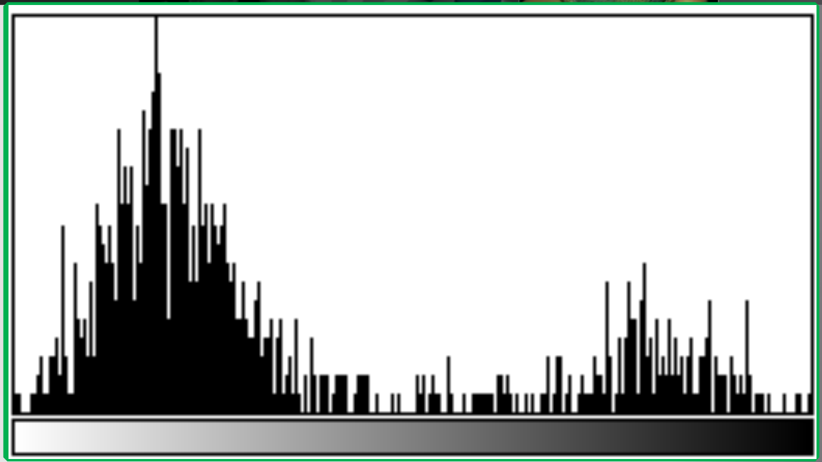
Hatt, *et al*. Accurate automatic delineation of heterogeneous functional volumes in positron emission tomography for oncology applications. *Int J Radiat Oncol Biol Phys*. 2010

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



Observation probability $P(Y|X)$



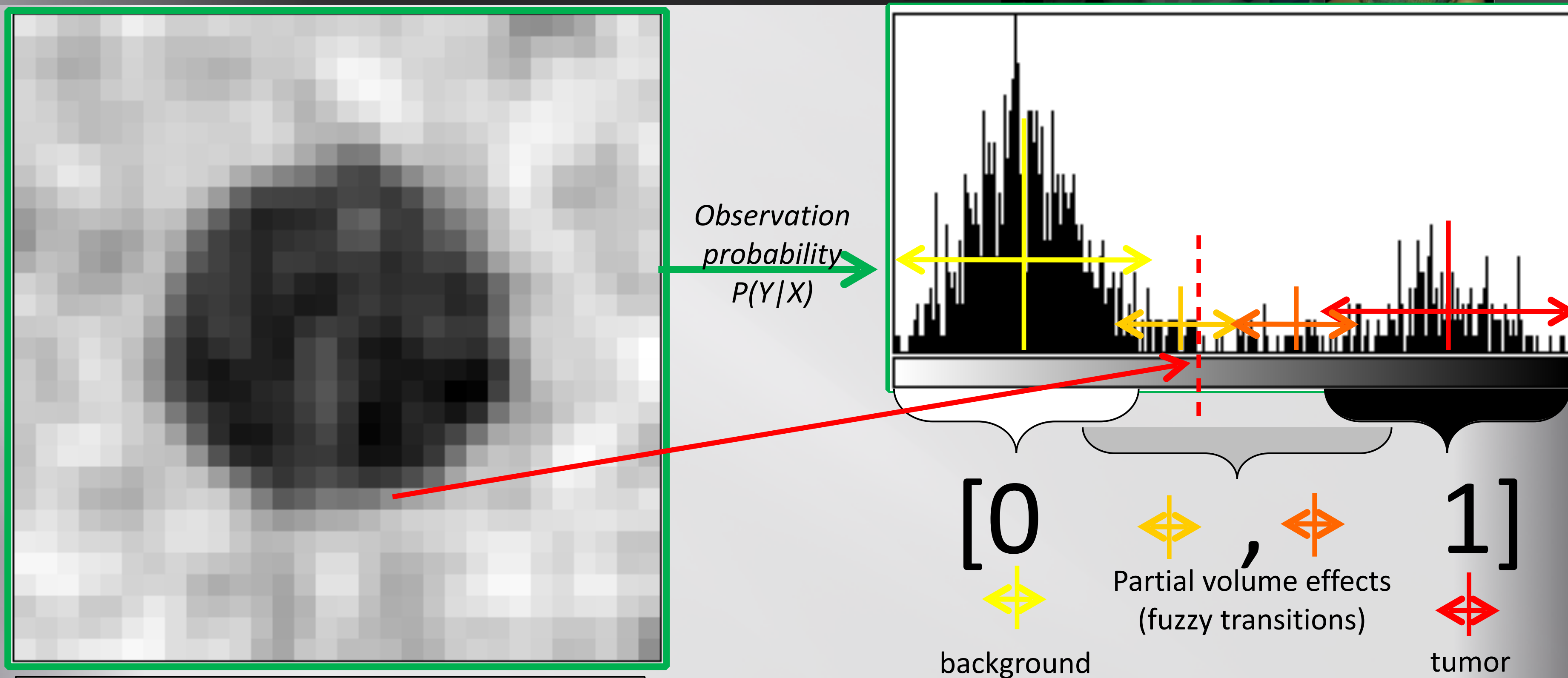
$$P(\mathrm{X}|\mathrm{Y}) = \frac{P(\mathrm{X},\mathrm{Y})}{P(\mathrm{Y})} = \frac{P(\mathrm{Y}|\mathrm{X})P(\mathrm{X})}{P(\mathrm{Y})}$$


Hatt, *et al*. A fuzzy locally adaptive Bayesian segmentation approach for volume determination in PET. *IEEE Trans Med Imaging*. 2009

Hatt, *et al*. Accurate automatic delineation of heterogeneous functional volumes in positron emission tomography for oncology applications. *Int J Radiat Oncol Biol Phys*. 2010

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



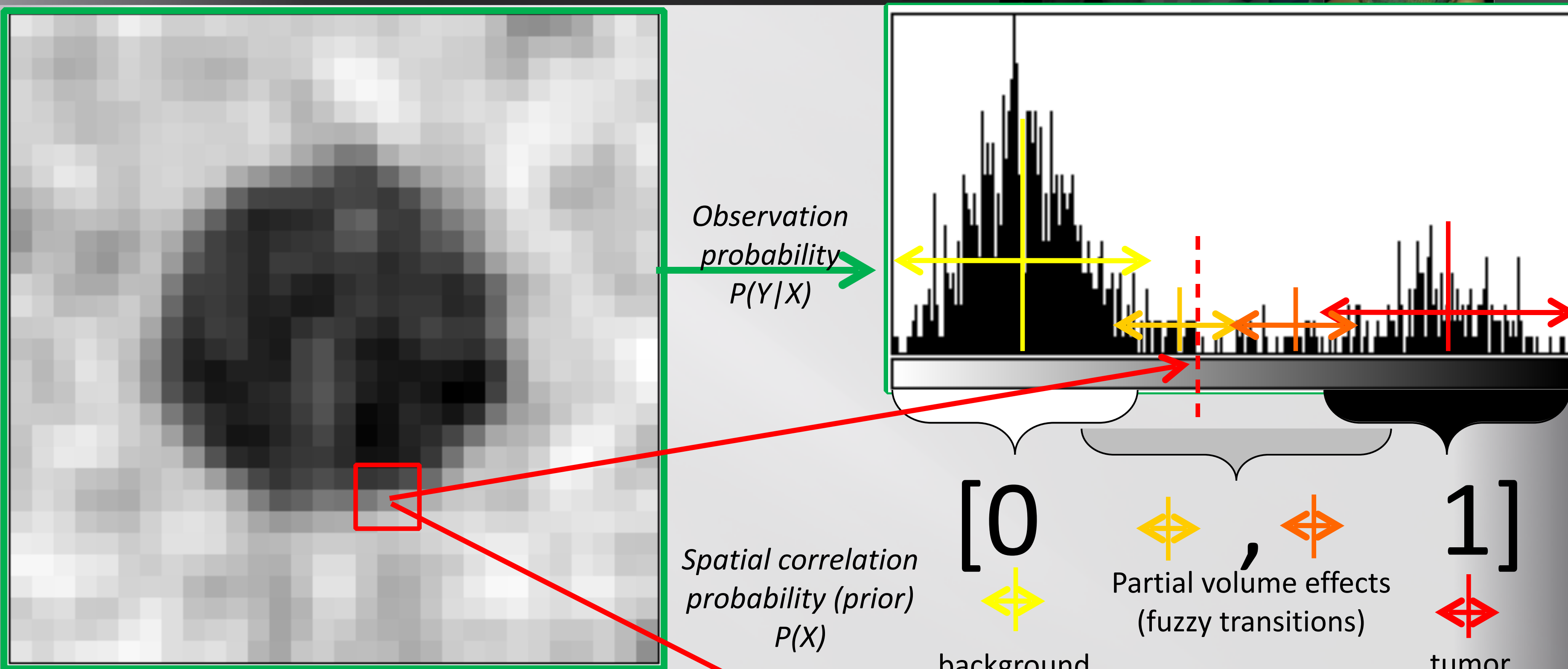

$$P(\mathrm{X}|\mathrm{Y}) = \frac{P(\mathrm{X},\mathrm{Y})}{P(\mathrm{Y})} = \frac{P(\mathrm{Y}|\mathrm{X})P(\mathrm{X})}{P(\mathrm{Y})}$$


Hatt, *et al*. A fuzzy locally adaptive Bayesian segmentation approach for volume determination in PET. *IEEE Trans Med Imaging*. 2009

Hatt, *et al*. Accurate automatic delineation of heterogeneous functional volumes in positron emission tomography for oncology applications. *Int J Radiat Oncol Biol Phys*. 2010

# PET segmentation

## Beyond thresholds: the era of advanced segmentation paradigms




$$P(\mathrm{X}|\mathrm{Y}) = \frac{P(\mathrm{X},\mathrm{Y})}{P(\mathrm{Y})} = \frac{P(\mathrm{Y}|\mathrm{X})P(\mathrm{X})}{P(\mathrm{Y})}$$

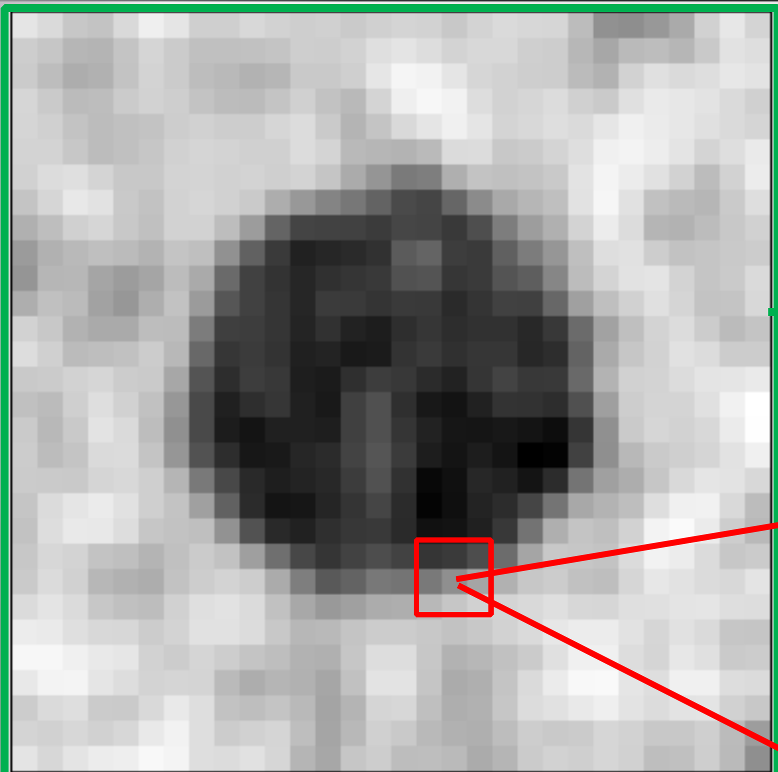


Hatt, *et al*. A fuzzy locally adaptive Bayesian segmentation approach for volume determination in PET. *IEEE Trans Med Imaging*. 2009

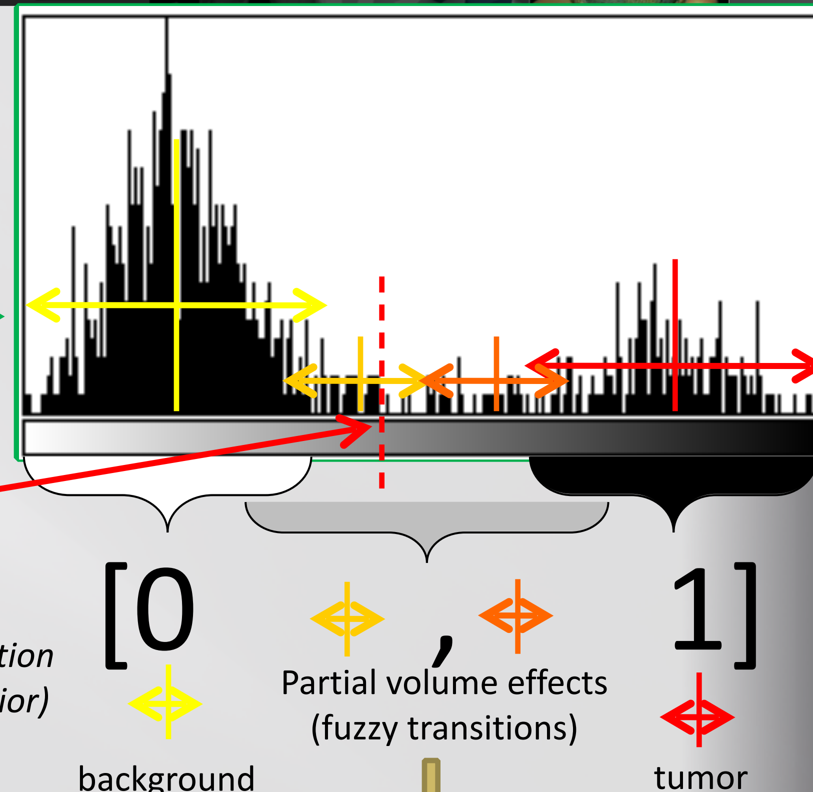
Hatt, *et al*. Accurate automatic delineation of heterogeneous functional volumes in positron emission tomography for oncology applications. *Int J Radiat Oncol Biol Phys*. 2010

# PET segmentation

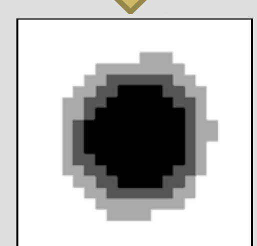
Beyond thresholds: the era of advanced segmentation paradigms



Observation probability $P(Y|X)$




Spatial correlation probability (prior) $P(X)$

Final map

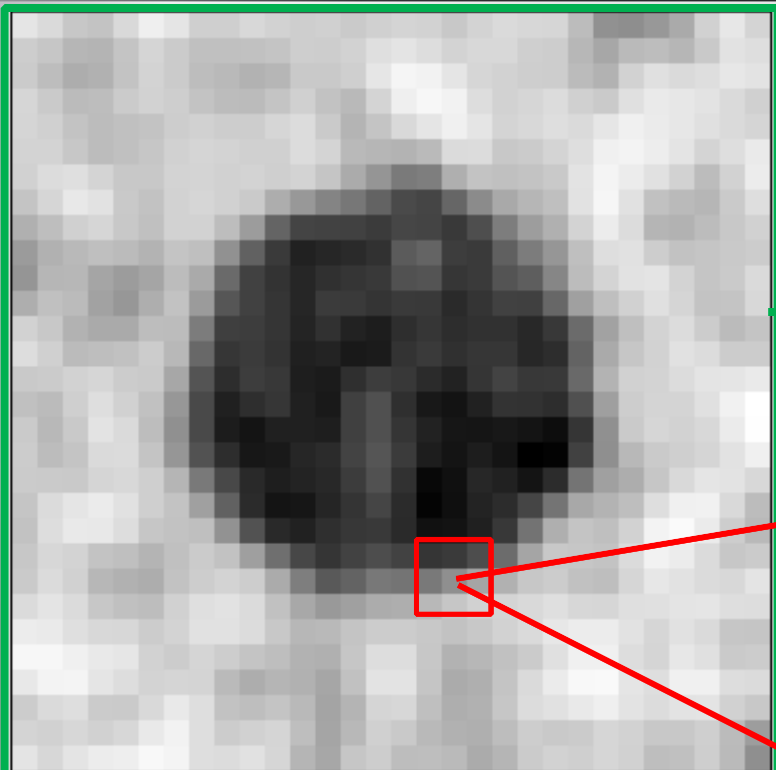
$$P(\mathrm{X}|\mathrm{Y}) = \frac{P(\mathrm{X},\mathrm{Y})}{P(\mathrm{Y})} = \frac{P(\mathrm{Y}|\mathrm{X})P(\mathrm{X})}{P(\mathrm{Y})}$$


Hatt, *et al*. A fuzzy locally adaptive Bayesian segmentation approach for volume determination in PET. *IEEE Trans Med Imaging*. 2009

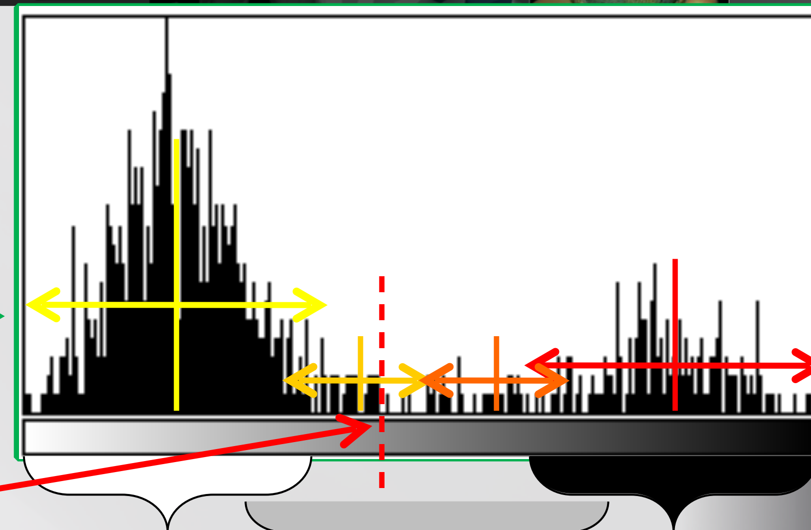
Hatt, *et al*. Accurate automatic delineation of heterogeneous functional volumes in positron emission tomography for oncology applications. *Int J Radiat Oncol Biol Phys*. 2010

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



*Observation probability P(Y|X)*



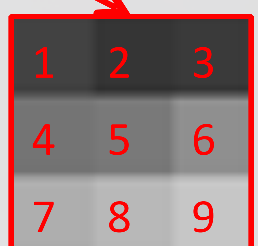
[0 , 1]

background

Partial volume effects (fuzzy transitions)

tumor

*Spatial correlation probability (prior) P(X)*




$$P(\mathrm{X}|\mathrm{Y}) = \frac{P(\mathrm{X},\mathrm{Y})}{P(\mathrm{Y})} = \frac{P(\mathrm{Y}|\mathrm{X})P(\mathrm{X})}{P(\mathrm{Y})}$$

Final map


Hatt, *et al*. A fuzzy locally adaptive Bayesian segmentation approach for volume determination in PET. *IEEE Trans Med Imaging*. 2009

Hatt, *et al*. Accurate automatic delineation of heterogeneous functional volumes in positron emission tomography for oncology applications. *Int J Radiat Oncol Biol Phys*. 2010

# PET segmentation

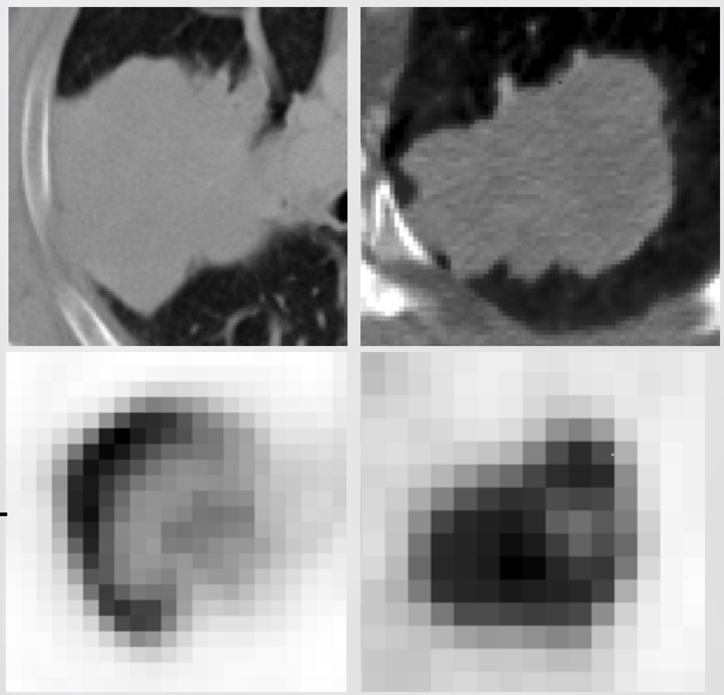
## Beyond thresholds: the era of advanced segmentation paradigms

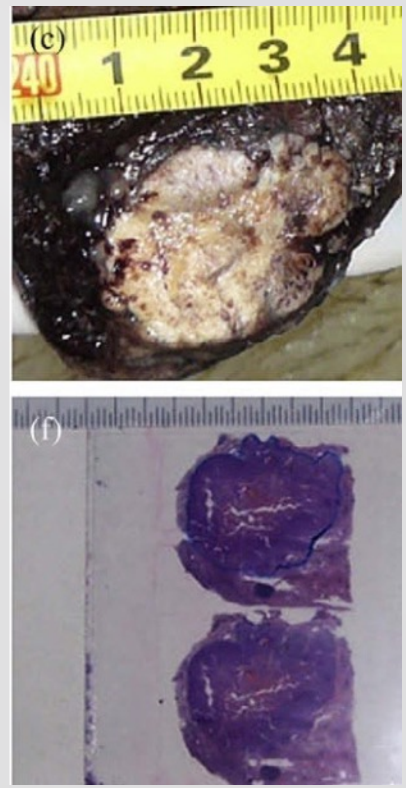
18 clinical NSCLC tumors with histopathology

