Segmentation et radiomique en TEP/TDM : aspects méthodologiques

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Introduction

Définition

Radiomique : extraction “haut-debit” de données quantitatives des images médicales multimodales.

Principe : transformer les images (*“pictures”*) en données numériques dans lesquelles il devient possible de “fouiller” (*data mining*)

P Lambin, *et al*. **Radiomics: extracting more information from medical images using advanced feature analysis**. *Eur J Cancer* 2012

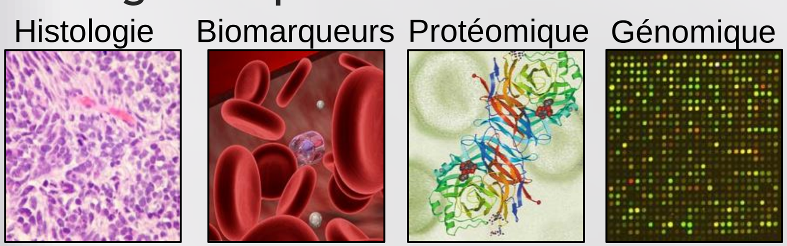
RJ. Gillies, *et al*. **Radiomics: images are more than pictures, they are data**. *Radiology* 2016

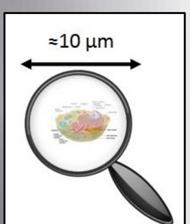
Introduction

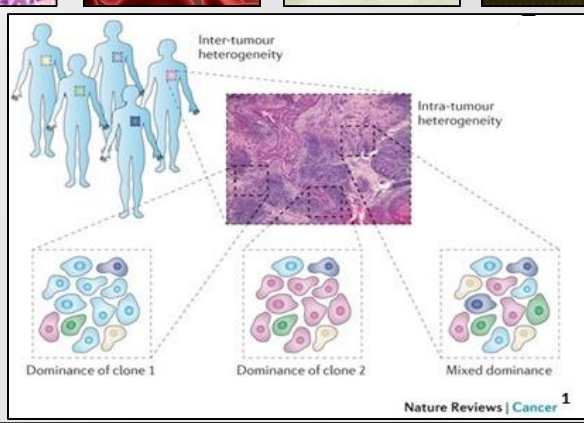
Rationel supportant la radiomique

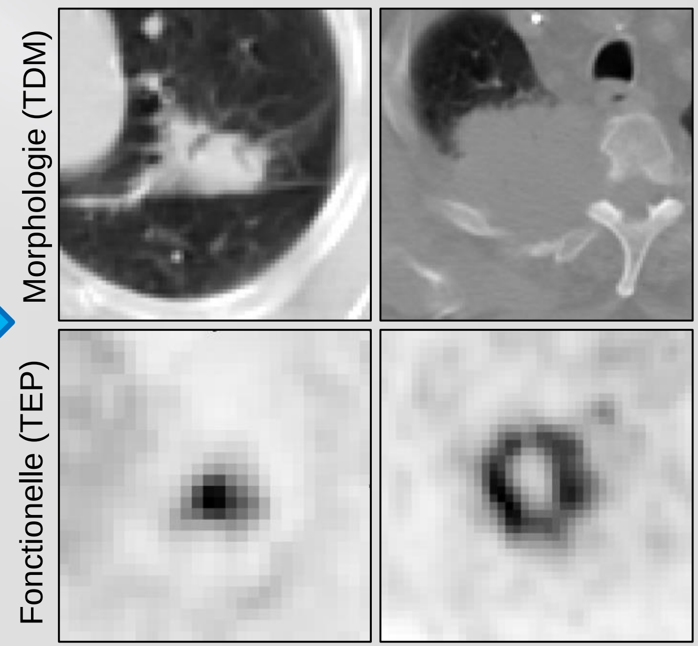
Hétérogénéité fonctionnelle et morphologique

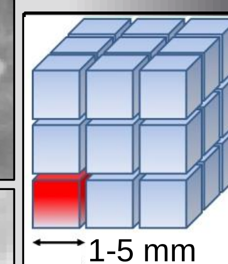
- Les tumeurs sont hétérogènes [1] à toutes les échelles
  - Génétique, cellulaire, tissulaire (macroscopique)
  - <u>Hypothèse</u> : les caractéristiques des tumeurs dans les images médicales (échelle macro) reflètent (partiellement) les échelles inférieures y compris génétiques [2]







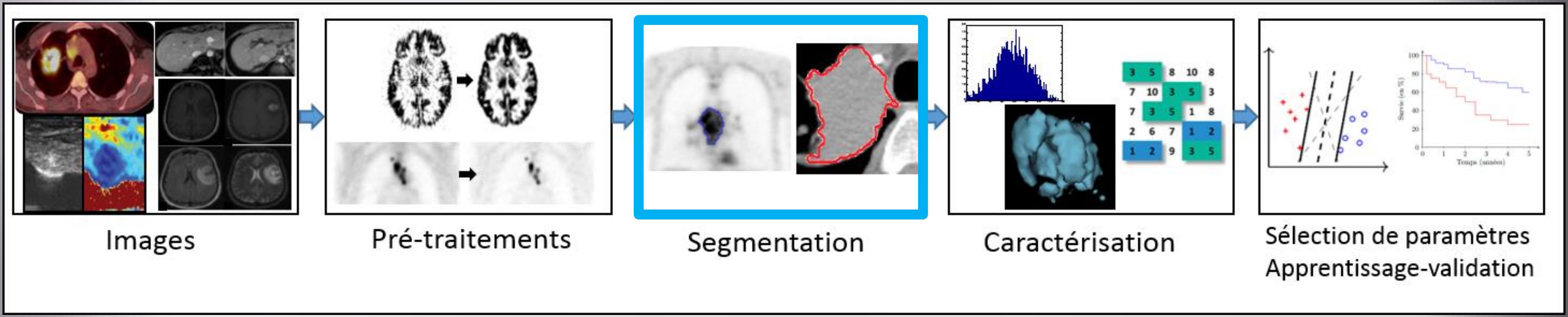




1. Gerlinger, *et al*. **Intratumor heterogeneity and branched evolution revealed by multiregion sequencing**. *N Engl J Med.* 2012
2. Segal, *et al*. **Decoding global gene expression programs in liver cancer by noninvasive imaging**. *Nat Biotechnol*. 2007

Radiomique en TEP/TDM

Segmentation



Défis en TEP

✓ Rapport signal à bruit limité

(sensibilité, durée d'acquisition...)

✓ Effets de volume partiel