- ✓ max diameter: 12-90 mm
- ✓ Heterogeneity: variable
- ✓ Shapes: variable

CT

PET





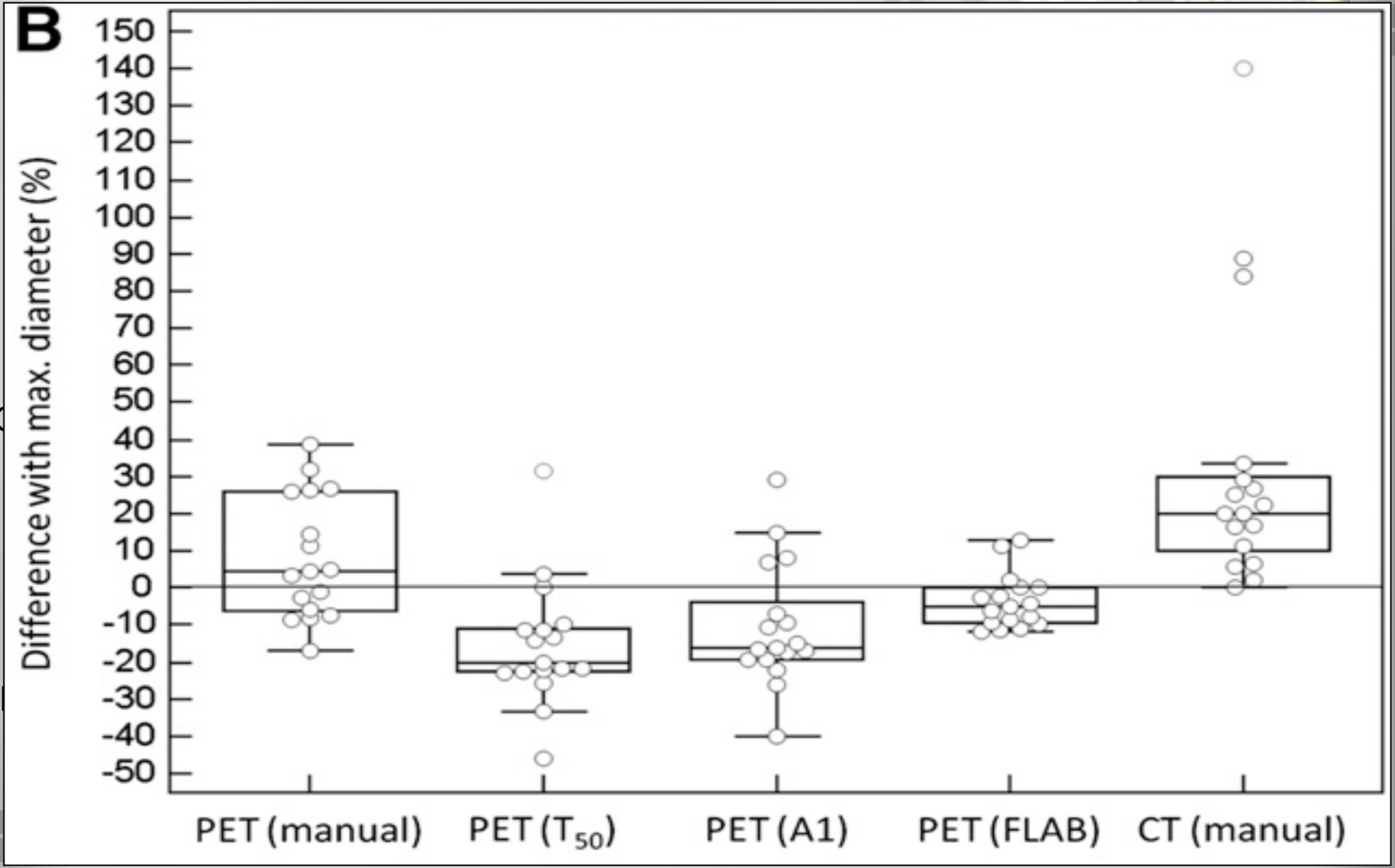

van Baardwijk et al, International Journal of Radiation Oncology Biology Physics, 2007



Hatt M, *et al*. Impact of tumor size and tracer uptake heterogeneity in (18)F-FDG PET and CT non-small cell lung cancer tumor delineation. *J Nucl Med*. 2011

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

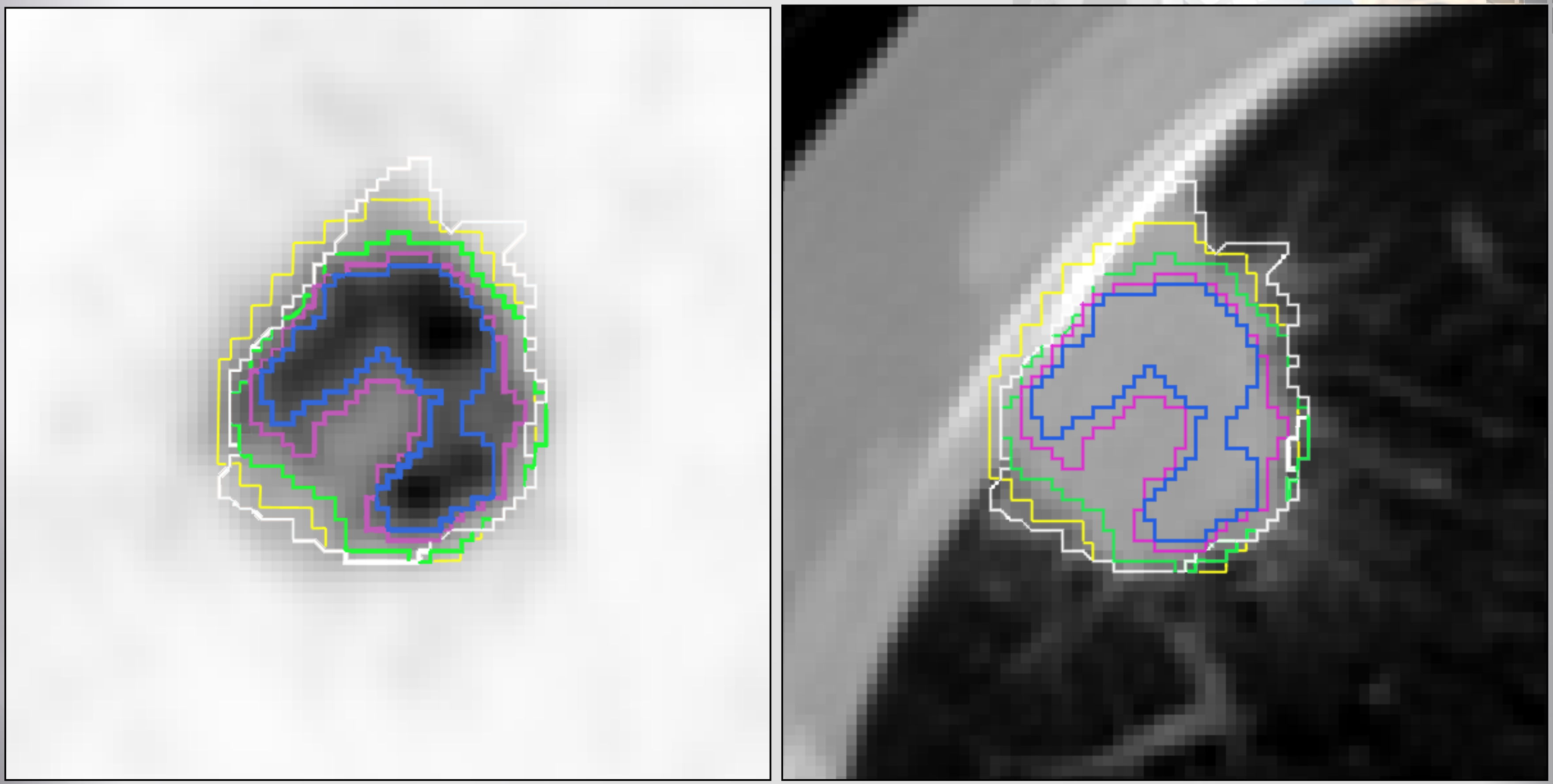



Hatt M, *et al*. Impact of tumor size and tracer uptake heterogeneity in (18)F-FDG PET and CT non-small cell lung cancer tumor delineation. *J Nucl Med*. 2011

Instituts thématiques Inserm Institut national de la santé et de la recherche médicale

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



White = manual CT  Yellow = manual PET

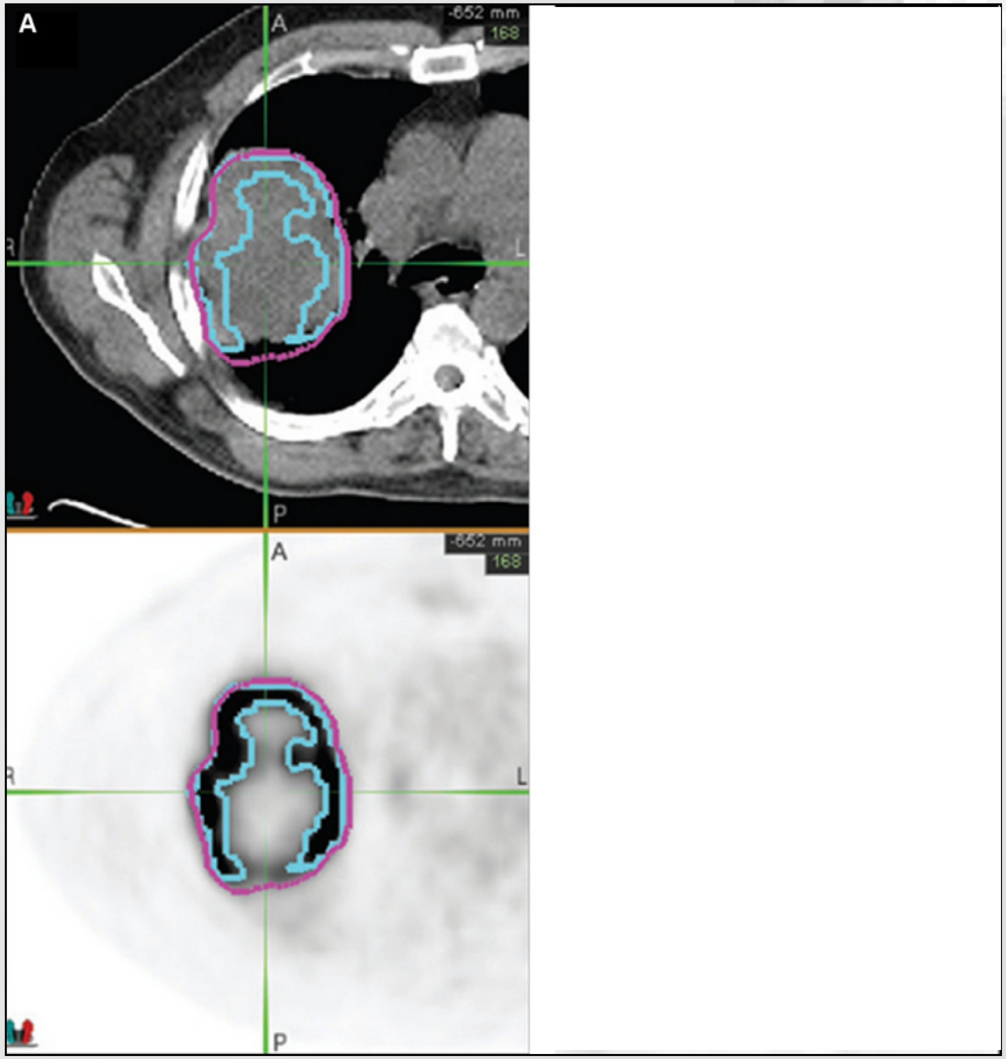
Blue = $T_{50}$  Purple = Adaptive Green = FLAB

Hatt M, *et al*. Impact of tumor size and tracer uptake heterogeneity in (18)F-FDG PET and CT non-small cell lung cancer tumor delineation. *J Nucl Med*. 2011

# PET segmentation

## Beyond thresholds: the era of advanced segmentation paradigms

Comparison between FLAB and gradient-based

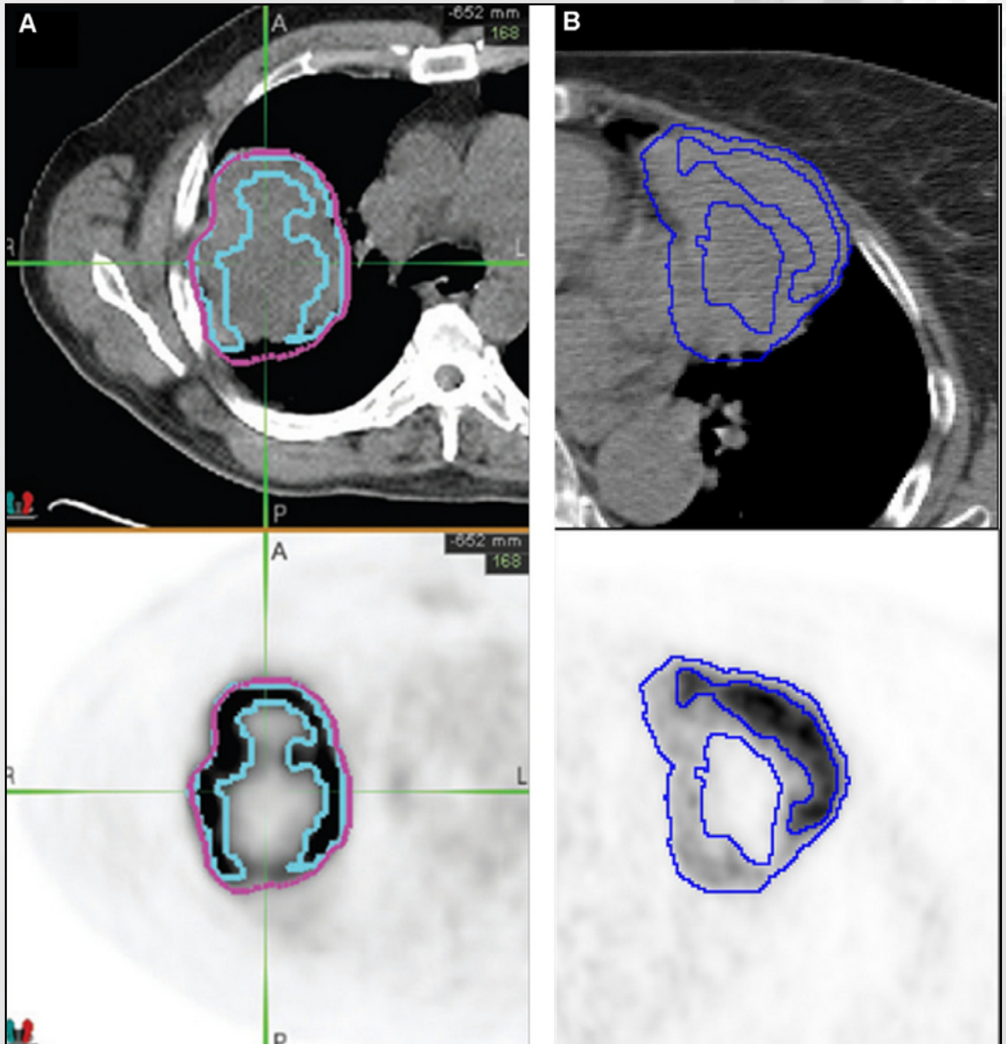



Hatt, *et al*. Metabolically active volumes automatic delineation methodologies in PET imaging: Review and perspectives. *Cancer Radiother* 2011

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

Comparison between FLAB and gradient-based

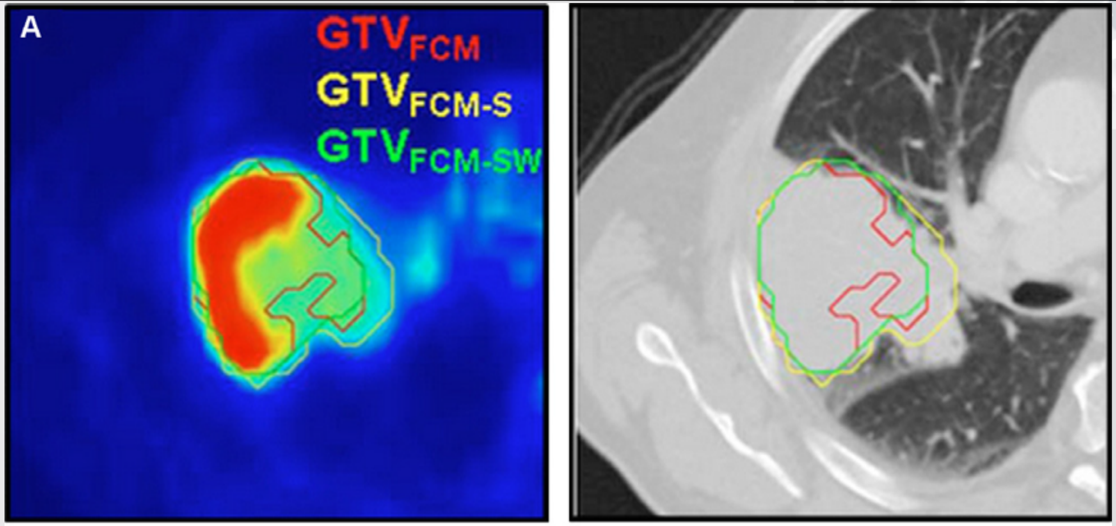



Hatt, *et al*. Metabolically active volumes automatic delineation methodologies in PET imaging: Review and perspectives. *Cancer Radiother* 2011

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

Comparison between FLAB and FCM

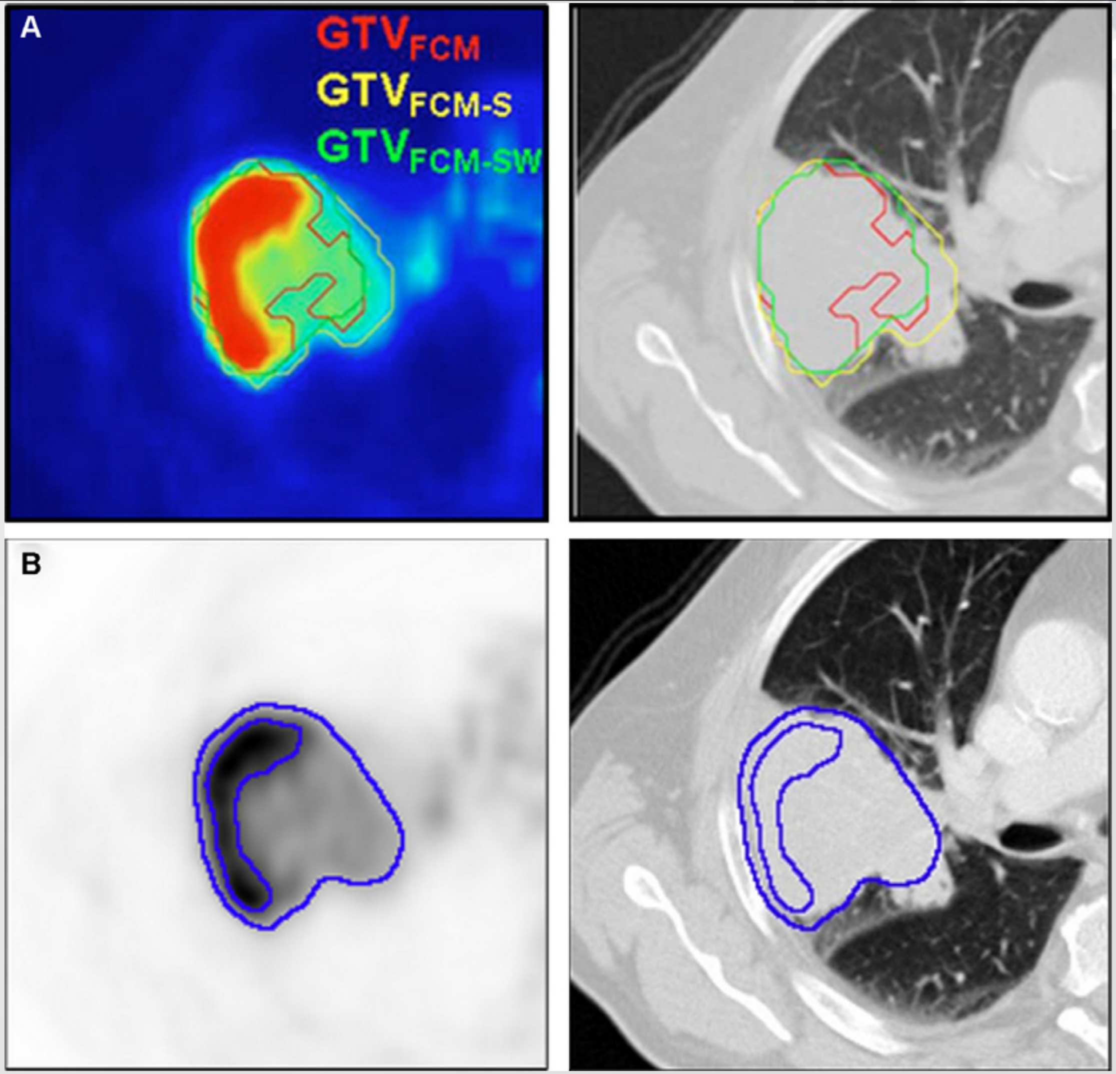



Hatt, *et al*. Metabolically active volumes automatic delineation methodologies in PET imaging: Review and perspectives. *Cancer Radiother* 2011

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

Comparison between FLAB and FCM

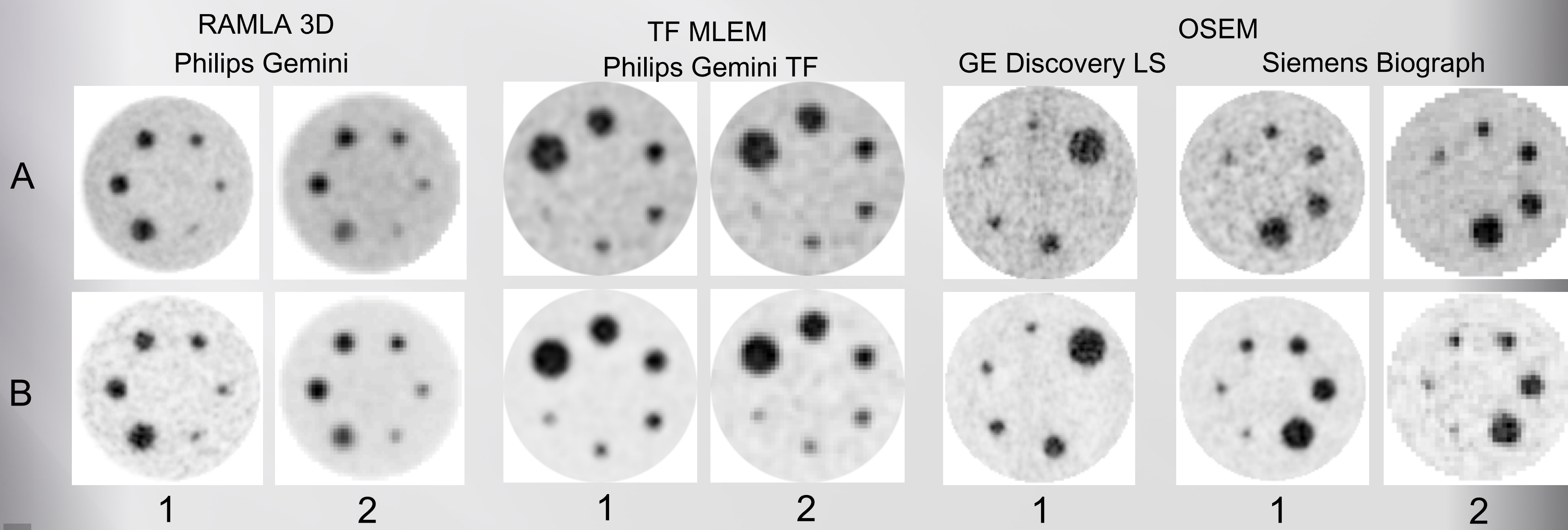



Hatt, *et al*. Metabolically active volumes automatic delineation methodologies in PET imaging: Review and perspectives. *Cancer Radiother* 2011

# PET segmentation

## Beyond thresholds: the era of advanced segmentation paradigms

- ➢ Scanners (Philips, Philips TOF, GE, Siemens) and algorithms (RAMLA, TF MLEM, OSEM) with standard clinical protocols
- ➢ parameters: sphere:background contrast (4:1 to 10:1), acquisition duration (1,2,5 min), voxels size (2 to 5mm)

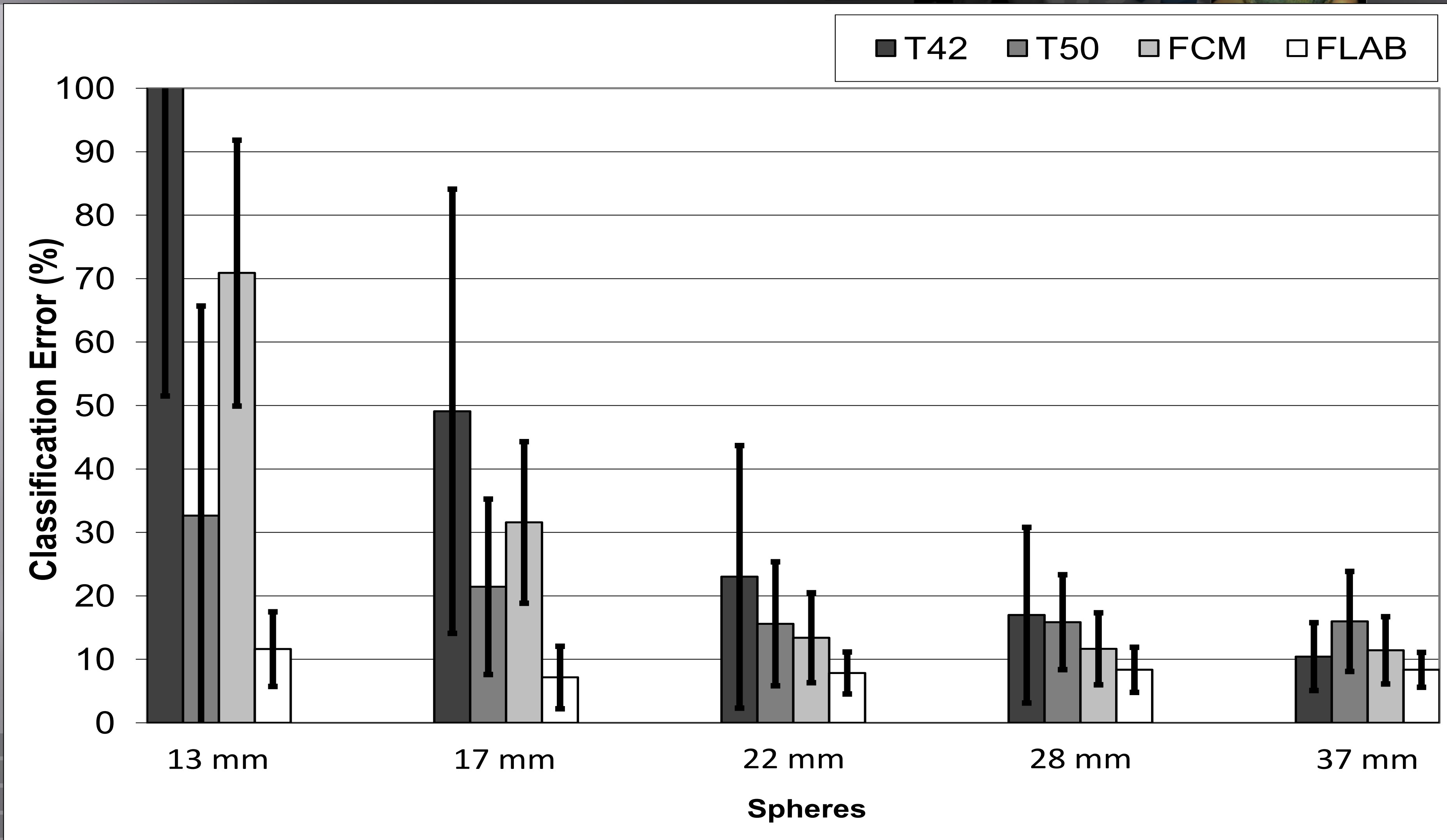



A = 4:1 or 5:1, B = 8:1 or 10:1        1 = 2x2 mm, 2 = 4x4 or 5x5 mm

Hatt M, *et al*. PET functional volume delineation: a robustness and repeatability study. *Eur J Nucl Med Mol Imaging*. 2011

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms




Hatt M, *et al*. PET functional volume delineation: a robustness and repeatability study. *Eur J Nucl Med Mol Imaging*. 2011

## Beyond FLAB: the SPEQTACLE method

- Spatial Positron Emission Quantification of Tumor volume: AutomatiC Lp-norm Estimation

Medical Physics
The International Journal of Medical Physics Research and Practice

**SPEQTACLE: An automated generalized fuzzy C-means algorithm for tumor delineation in PET**

Jérôme Lapuyade-Lahorgue, Dimitris Visvikis, Olivier Pradier, Catherine Cheze Le Rest, and Mathieu Hatt

Citation: Medical Physics **42**, 5720 (2015); doi: 10.1118/1.4929561

## SPEQTACLE is based on fuzzy C-Means

- Principle: divide the set of voxels into clusters sharing similar properties (intensities)

- **Estimation:** For each observation $y_u \in R$, estimate the probabilities $p_{u,i}$ and the centers $\mu_i$ of clusters $i \in \{1, \cdots, K\}$ by minimizing:

$$\sum_{u \in V} \sum_{i=1}^{K} p_{u,i}^2 \left| y_u - \mu_i \right|^2$$

- **Decision:** $y_u \rightarrow i(y_u)$ such that $p_{u,i(y_u)}$ is maximal.



Lapuyade-Lahorgue, *et al*. SPEQTACLE: an automated generalized fuzzy C-means algorithm for tumor delineation in PET. *Med Phys* 2015

## SPEQTACLE is based on fuzzy C-Means

- Principle: divide the set of voxels into clusters sharing similar properties (intensities)

- **Estimation:** For each observation $y_u \in R$, estimate the probabilities $p_{u,i}$ and the centers $\mu_i$ of clusters $i \in \{1, \cdots, K\}$ by minimizing:

$$\sum_{u \in V} \sum_{i=1}^{K} p_{u,i}^2 \left| y_u - \mu_i \right|^2$$

Norm parameter

- **Decision:** $y_u \to i(y_u)$ such that $p_{u,i(y_u)}$ is maximal.

Lapuyade-Lahorgue, *et al*. SPEQTACLE: an automated generalized fuzzy C-means algorithm for tumor delineation in PET. *Med Phys* 2015

## SPEQTACLE is based on fuzzy C-Means

- Principle: divide the set of voxels into clusters sharing similar properties (intensities)

- **Estimation:** For each observation $y_u \in R$, estimate the probabilities $p_{u,i}$ and the centers $\mu_i$ of clusters $i \in \{1, \cdots, K\}$ by minimizing:

$$\sum_{u \in V} \sum_{i=1}^{K} p_{u,i}^{2} \left| y_u - \mu_i \right|^{2}$$

Norm parameter

→ *Generalized* FCM:
Replace 2 by another value (*e.g.* 5, 10…)

- **Decision:** $y_u \rightarrow i(y_u)$ such that $p_{u,i(y_u)}$ is maximal.

Lapuyade-Lahorgue, *et al*. SPEQTACLE: an automated generalized fuzzy C-means algorithm for tumor delineation in PET. *Med Phys* 2015

## SPEQTACLE is based on fuzzy C-means

- Principle: divide the set of voxels into clusters sharing similar properties (intensities)

- **Estimation:** For each observation $y_u \in R$, estimate the probabilities $p_{u,i}$ and the centers $\mu_i$ of clusters $i \in \{1, \cdots, K\}$ by minimizing:

$$\sum_{u \in V} \sum_{i=1}^{K} p_{u,i}^2 \left| y_u - \mu_i \right|^{\alpha}$$

Norm parameter

The norm parameter $\alpha > 1$ is **automatically** estimated

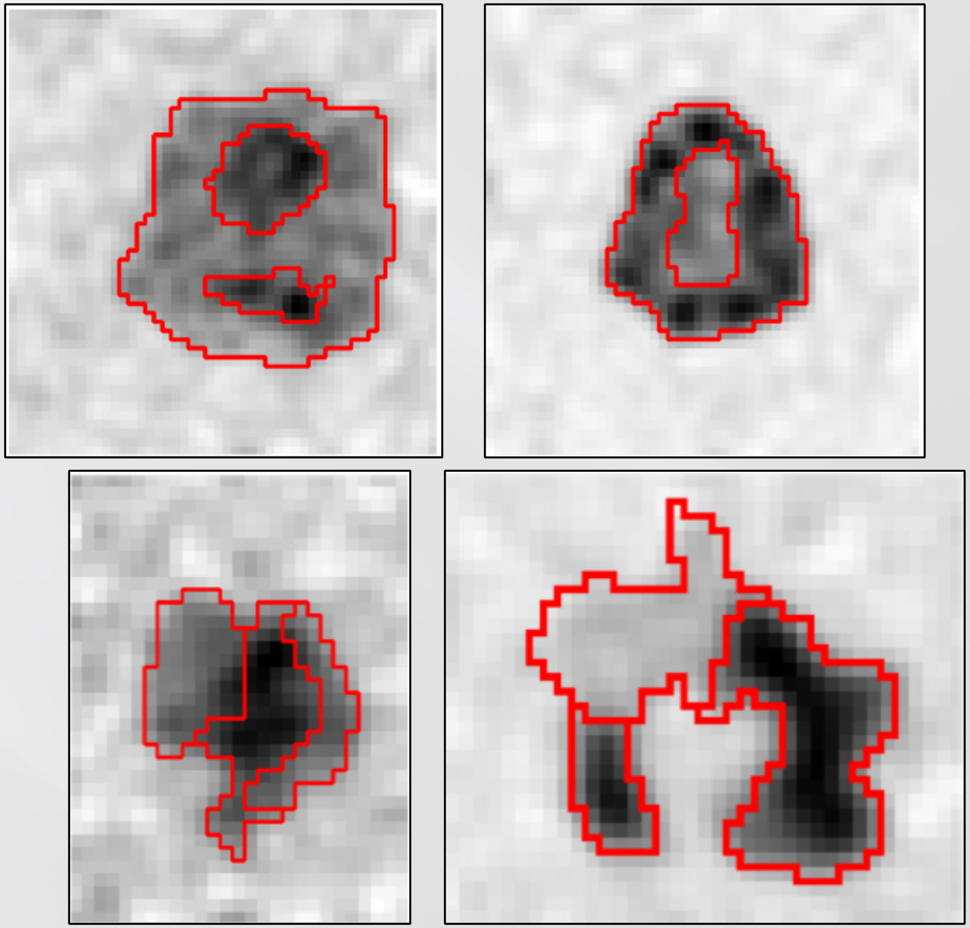
- **Decision:** $y_u \rightarrow i(y_u)$ such that $p_{u,i(y_u)}$ is maximal.

Lapuyade-Lahorgue, *et al*. SPEQTACLE: an automated generalized fuzzy C-means algorithm for tumor delineation in PET. *Med Phys* 2015

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms

34 tumors simulated with Geant4 Application for Tomography Emission[1-2]

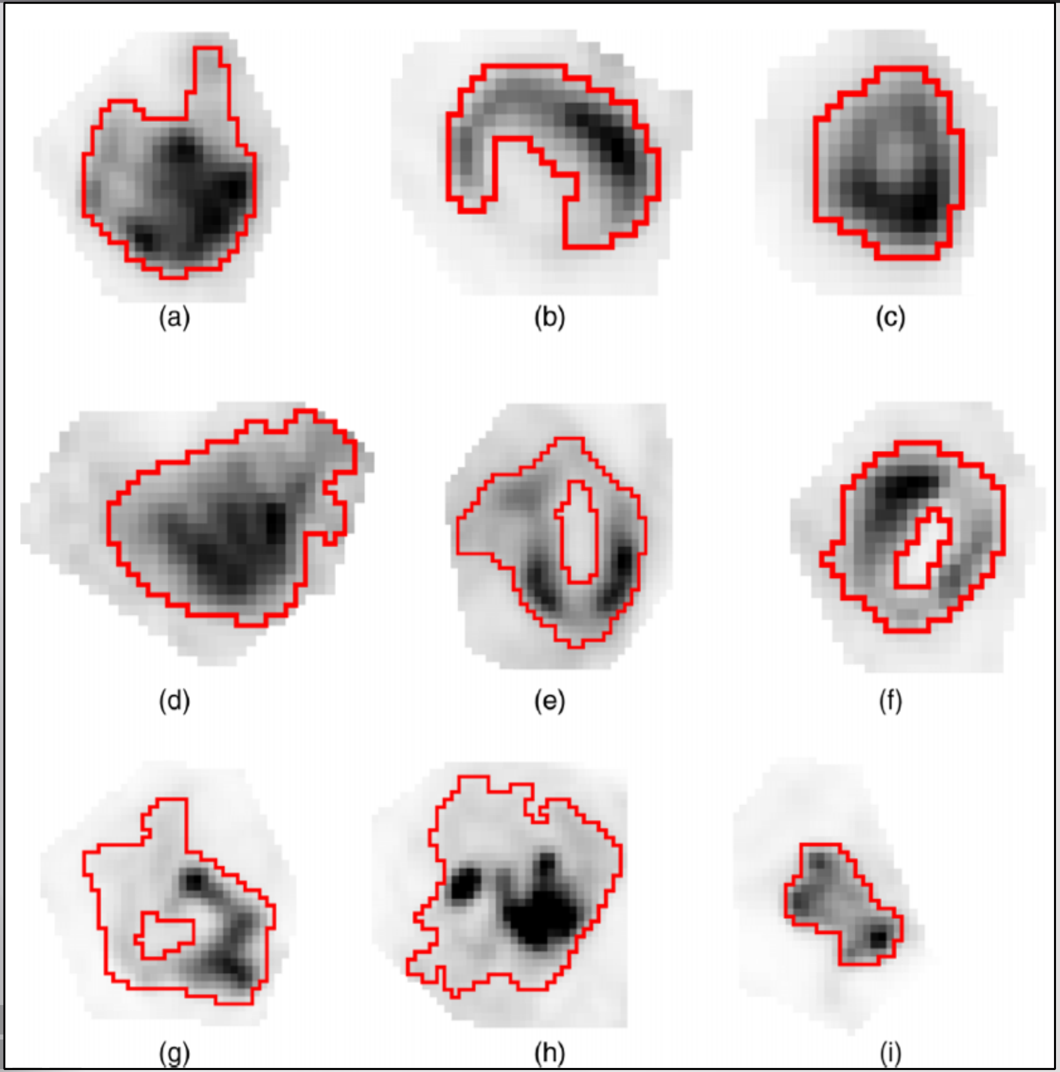


Ground-truth provided by known simulated map

1. P. Papadimitroulas, *et al*. Investigation of realistic PET simulations incorporating tumor patient's specificity using anthropomorphic models: creation of an oncology database. *Med Phys* 2013
2. A. Le Maitre, *et al*. Incorporating patient specific variability in the simulation of realistic whole body 18F-FDG distributions for oncology applications. *Proceedings of the IEEE* 2009

# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



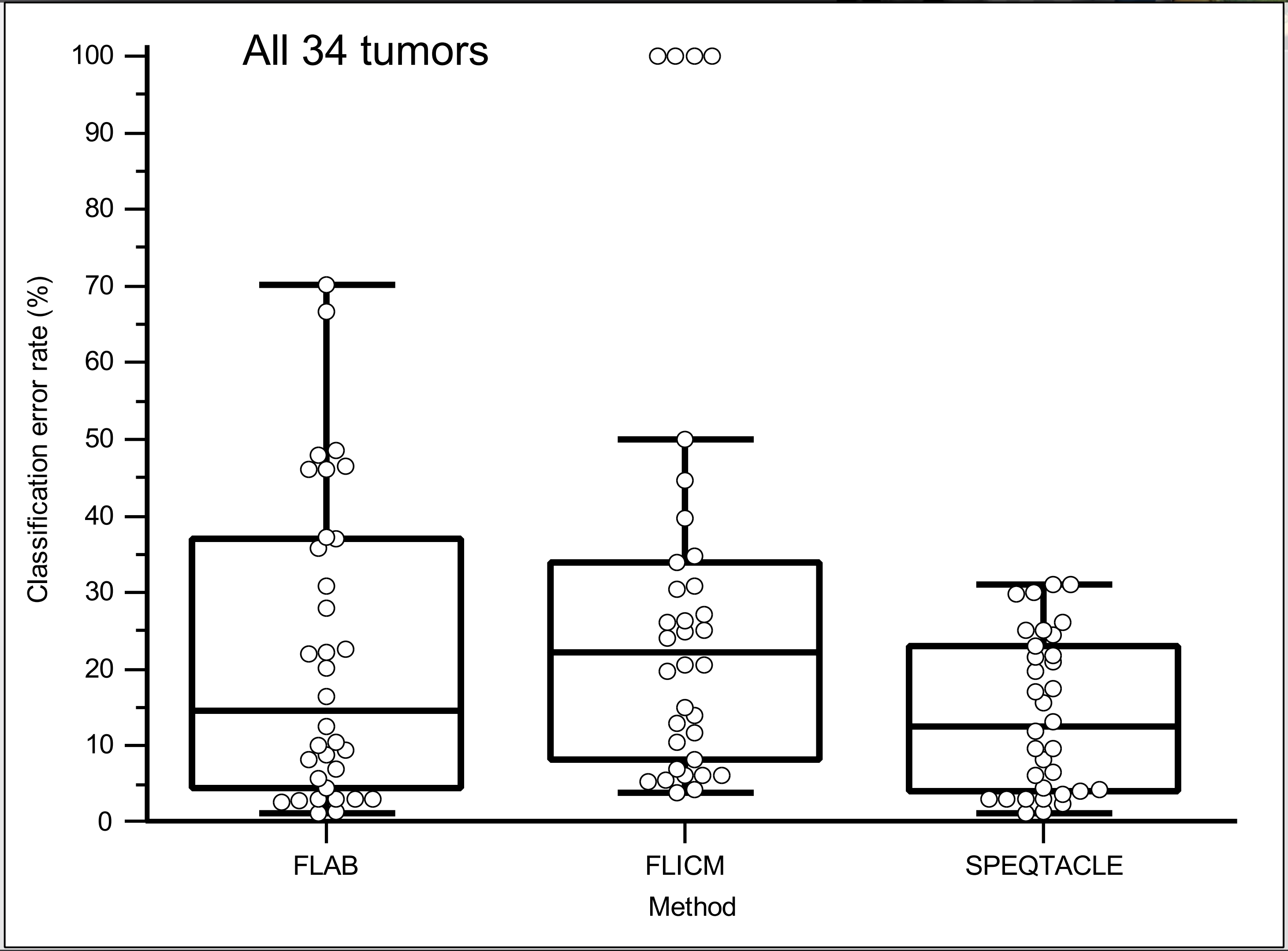

9 clinical non-small cell lung tumors

Ground-truth provided by statistical consensus of 3 # manual delineations with the STAPLE[1] algorithm

1. SK. Warfield, *et al*. Simultaneous truth and performance level estimation (STAPLE): an algorithm for the validation of image segmentation. *IEEE Trans Med Imaging*. 2004

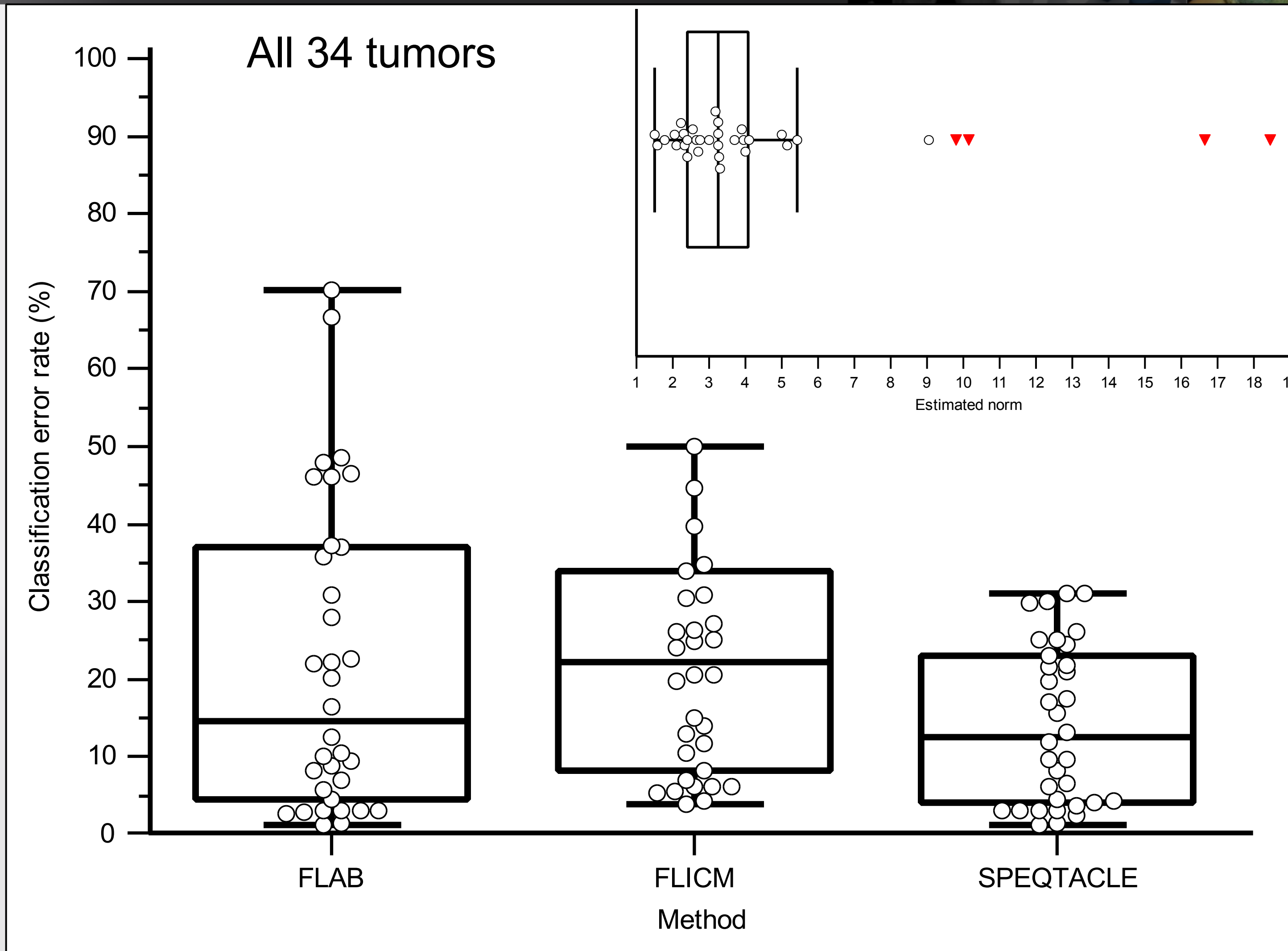
# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



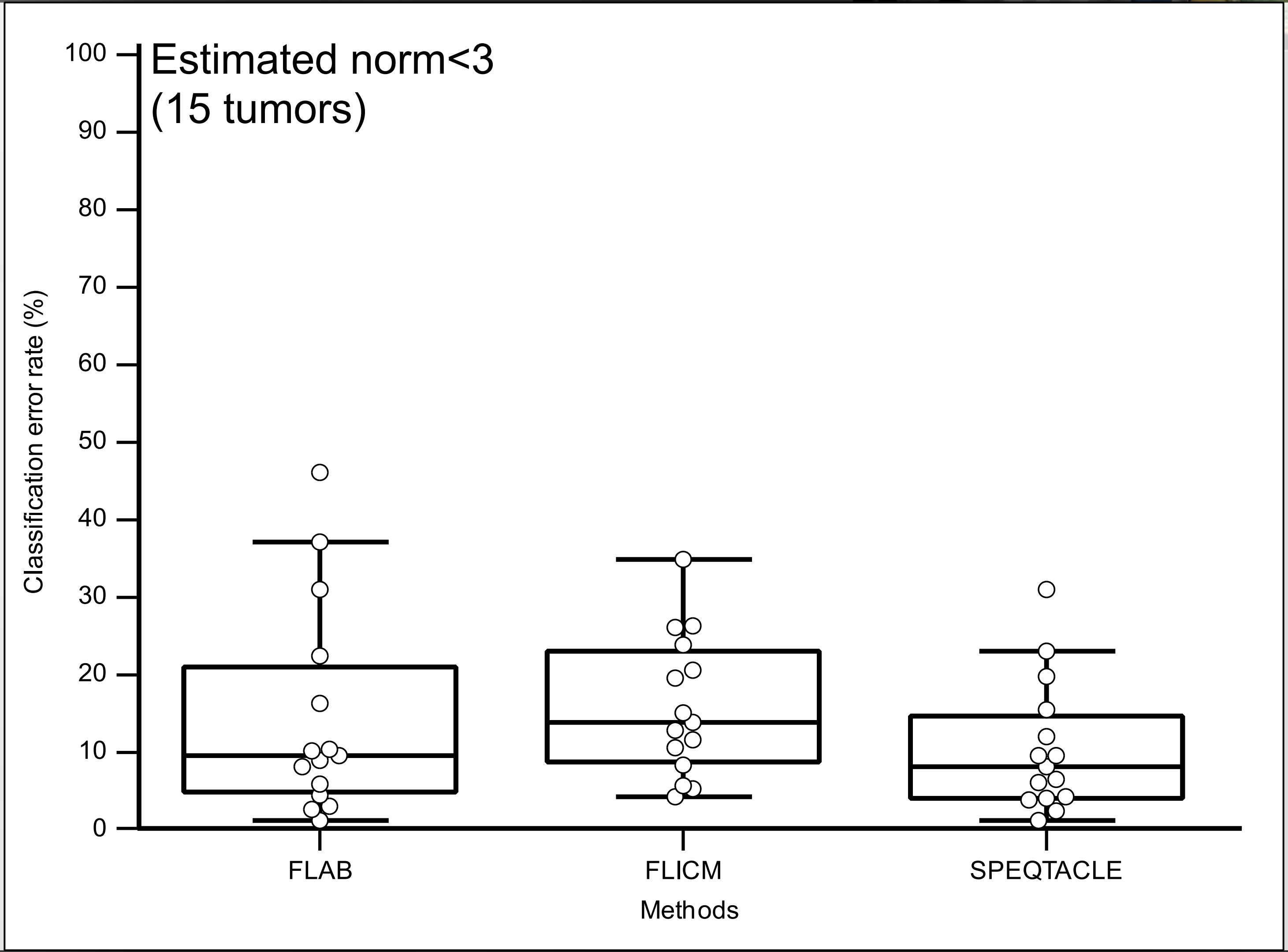
# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



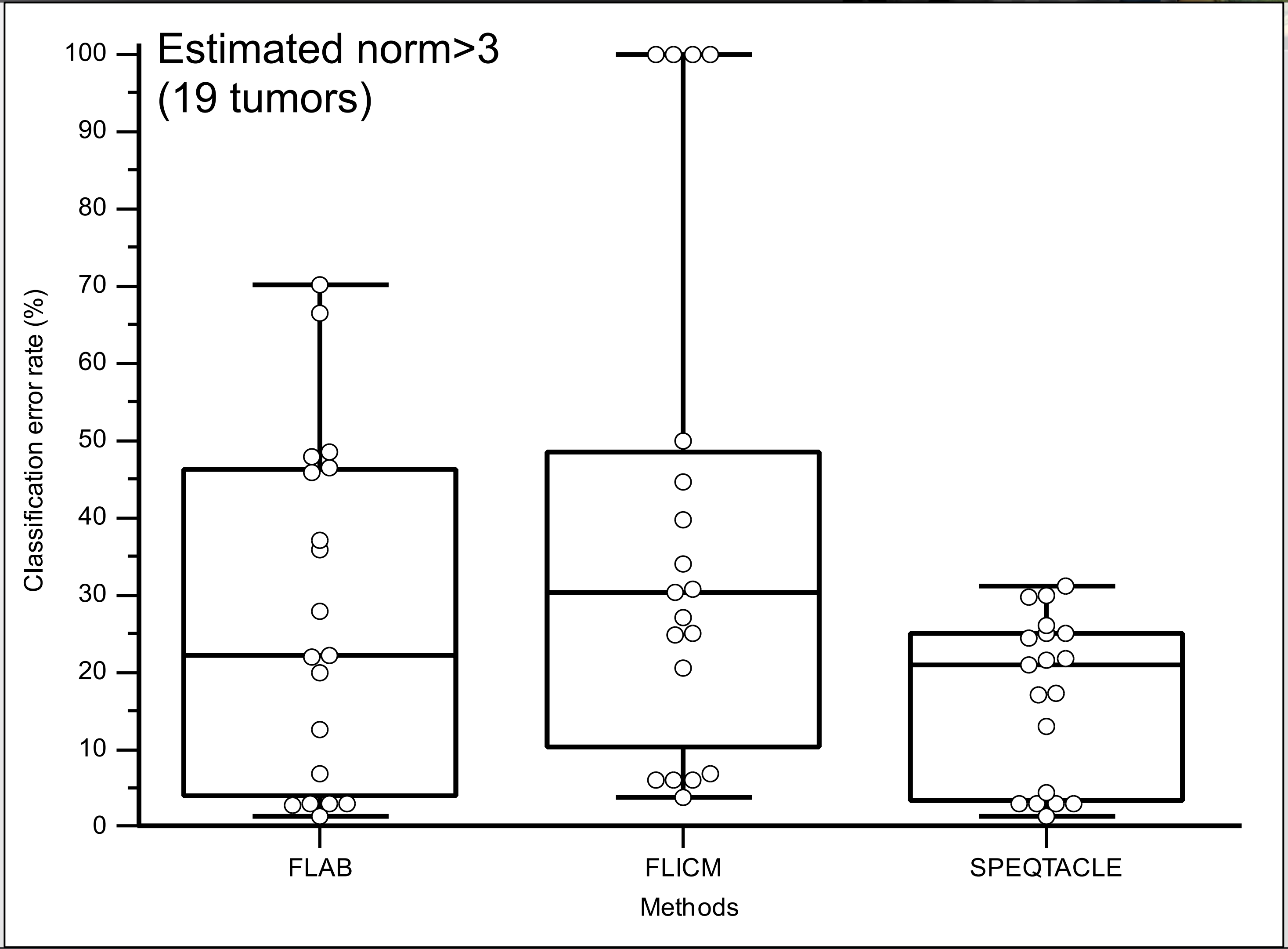
# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



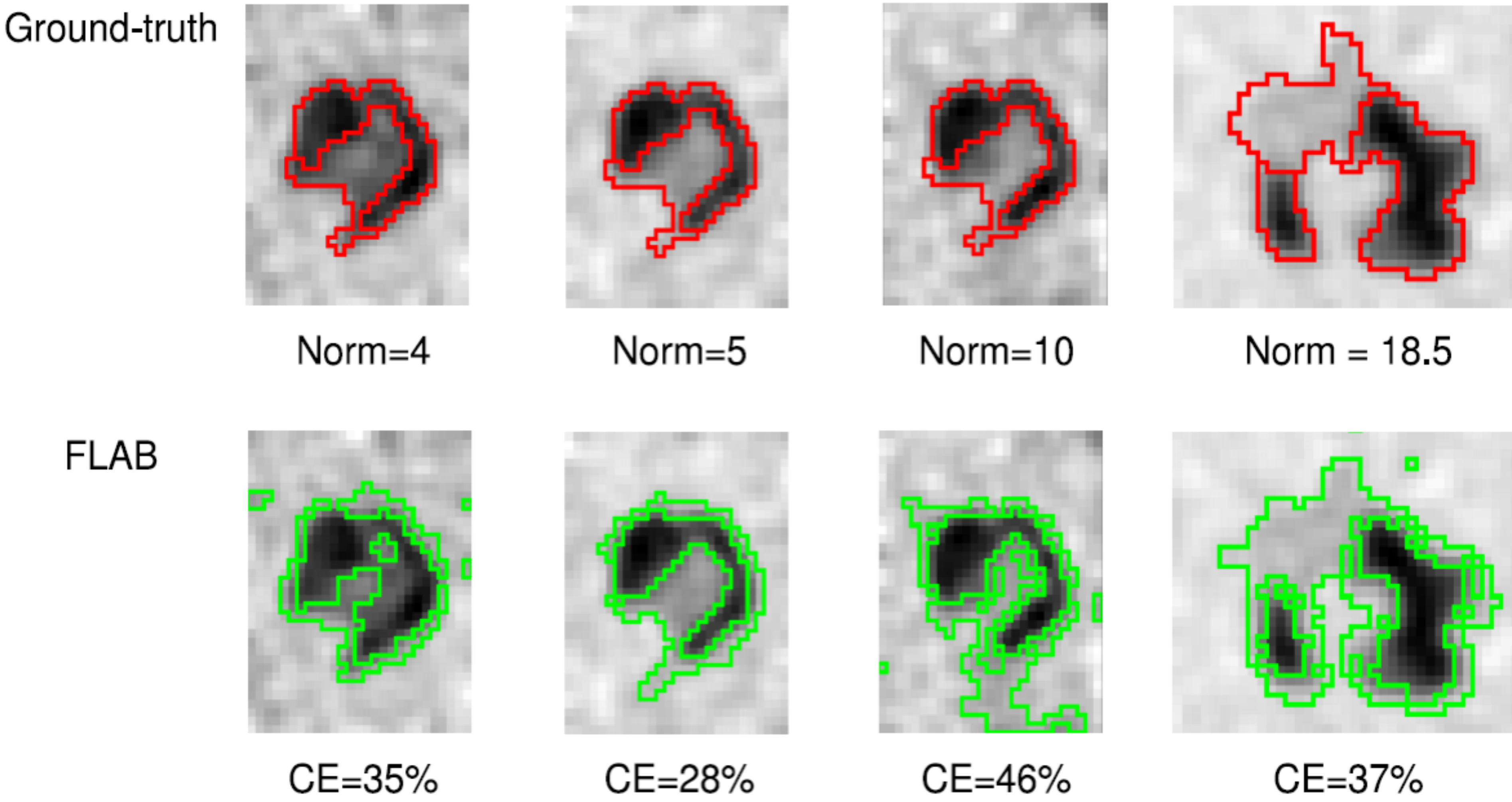
# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



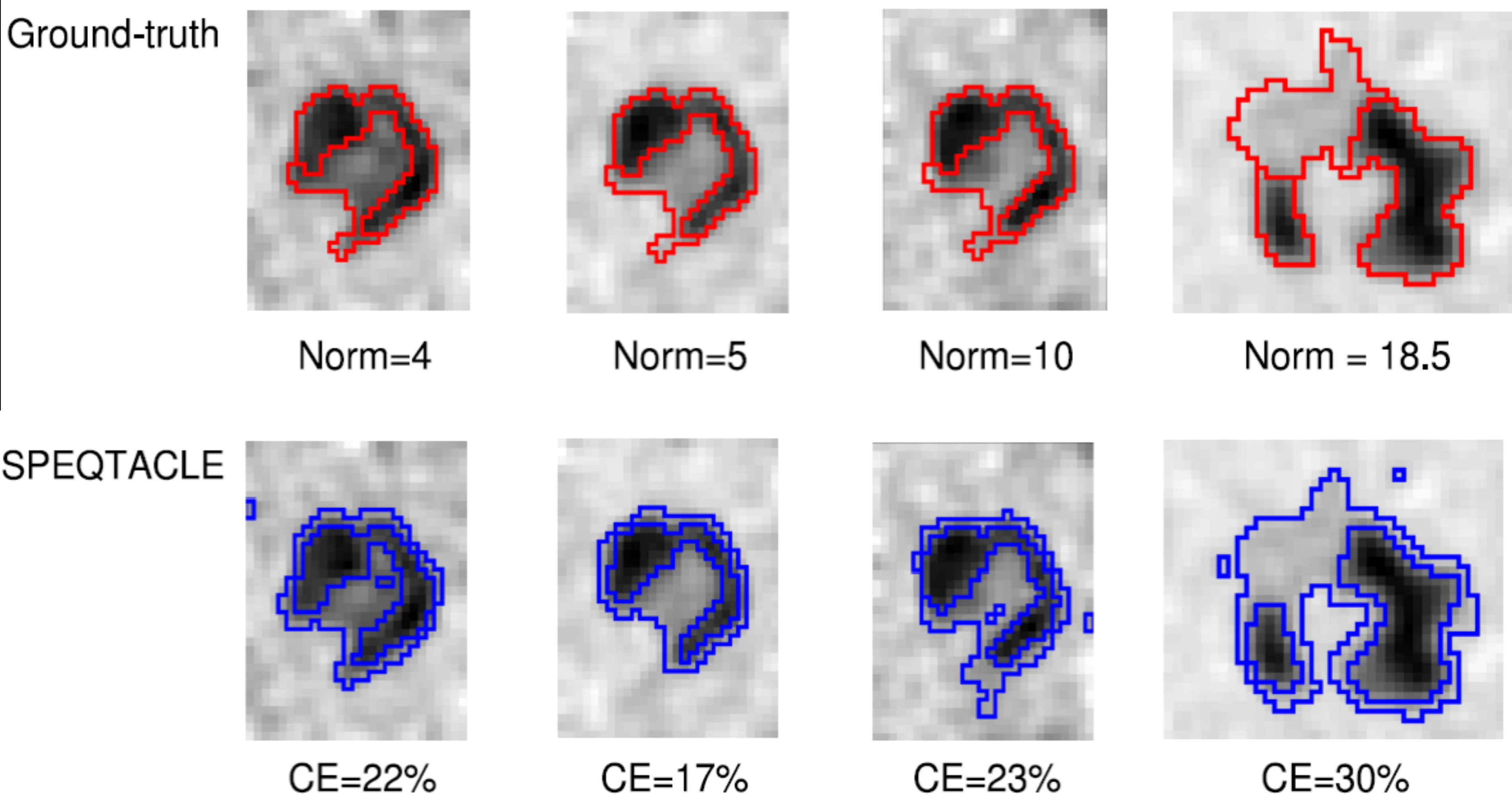
# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



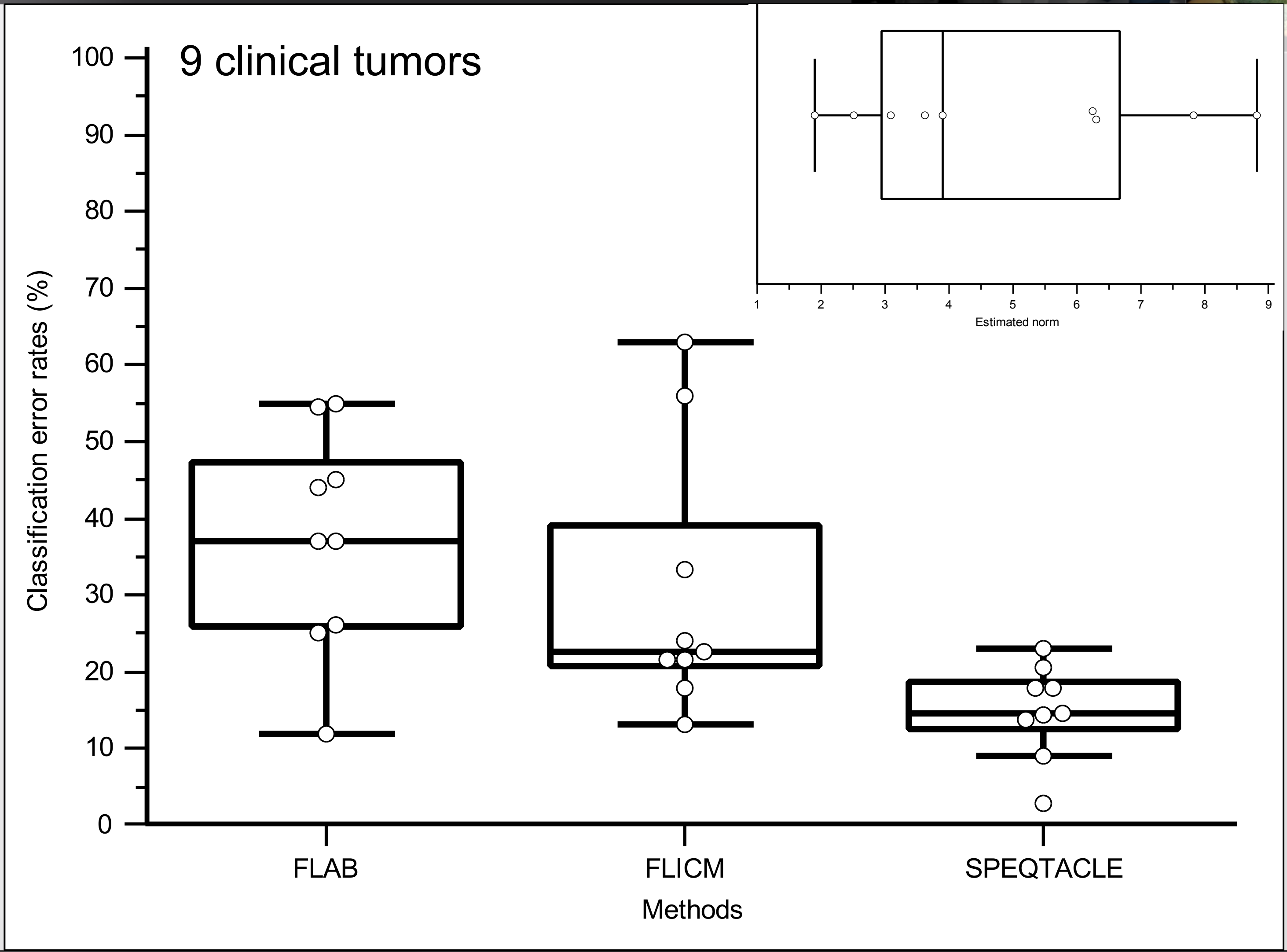
# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



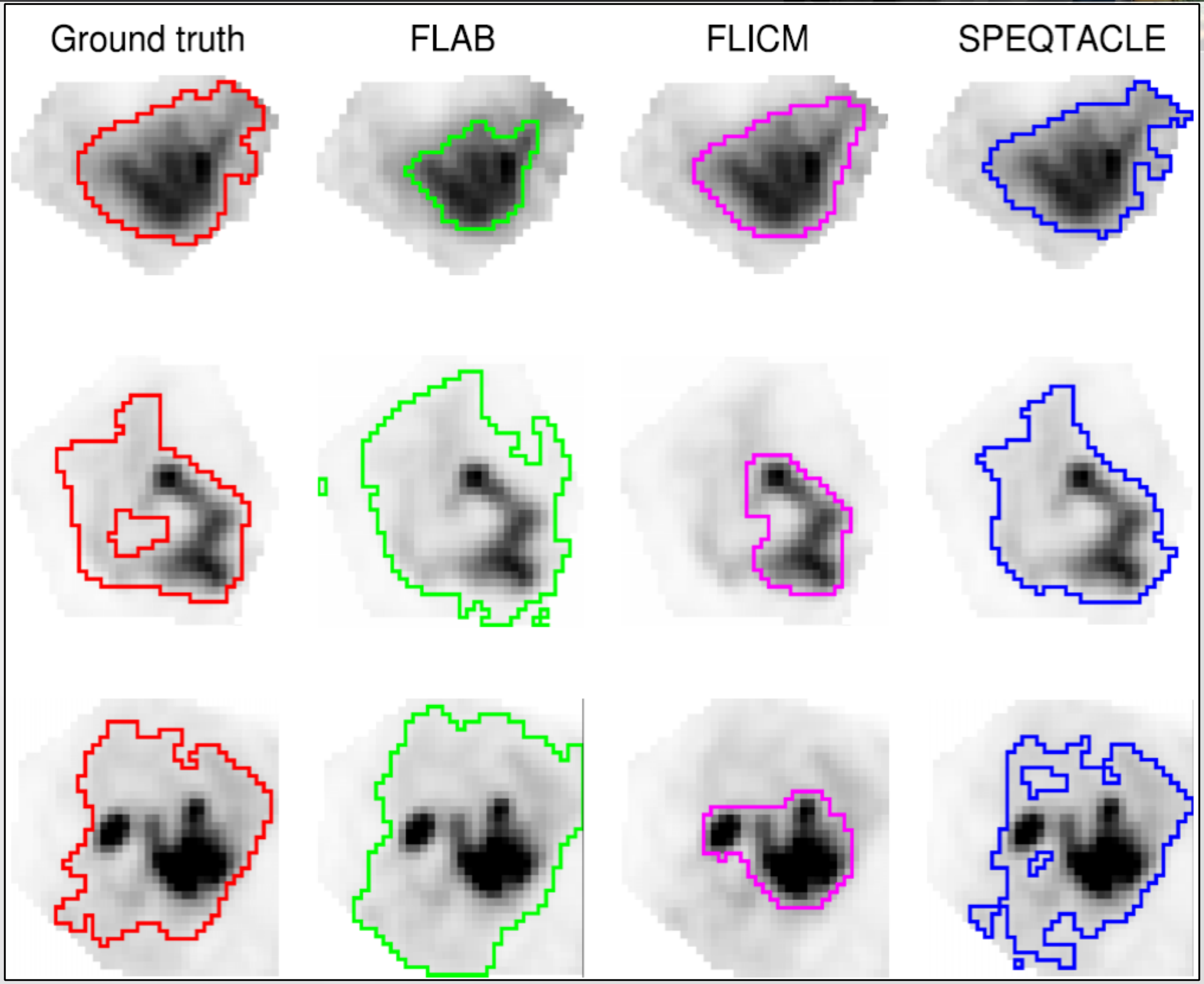
# PET segmentation

Beyond thresholds: the era of advanced segmentation paradigms



# PET segmentation

## Beyond thresholds: the era of advanced segmentation paradigms



# PET/CT segmentation

## Multimodality segmentation

- 2007, 2009
  - First papers

**Concurrent multimodality image segmentation by active contours for radiotherapy treatment planning**[a)]

Issam El Naqa,[b)] Deshan Yang, Aditya Apte, Divya Khullar, Sasa Mutic, Jie Zheng, Jeffrey D. Bradley, Perry Grigsby, and Joseph O. Deasy
*Department of Radiation Oncology, School of Medicine, Washington University, St. Louis, Missouri 63110*

(Received 18 December 2006; revised 24 September 2007; accepted for publication 24 September 2007; published 20 November 2007)

Int. J. Radiation Oncology Biol. Phys., Vol. ■, No. ■, pp. 1–8, 2009

0360-3016/09/$–see front matter

ELSEVIER

doi:10.1016/j.ijrobp.2009.04.043

**PHYSICS CONTRIBUTION**

**AUTOMATED RADIATION TARGETING IN HEAD-AND-NECK CANCER USING REGION-BASED TEXTURE ANALYSIS OF PET AND CT IMAGES**

Huan Yu, M.Sc.,* Curtis Caldwell, Ph.D.,*† Katherine Mah, M.Sc.,†‡ Ian Poon, M.D.,‡§ Judith Balogh, M.D.,‡§ Robert MacKenzie, M.D.,‡§ Nader Khaouam, M.D.,‡§ and Romeo Tirona, B.S.†

Departments of *Medical Biophysics and ‡Radiation Oncology, University of Toronto, Toronto, ON, Canada; Departments of †Medical Physics and §Radiation Oncology, Odette Cancer Centre, Sunnybrook Health Science Center, Toronto, ON, Canada

## Segmentation using textural features

- Goal: delineate the tumors in H&N cancer using both PET and CT images


Yu, *et al*. Automated radiation targeting in head-and-neck cancer using region-based texture analysis of PET and CT images. *Int J Radiat Oncol Biol Phys*. 2009

Yu, *et al*. Coregistered FDG PET/CT-based textural characterization of head and neck cancer for radiation treatment planning. *IEEE Trans Med Imaging*. 2009

# PET/CT segmentation

Multimodality segmentation

## Segmentation using textural features

- Goal: delineate the tumors in H&N cancer using both PET and CT images
- Method: mimic radiation oncologists: train the algorithm to differentiate pathological from normal tissues using their PET/CT textural properties


Yu, *et al*. Automated radiation targeting in head-and-neck cancer using region-based texture analysis of PET and CT images. *Int J Radiat Oncol Biol Phys*. 2009

Yu, *et al*. Coregistered FDG PET/CT-based textural characterization of head and neck cancer for radiation treatment planning. *IEEE Trans Med Imaging*. 2009

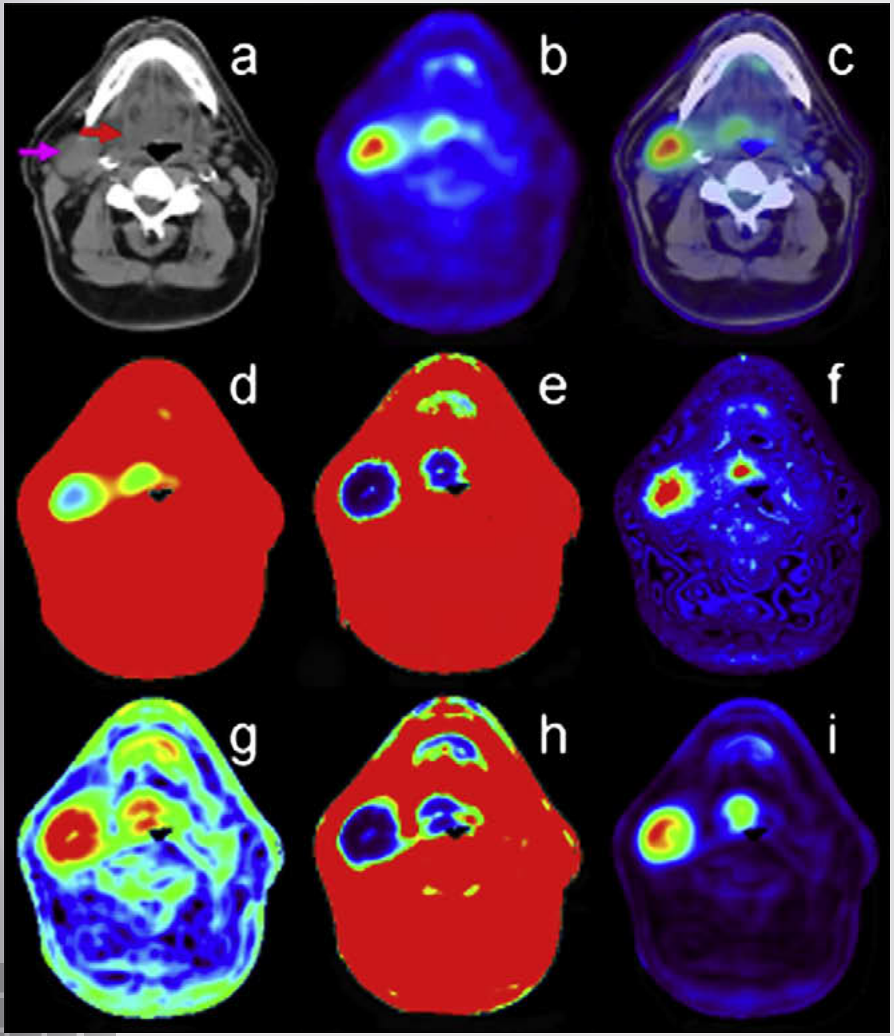
## Segmentation using textural features

- Goal: delineate the tumors in H&N cancer using both PET and CT images
- Method: mimic radiation oncologists: train the algorithm to differentiate pathological from normal tissues using their PET/CT textural properties
- Assumptions: radiation oncologists' delineations are accurate and reliable, training is not too specific

Yu, *et al*. Automated radiation targeting in head-and-neck cancer using region-based texture analysis of PET and CT images. *Int J Radiat Oncol Biol Phys*. 2009
Yu, *et al*. Coregistered FDG PET/CT-based textural characterization of head and neck cancer for radiation treatment planning. *IEEE Trans Med Imaging*. 2009

# PET/CT segmentation

## Multimodality segmentation



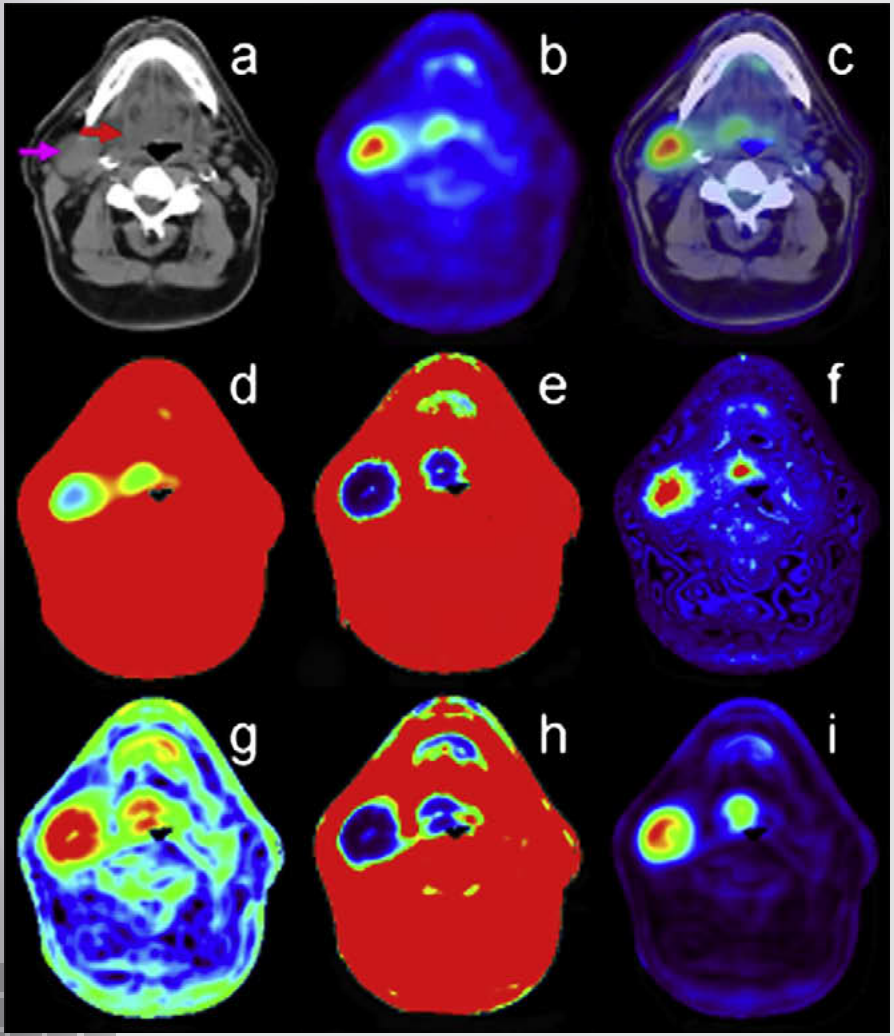

(a) CT, (b) PET, (c) PET/CT fusion
(d,j) coarseness, (e,k) busyness, (f,l) contrast, (g,m) entropy, (h,n) energy, (i,o) standard deviation


Yu, *et al*. Automated radiation targeting in head-and-neck cancer using region-based texture analysis of PET and CT images. *Int J Radiat Oncol Biol Phys*. 2009

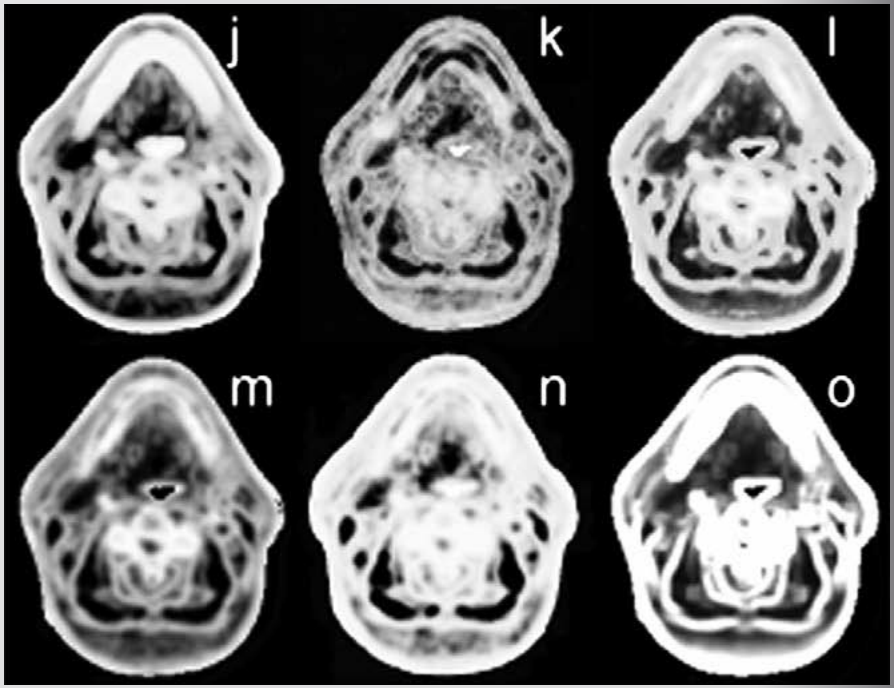
Yu, *et al*. Coregistered FDG PET/CT-based textural characterization of head and neck cancer for radiation treatment planning. *IEEE Trans Med Imaging*. 2009

# PET/CT segmentation

## Multimodality segmentation




(a) CT, (b) PET, (c) PET/CT fusion (d,j) coarseness, (e,k) busyness, (f,l) contrast, (g,m) entropy, (h,n) energy, (i,o) standard deviation

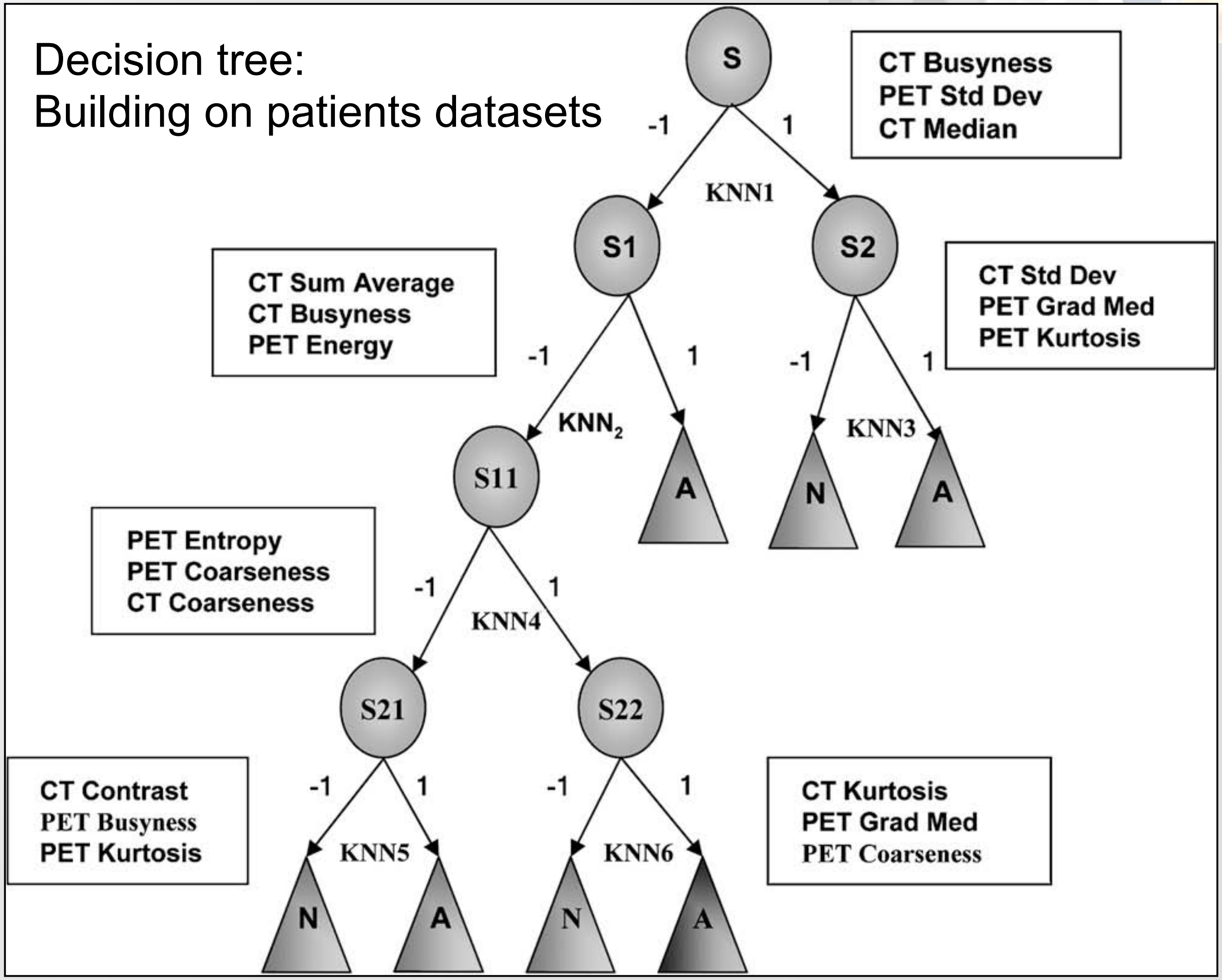



Yu, *et al*. Automated radiation targeting in head-and-neck cancer using region-based texture analysis of PET and CT images. *Int J Radiat Oncol Biol Phys*. 2009

Yu, *et al*. Coregistered FDG PET/CT-based textural characterization of head and neck cancer for radiation treatment planning. *IEEE Trans Med Imaging*. 2009

# PET/CT segmentation

## Multimodality segmentation



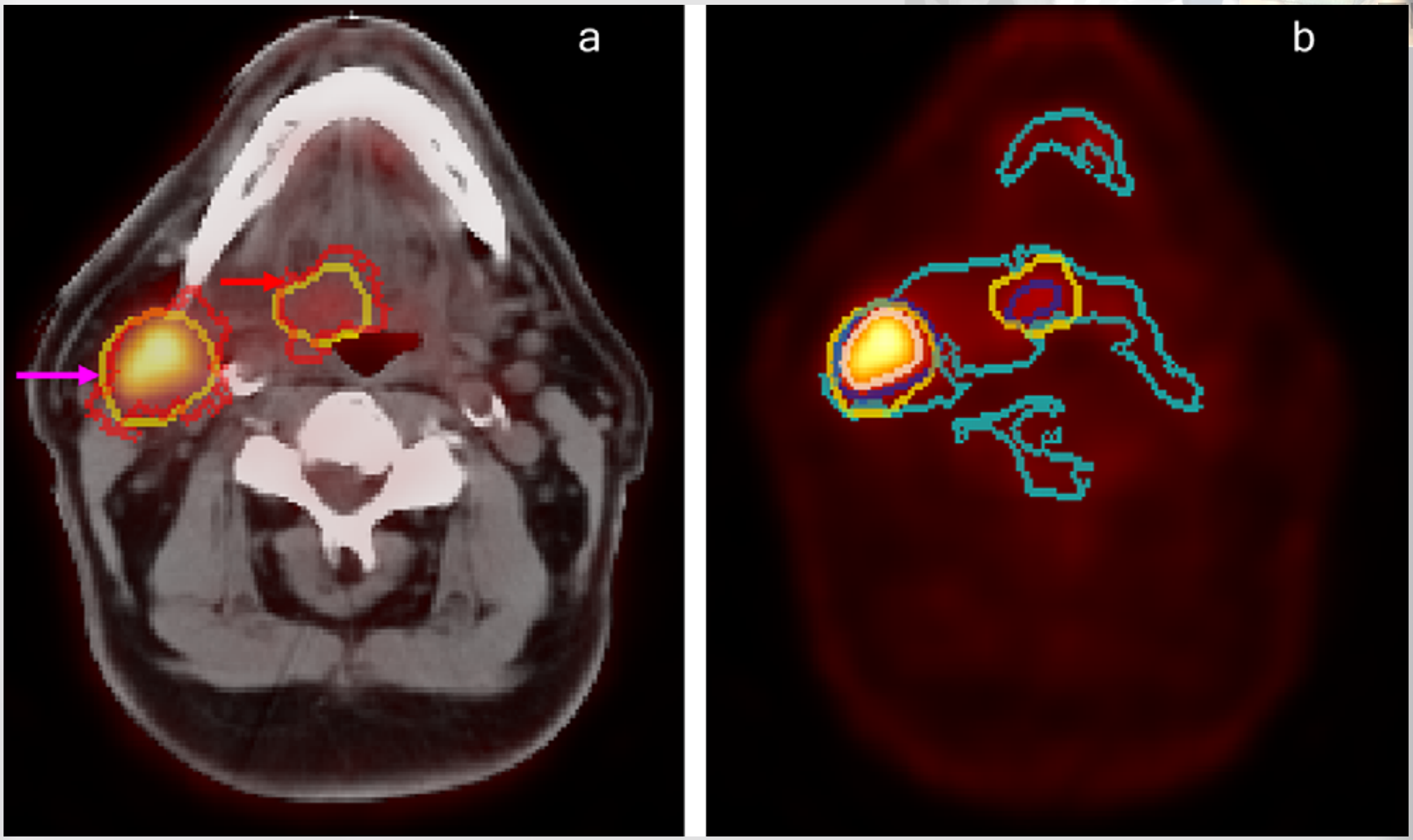


Yu, *et al*. Automated radiation targeting in head-and-neck cancer using region-based texture analysis of PET and CT images. *Int J Radiat Oncol Biol Phys*. 2009

Yu, *et al*. Coregistered FDG PET/CT-based textural characterization of head and neck cancer for radiation treatment planning. *IEEE Trans Med Imaging*. 2009

# PET/CT segmentation

## Multimodality segmentation




Experts Textures SUV>2.5 Adaptive thresholding 50% SUVmax

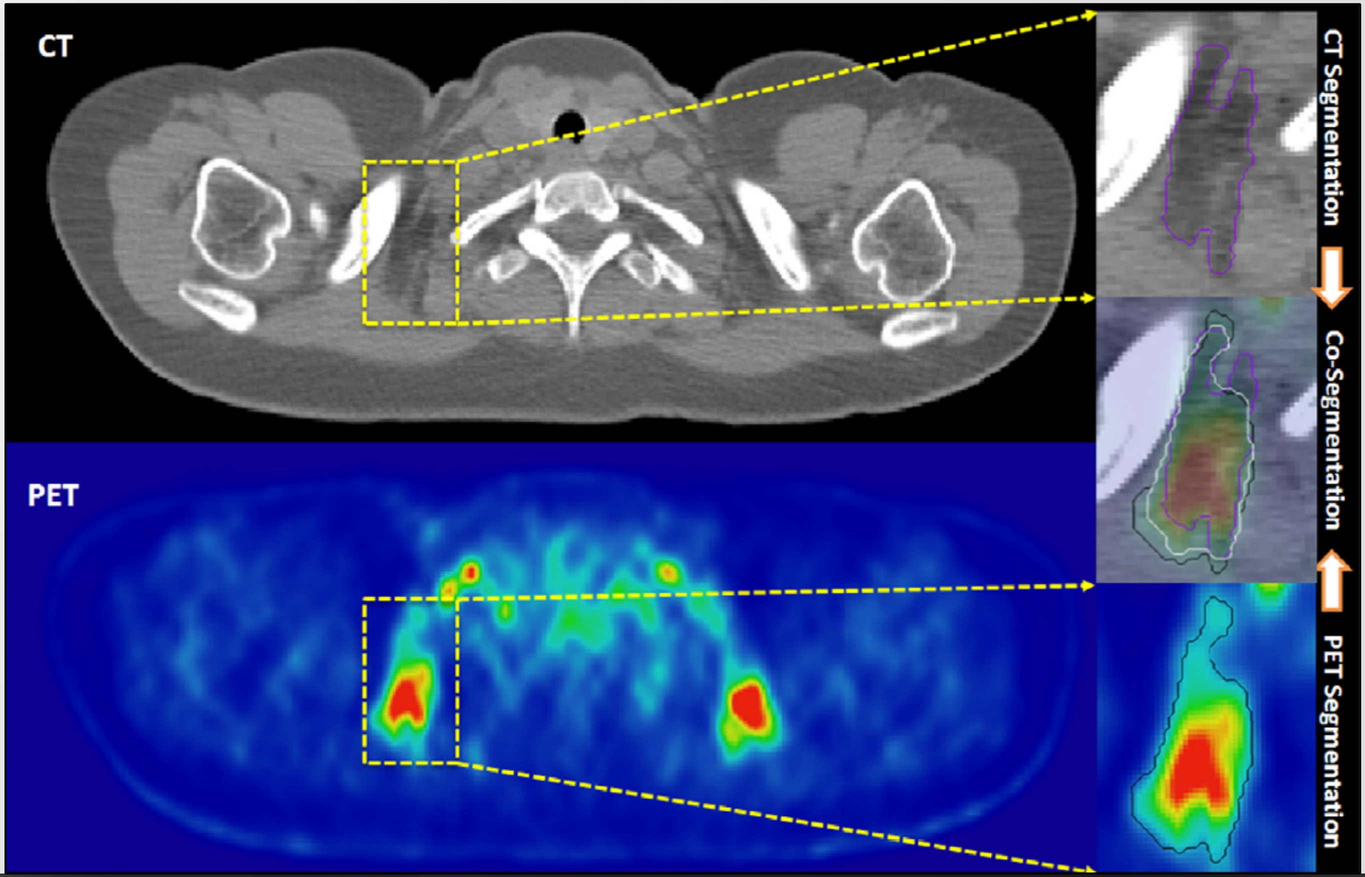

Yu, *et al*. Automated radiation targeting in head-and-neck cancer using region-based texture analysis of PET and CT images. *Int J Radiat Oncol Biol Phys*. 2009

Yu, *et al*. Coregistered FDG PET/CT-based textural characterization of head and neck cancer for radiation treatment planning. *IEEE Trans Med Imaging*. 2009

# PET/CT segmentation

Multimodality segmentation

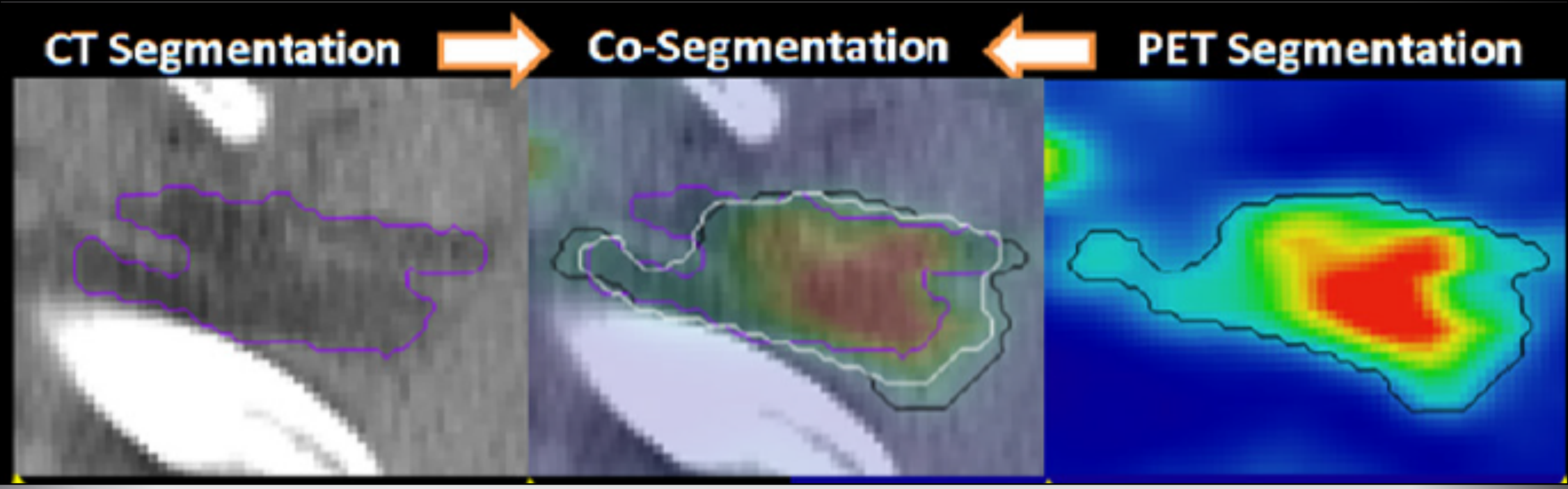
- 2011-today
  - Numerous new papers



# PET/CT segmentation

Multimodality segmentation

- 2011-today
  - Numerous new papers



# PET/CT segmentation

## Multimodality segmentation

- 2011-today
  - Numerous new papers

Medical Image Analysis 17 (2013) 929–945

Contents lists available at SciVerse ScienceDirect

Medical Image Analysis

journal homepage: www.elsevier.com/locate/media

ELSEVIER

Joint segmentation of anatomical and functional images: Applications in quantification of lesions from PET, PET-CT, MRI-PET, and MRI-PET-CT images

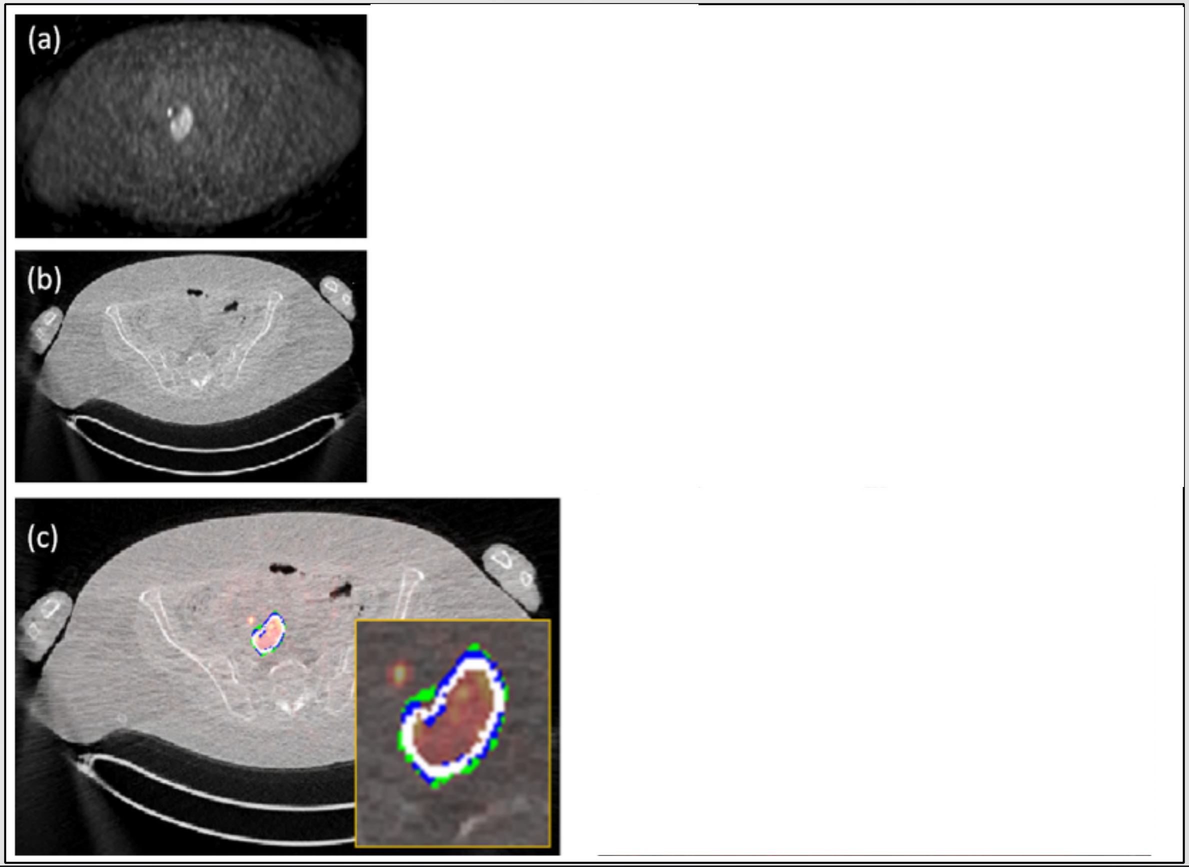
Ulas Bagci [a,b,*], Jayaram K. Udupa [c], Neil Mendhiratta [b,d], Brent Foster [b], Ziyue Xu [b], Jianhua Yao [b], Xinjian Chen [e], Daniel J. Mollura [a,b]

[a] Center for Infectious Diseases Imaging, National Institutes of Health, Bethesda, MD, United States
[b] Department of Radiology and Imaging Sciences, National Institutes of Health, Bethesda, MD, United States
[c] Department of Radiology, University of Pennsylvania, Philadelphia, PA, United States
[d] NYU School of Medicine, New York City, NY, United States
[e] School of electronics and Information Engineering, Soochow University, China

# PET/CT segmentation

Multimodality segmentation

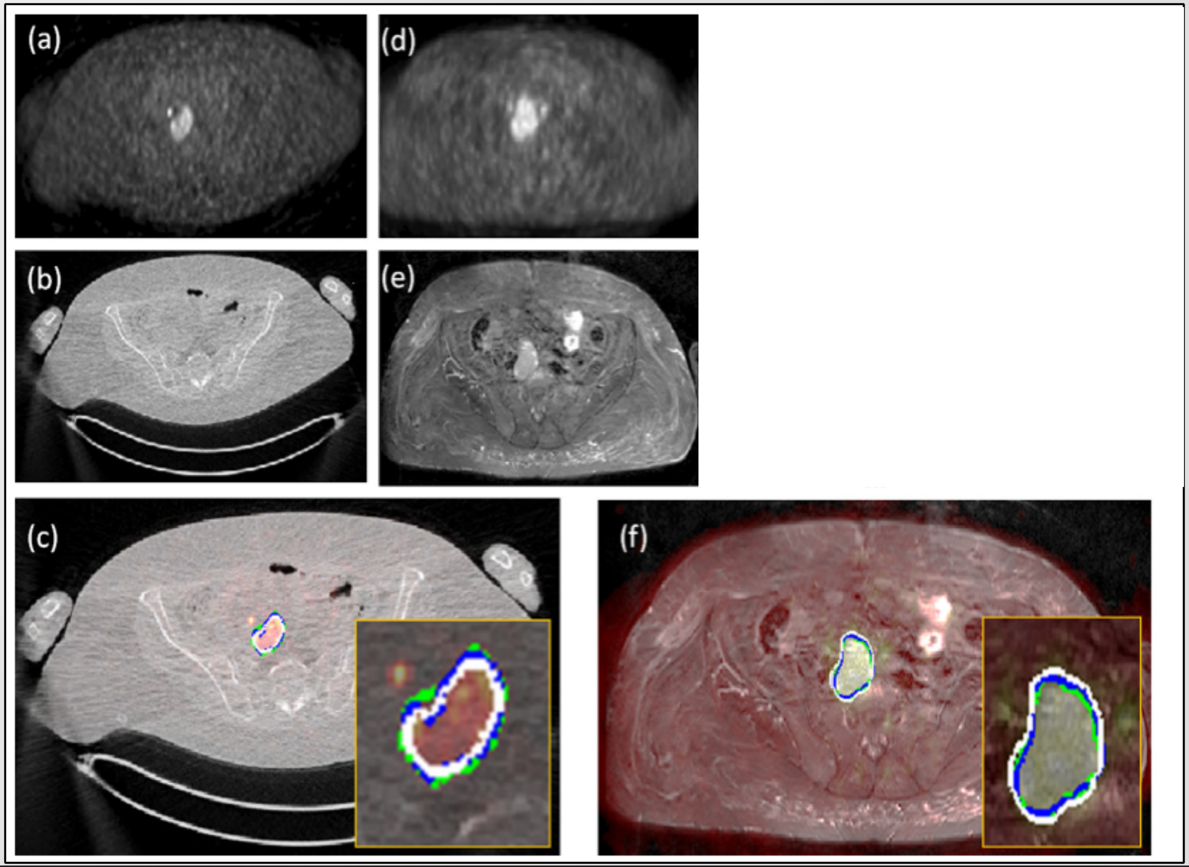
- 2011-today
  - Numerous new papers



# PET/CT segmentation

Multimodality segmentation

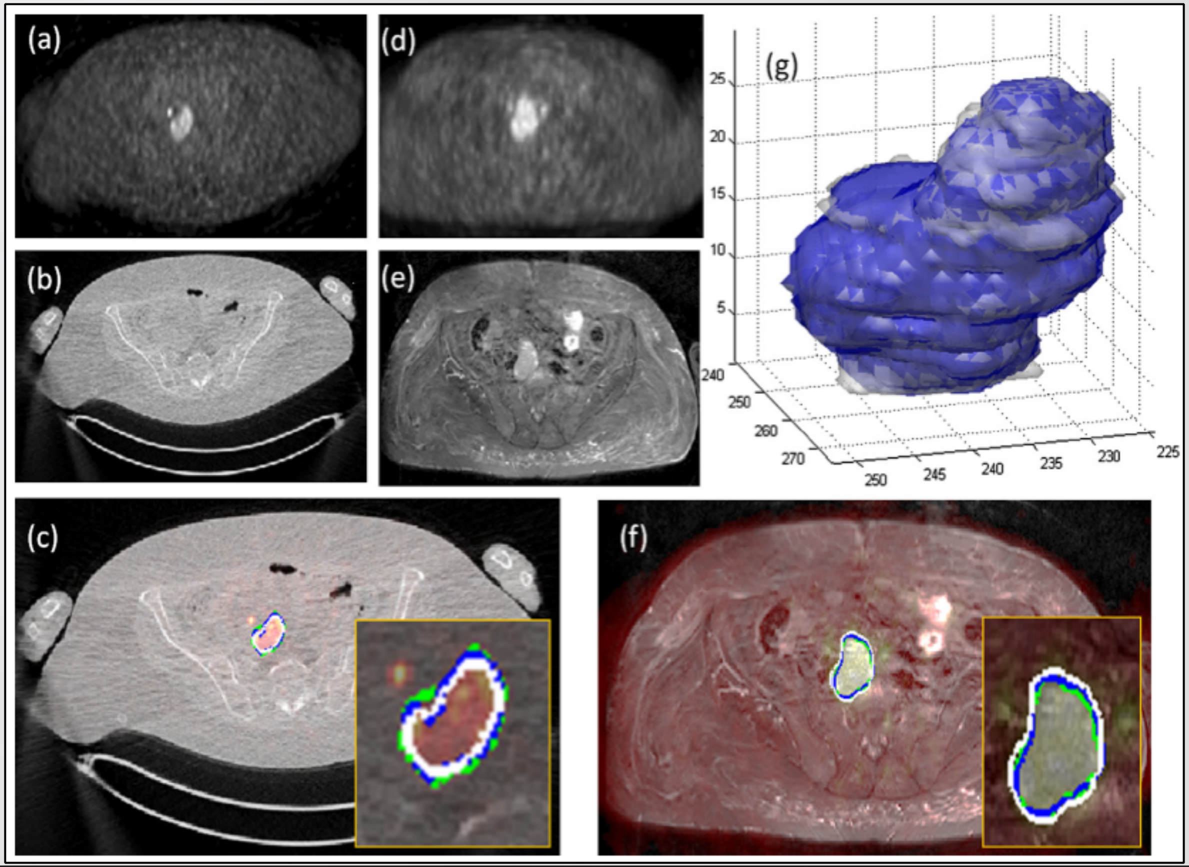
- 2011-today
  - Numerous new papers



# PET/CT segmentation

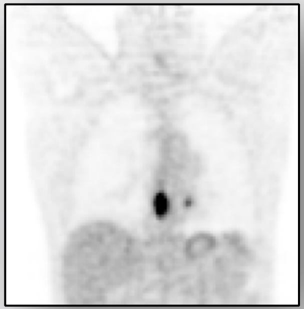
Multimodality segmentation

- 2011-today
  - Numerous new papers



## PET/CT: therapy response monitoring/prediction

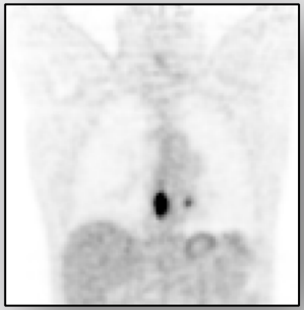
Pre treatment
(« baseline »)



## PET/CT: therapy response monitoring/prediction

Treatment

Pre treatment
(« baseline »)



Post treatment

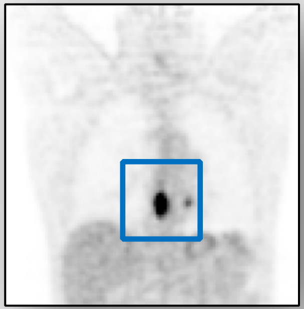
# PET segmentation

Reproducibility and robustness

## PET/CT: therapy response monitoring/prediction

Treatment

Pre treatment
(« baseline »)



Quantif 1

Post treatment

Quantif 2

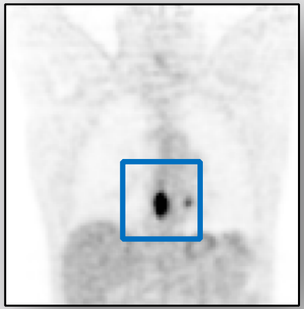
# PET segmentation

Reproducibility and robustness

## PET/CT: therapy response monitoring/prediction

Treatment

Pre treatment
(« baseline »)



Quantif 1

Post treatment

Quantif 2

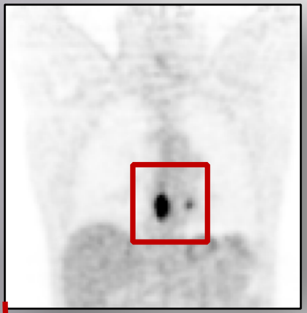
# PET segmentation

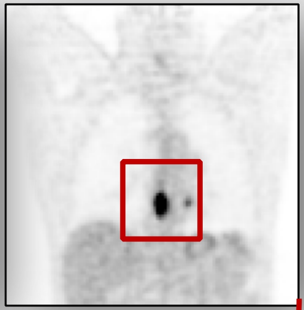
## Reproducibility and robustness

### PET/CT: therapy response monitoring/prediction

Treatment

Pre treatment
(« baseline »)





Post treatment

Test-retest / « double baseline » scans

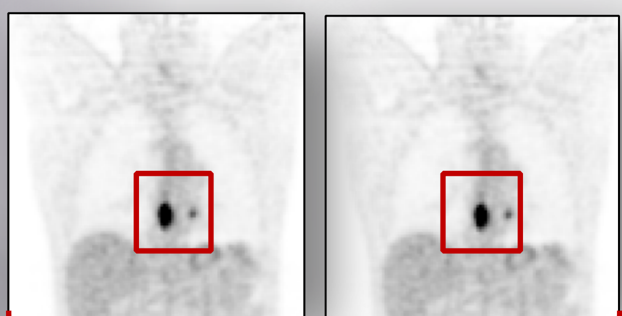
# PET segmentation

## Reproducibility and robustness

### PET/CT: therapy response monitoring/prediction

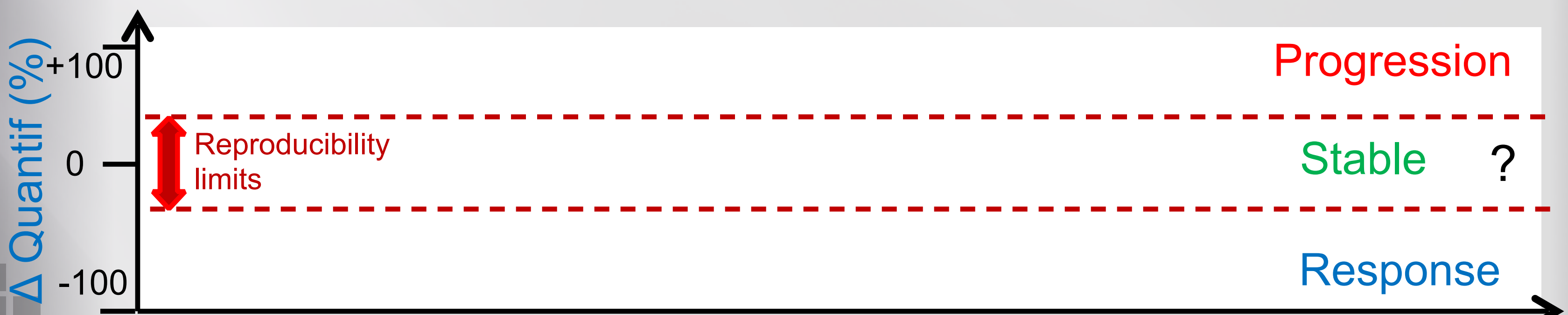
Treatment

Pre treatment
(« baseline »)



Test-retest / « double baseline » scans

Post treatment



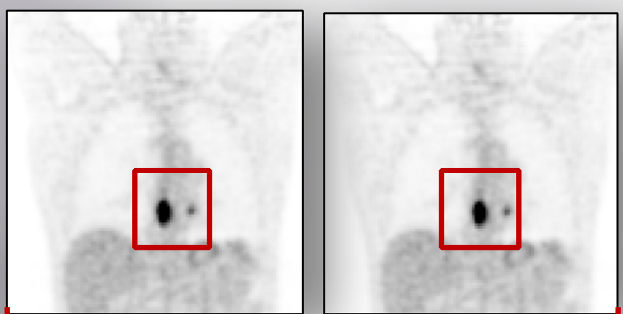
# PET segmentation

## Reproducibility and robustness

- PET/CT: therapy response monitoring/prediction

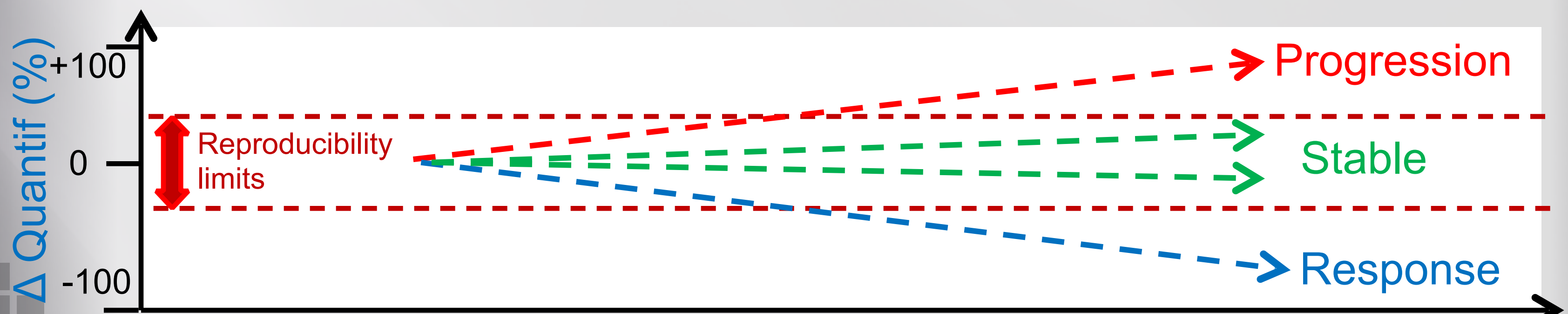
Treatment

Pre treatment
(« baseline »)

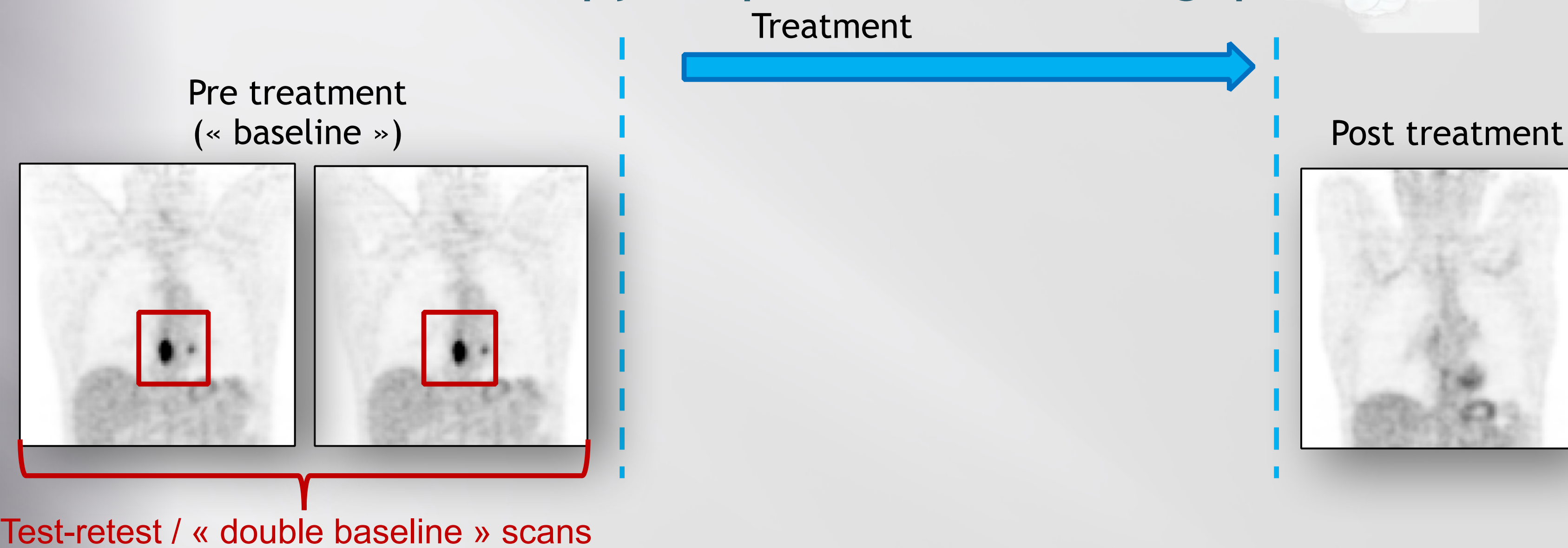


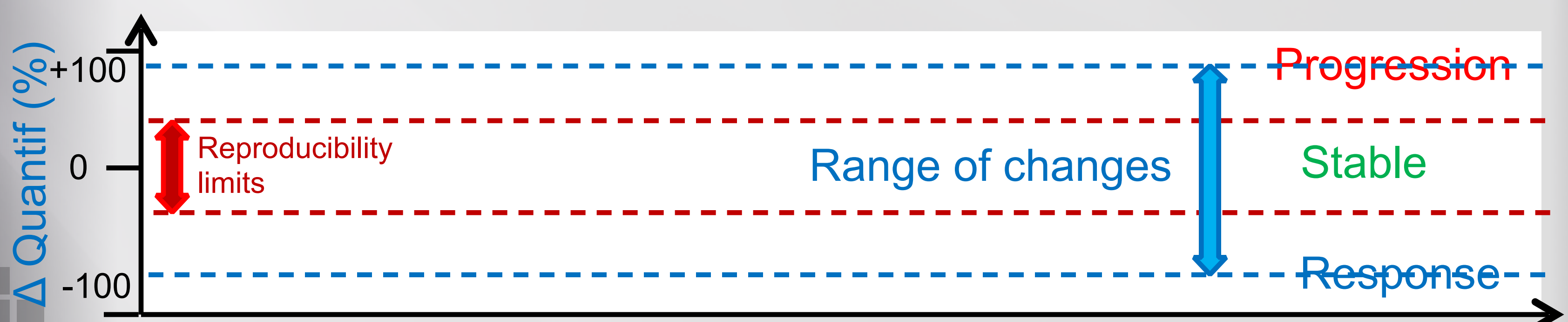
Test-retest / « double baseline » scans

Post treatment



## PET/CT: therapy response monitoring/prediction



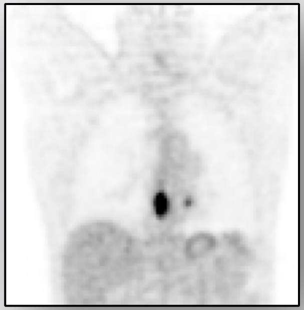
# PET segmentation

Reproducibility and robustness

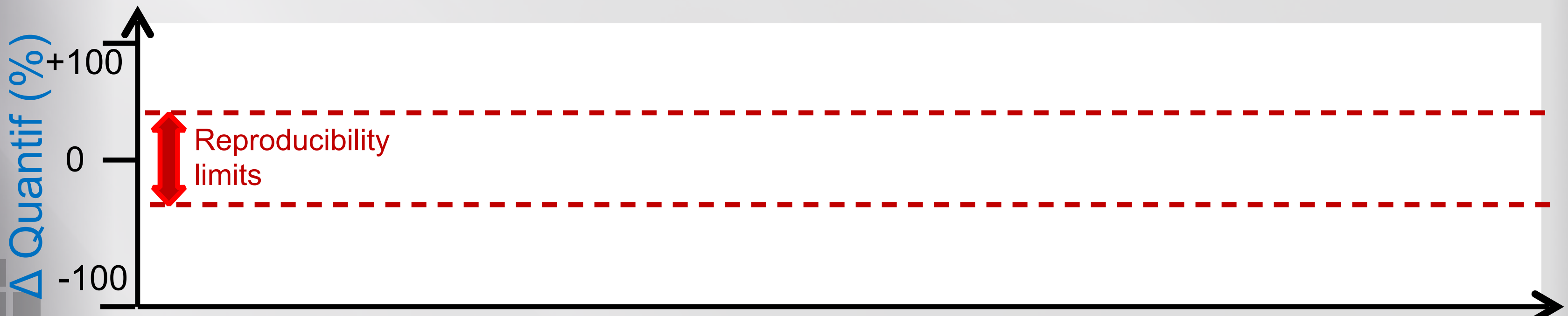
## PET/CT: therapy response monitoring/prediction

Treatment

Pre treatment
(« baseline »)



Post treatment

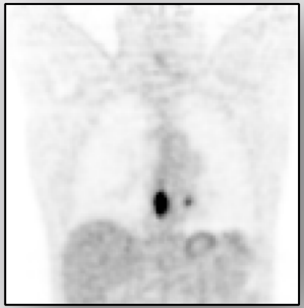


# PET segmentation
Reproducibility and robustness

## PET/CT: therapy response monitoring/prediction

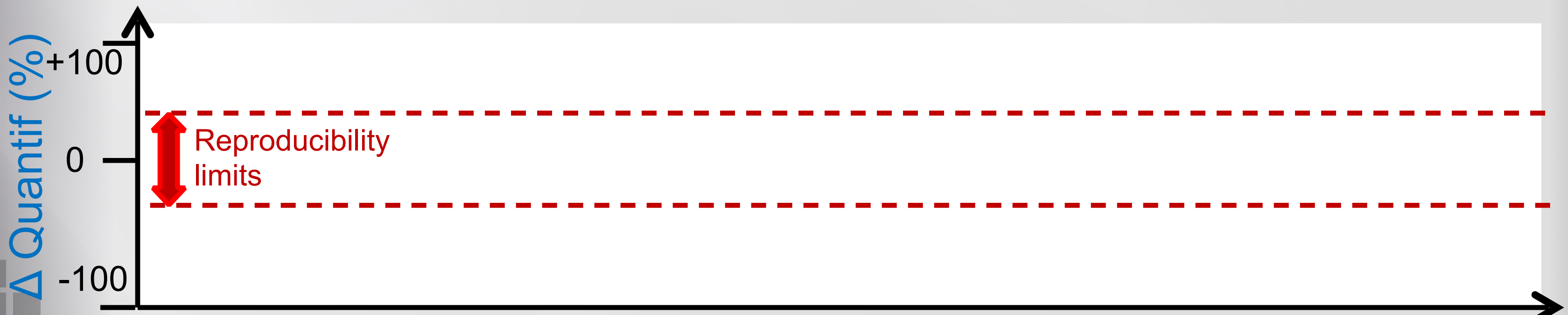
Treatment

Pre treatment
(« baseline »)



During treatment
(1, 2 weeks /cycles)

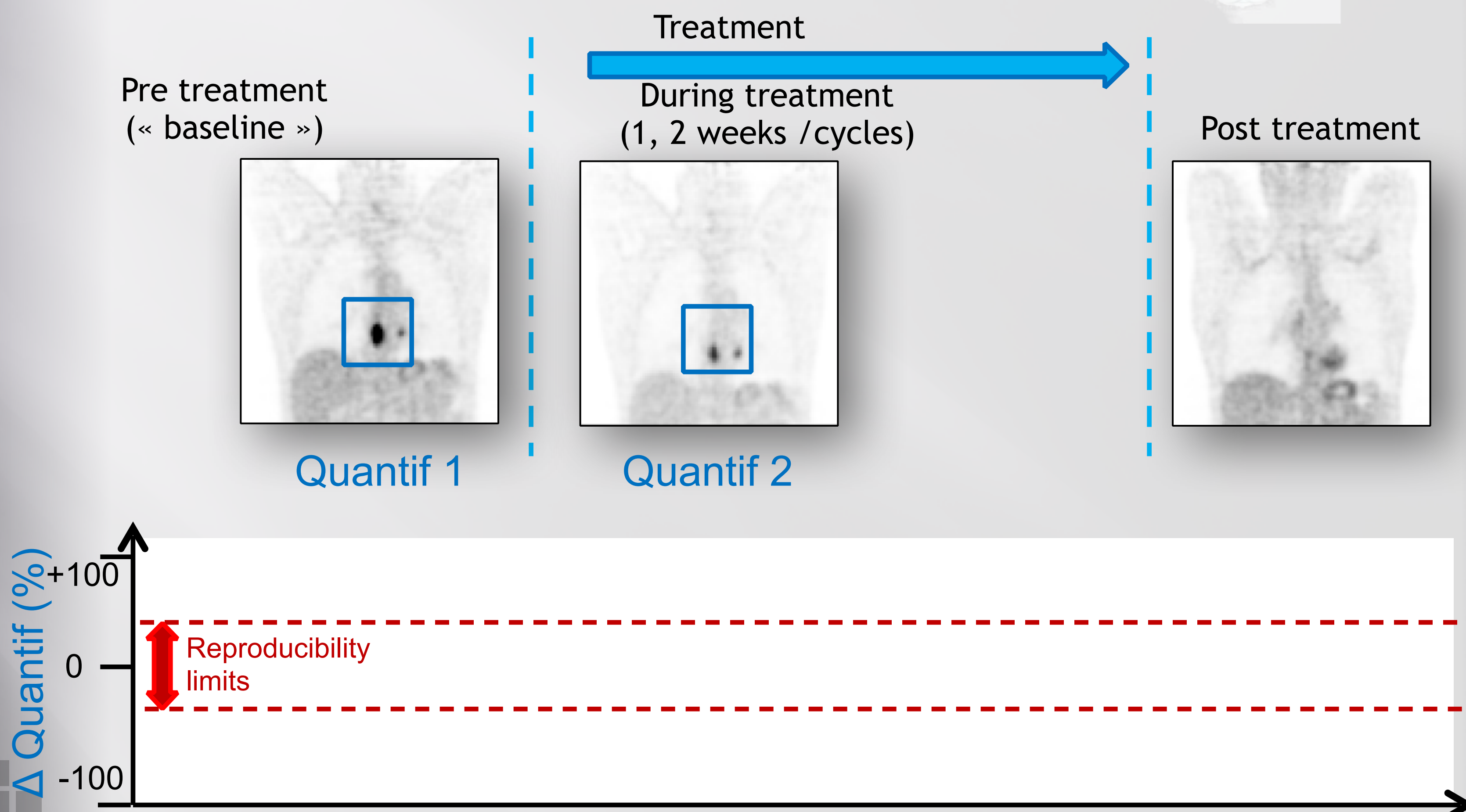
Post treatment



# PET segmentation

Reproducibility and robustness

## PET/CT: therapy response monitoring/prediction



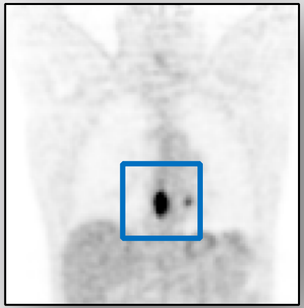
# PET segmentation

Reproducibility and robustness

## PET/CT: therapy response monitoring/prediction

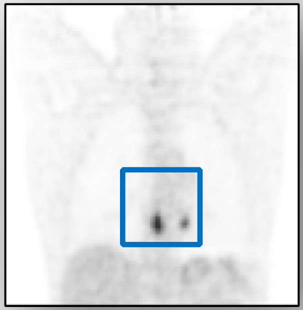
Treatment

Pre treatment
(« baseline »)



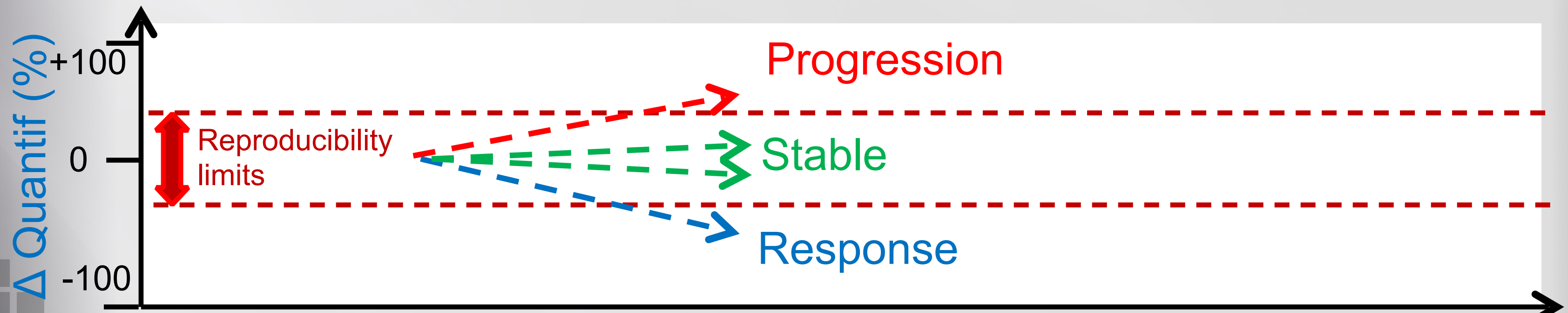
Quantif 1

During treatment
(1, 2 weeks /cycles)



Quantif 2

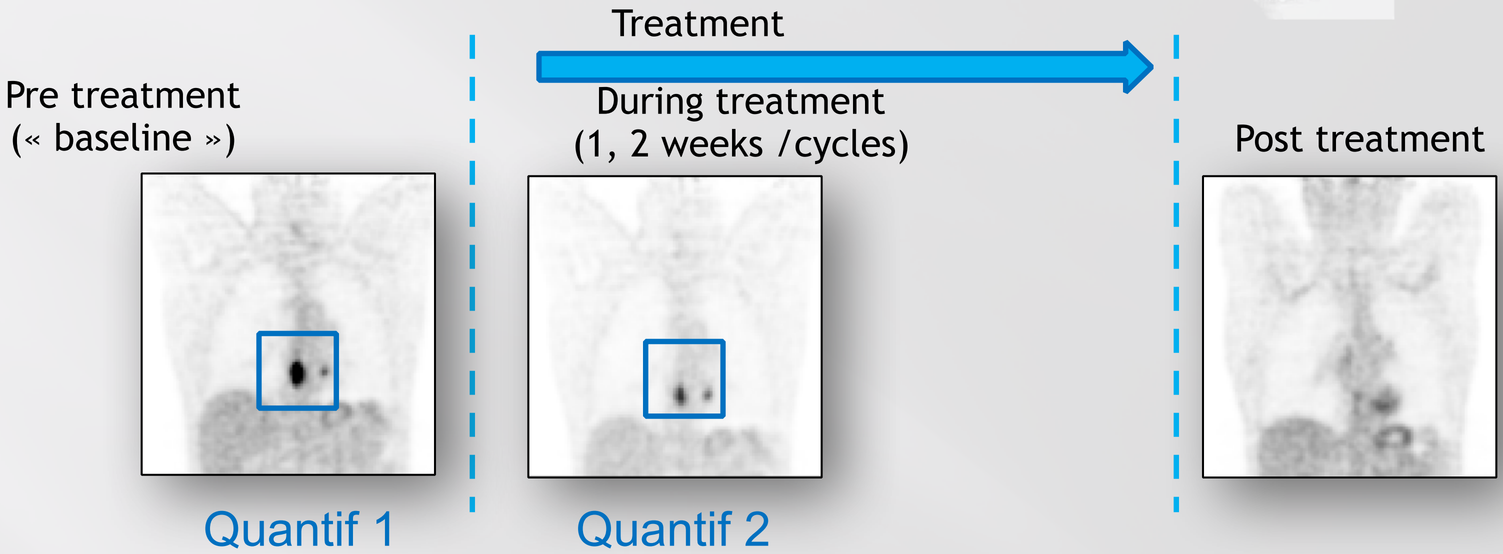
Post treatment

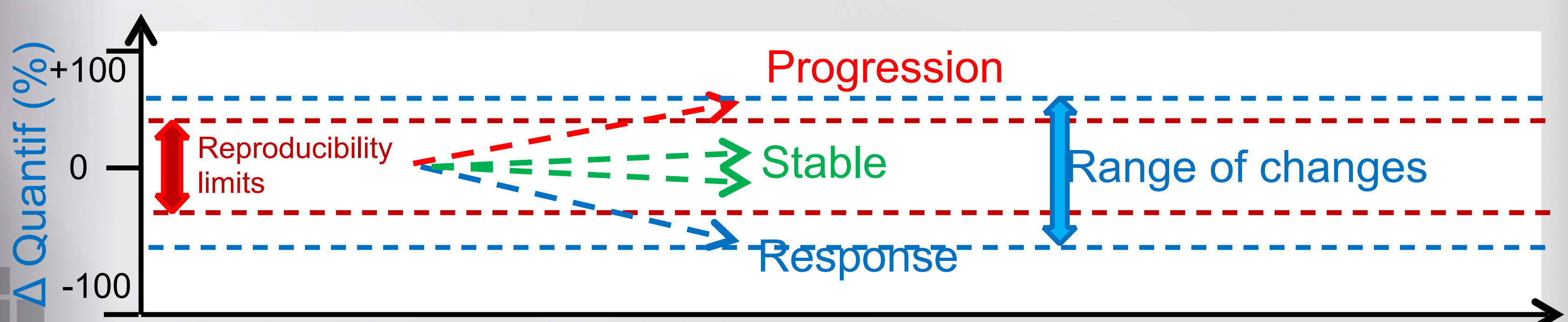


# PET segmentation

## Reproducibility and robustness

- PET/CT: therapy response monitoring/prediction

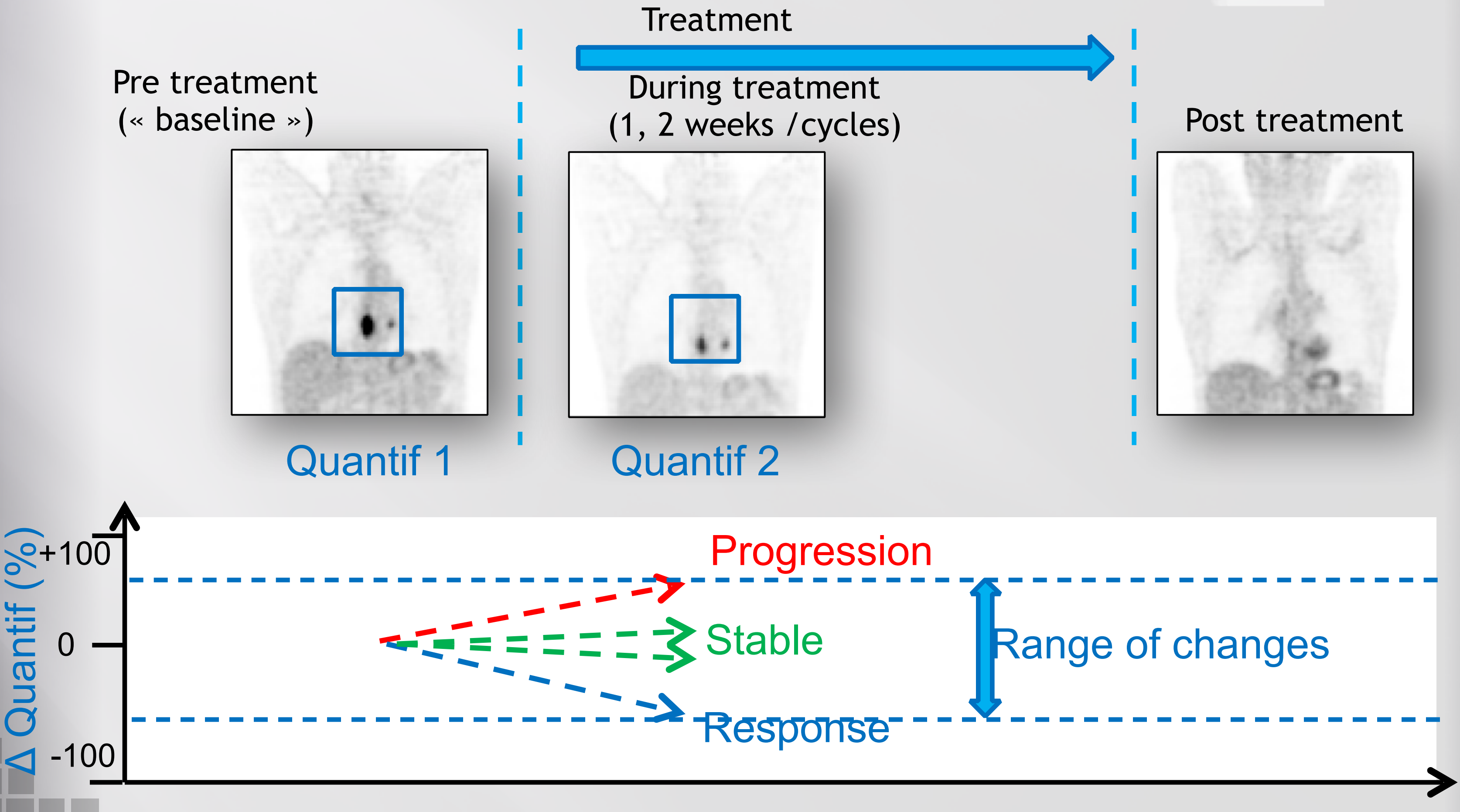


# PET segmentation

Reproducibility and robustness

## PET/CT: therapy response monitoring/prediction



# PET segmentation

Reproducibility and robustness

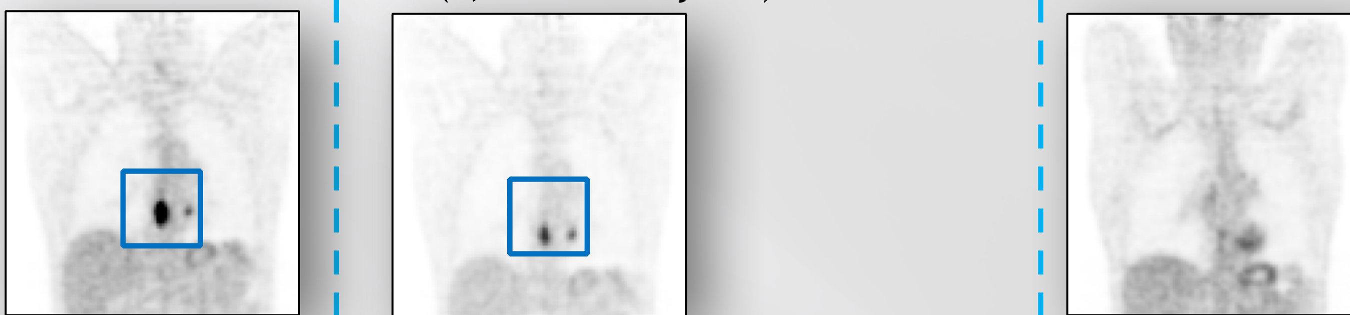
## PET/CT: therapy response monitoring/prediction

Treatment

Pre treatment
(« baseline »)

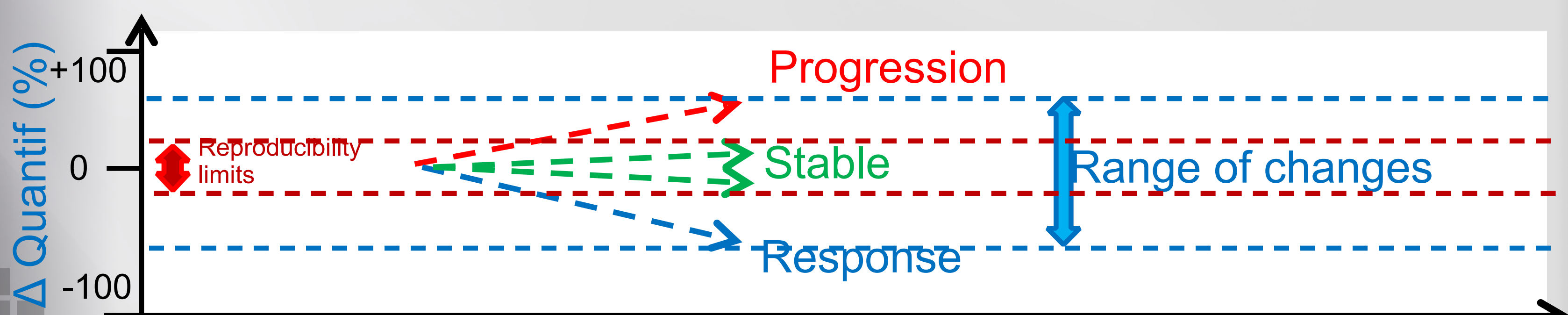
During treatment
(1, 2 weeks /cycles)

Post treatment



Quantif 1

Quantif 2



# PET segmentation

## Reproducibility and robustness

- Evaluation of reproducibility
  - A few studies for SUVs (about ±15 to ±30%)[1-2]

# PET segmentation

## Reproducibility and robustness

- Evaluation of reproducibility
  - A few studies for SUVs (about ±15 to ±30%)[1-2]


1. Nahmias, *et al.* Reproducibility of standardized uptake value measurements determined by 18F-FDG PET in malignant tumors. *J Nucl Med*. 2008
2. Velasquez, *et al*. Repeatability of 18F-FDG PET in a multicenter phase I study of patients with advanced gastrointestinal malignancies. *J Nucl Med*. 2009

# PET segmentation

## Reproducibility and robustness

- Evaluation of reproducibility
  - A few studies for SUVs (about ±15 to ±30%)[1-2]

**Reproducibility of $^{18}$F-FDG and 3′-Deoxy-3′-$^{18}$F-Fluorothymidine PET Tumor Volume Measurements**

Journal of nuclear medicine

Mathieu Hatt[1], Catherine Cheze-Le Rest[1,2], Eric O. Aboagye[3], Laura M. Kenny[3], Lula Rosso[3], Federico E. Turkheimer[3], Nidal M. Albarghach[1,4], Jean-Philippe Metges[4], Olivier Pradier[1,4], and Dimitris Visvikis[1]



1. Nahmias, *et al.* Reproducibility of standardized uptake value measurements determined by 18F-FDG PET in malignant tumors. *J Nucl Med*. 2008
2. Velasquez, *et al*. Repeatability of 18F-FDG PET in a multicenter phase I study of patients with advanced gastrointestinal malignancies. *J Nucl Med*. 2009

# PET segmentation

## Reproducibility and robustness

- Evaluation of reproducibility
  - A few studies for SUVs (about ±15 to ±30%)[1-2]

**Reproducibility of $^{18}$F-FDG and 3′-Deoxy-3′-$^{18}$F-Fluorothymidine PET Tumor Volume Measurements**

Mathieu Hatt[1], Catherine Cheze-Le Rest[1,2], Eric O. Aboagye[3], Laura M. Kenny[3], Lula Rosso[3], Federico E. Turkheimer[3], Nidal M. Albarghach[1,4], Jean-Philippe Metges[4], Olivier Pradier[1,4], and Dimitris Visvikis[1]

Journal of nuclear medicine

SUVs: ±30%

MATVs: ±20-35%
TLG: ±15-40%

FLAB

Institut national de la santé et de la recherche médicale

1. Nahmias, *et al.* Reproducibility of standardized uptake value measurements determined by 18F-FDG PET in malignant tumors. *J Nucl Med*. 2008
2. Velasquez, *et al*. Repeatability of 18F-FDG PET in a multicenter phase I study of patients with advanced gastrointestinal malignancies. *J Nucl Med*. 2009

# PET segmentation

## Reproducibility and robustness

- Evaluation of reproducibility
  - A few studies for SUVs (about ±15 to ±30%)[1-2]

**Reproducibility of $^{18}$F-FDG and 3′-Deoxy-3′-$^{18}$F-Fluorothymidine PET Tumor Volume Measurements**

Journal of nuclear medicine

Mathieu Hatt[1], Catherine Cheze-Le Rest[1,2], Eric O. Aboagye[3], Laura M. Kenny[3], Lula Rosso[3], Federico E. Turkheimer[3], Nidal M. Albarghach[1,4], Jean-Philippe Metges[4], Olivier Pradier[1,4], and Dimitris Visvikis[1]

SUVs: ±30%

MATVs: ±20-35%
TLG: ±15-40%
FLAB

MATVs: ±50-90%
TLG: ±35-120%
Threshold based

1. Nahmias, *et al.* Reproducibility of standardized uptake value measurements determined by 18F-FDG PET in malignant tumors. *J Nucl Med*. 2008
2. Velasquez, *et al*. Repeatability of 18F-FDG PET in a multicenter phase I study of patients with advanced gastrointestinal malignancies. *J Nucl Med*. 2009

# PET segmentation

## Reproducibility and robustness

- Evaluation of reproducibility
  - A few studies for SUVs (about ±15 to ±30%)[1-2]

**Reproducibility of $^{18}$F-FDG and 3′-Deoxy-3′-$^{18}$F-Fluorothymidine PET Tumor Volume Measurements**

Journal of nuclear medicine

Mathieu Hatt[1], Catherine Cheze-Le Rest[1,2], Eric O. Aboagye[3], Laura M. Kenny[3], Lula Rosso[3], Federico E. Turkheimer[3], Nidal M. Albarghach[1,4], Jean-Philippe Metges[4], Olivier Pradier[1,4], and Dimitris Visvikis[1]

SUVs: ±30%

MATVs: ±20-35%
TLG: ±15-40%
FLAB

MATVs: ±50-90%
TLG: ±35-120%
Threshold based

Journal of nuclear medicine

**Repeatability of Metabolically Active Volume Measurements with $^{18}$F-FDG and $^{18}$F-FLT PET in Non–Small Cell Lung Cancer**

Virginie Frings[1], Adrianus J. de Langen[2], Egbert F. Smit[2], Floris H.P. van Velden[1], Otto S. Hoekstra[1], Harm van Tinteren[3], and Ronald Boellaard[1]



1. Nahmias, *et al.* Reproducibility of standardized uptake value measurements determined by 18F-FDG PET in malignant tumors. *J Nucl Med*. 2008
2. Velasquez, *et al*. Repeatability of 18F-FDG PET in a multicenter phase I study of patients with advanced gastrointestinal malignancies. *J Nucl Med*. 2009

# PET segmentation

## Reproducibility and robustness

- Evaluation of reproducibility
  - A few studies for SUVs (about ±15 to ±30%)[1-2]

**Reproducibility of $^{18}$F-FDG and 3′-Deoxy-3′-$^{18}$F-Fluorothymidine PET Tumor Volume Measurements**

Journal of nuclear medicine

Mathieu Hatt[1], Catherine Cheze-Le Rest[1,2], Eric O. Aboagye[3], Laura M. Kenny[3], Lula Rosso[3], Federico E. Turkheimer[3], Nidal M. Albarghach[1,4], Jean-Philippe Metges[4], Olivier Pradier[1,4], and Dimitris Visvikis[1]

SUVs: ±30%

MATVs: ±20-35%
TLG: ±15-40%
FLAB

MATVs: ±50-90%
TLG: ±35-120%
Threshold based

Journal of nuclear medicine

**Repeatability of Metabolically Active Volume Measurements with $^{18}$F-FDG and $^{18}$F-FLT PET in Non–Small Cell Lung Cancer**

Virginie Frings[1], Adrianus J. de Langen[2], Egbert F. Smit[2], Floris H.P. van Velden[1], Otto S. Hoekstra[1], Harm van Tinteren[3], and Ronald Boellaard[1]

SUVs: N/A

MATVs:
±45-70% (FDG)
±35-95% (FLT)
Threshold based



1. Nahmias, *et al.* Reproducibility of standardized uptake value measurements determined by 18F-FDG PET in malignant tumors. *J Nucl Med*. 2008
2. Velasquez, *et al*. Repeatability of 18F-FDG PET in a multicenter phase I study of patients with advanced gastrointestinal malignancies. *J Nucl Med*. 2009

# PET segmentation

## Standardization

- Issues today:
  - No consensus reached
  - Limited implementation by vendors
  - Need for standardization

# PET segmentation

## Standardization

- Issues today:
  - No consensus reached
  - Limited implementation by vendors
  - Need for standardization
- AAPM TG211:

**AAPM COMMITTEE TREE**

**Task Group No. 211 - Classification, Advantages and Limitations of the Auto-Segmentation Approaches for PET**

**Chair**

Assen Kirov
Task Group Chair

AAPM Members, Affiliates and Non-Member Affiliates - Login for access to additional information

**Charge** 1. Provide a classification of the PET segmentation methods based on their assumptions, algorithmic approach, detail, complexity and goal. Provide information on the advantages, limitations and applicability of each class of methods based on the limitations imposed by their assumptions and on current literature. Consider the different applications of interest such as "dose painting" or simpler functional volume definition for radiotherapy treatment planning, or volume changes in treatment with PET. 2. Draft a list of minimum requirements which PET segmentation methods should satisfy, as well as acceptance and implementation procedures for these methods. 3. Propose a protocol for evaluation of current and future segmentation methods based on a general framework [39], which will be expanded and adapted to PET imaging [40].

**Bylaws:** Not Referenced. **Rules:** Not Referenced.

**Approved Date(s)** Start: 10/13/2010
End: 12/31/2015

**Committee Keywords:** Image Segmentation Algorithms, PET, Radiation Therapy, TG211

AMERICAN ASSOCIATION of PHYSICISTS IN MEDICINE

# PET segmentation

## Standardization

- Produce a report on the state-of-the art[1]
- Propose and develop a benchmark standard[1,2]
- Provide the benchmark to the community[2]
- Carry out studies to validate methods


1. M. Hatt, *et al*. Report of AAPM TG211: Classification and evaluation strategies of auto-segmentation approaches for PET. *Med Phys* 2016 (in minor revision)
2. B. Berthon, *et al*. Part II: Design and Implementation of PETASset: Benchmark Evaluation Software for PET Auto-Segmentation Methods. *Med Phys* 2016 (to appear)

# PET segmentation

## Standardization

### Datasets

- ❑ Clinical images
- ❑ Physical phantoms
- ❑ Numerical phantoms (GATE)
- ❑ Synthetic simulations

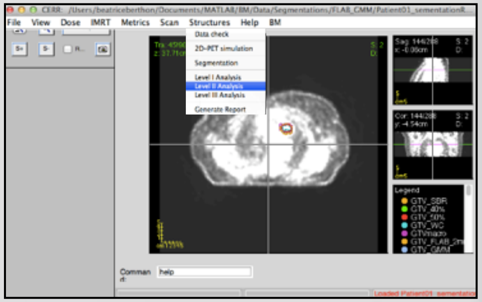
All with ground-truth or « surrogate » of truth

### Evaluation metrics

- ❑ Volumetric statistics
- ❑ Dice, Hausdorff, SE/PPV…
- ❑ DVH in RT planning
- ❑ Quantification of robustness

### User interface

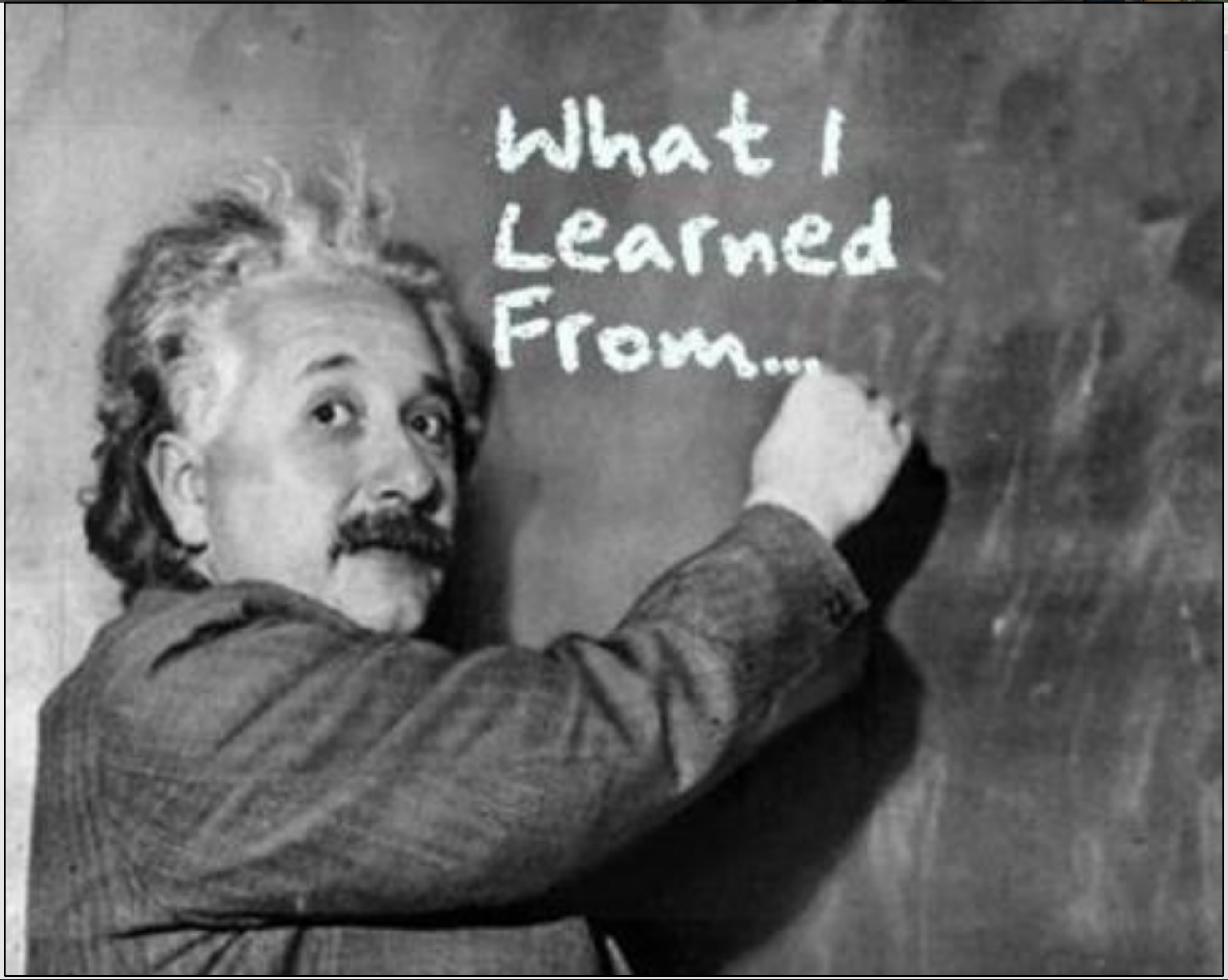
- ❑ Report
- ❑ Ranking




1. M. Hatt, *et al*. Report of AAPM TG211: Classification and evaluation strategies of auto-segmentation approaches for PET. *Med Phys* 2016 (in minor revision)
2. B. Berthon, *et al*. Part II: Design and Implementation of PETASset: Benchmark Evaluation Software for PET Auto-Segmentation Methods. *Med Phys* 2016 (to appear)

# PET and PET/CT segmentation

Take-home messages



# PET and PET/CT segmentation

Take-home messages

## PET segmentation

- Forget about fixed thresholds!
- Be well aware of limitations of adaptive thresholding!
- Numerous advanced methods exist that can be used instead with acceptable implementation complexity
- Standardization and benchmarking will be available soon for the community
- User interaction remains important (*e.g.* for tumor detection and initial ROI definition, and for delineation check/validation)

# PET and PET/CT segmentation

Take-home messages

## PET/CT/MRI segmentation

- Much more complex
  - To automate and implement
  - To evaluate and validate
- More highly dependent on the application
- Manual supervision will remain crucial

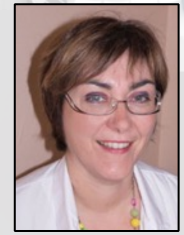
# Acknowledgments

## LaTIM team

### Team leader

D. Visvikis

### Associated clinicians



O. Pradier

C. Cheze Le Rest

### Post-docs

F. Tixier

J. Lapuyade

### Medical physicist

N. Boussion

### PhD students

M. Majdoub

M-C. Desseroit

T. Upadhaya

# Thank your for your attention

La pointe Saint-Mathieu, Finistère, Bretagne, France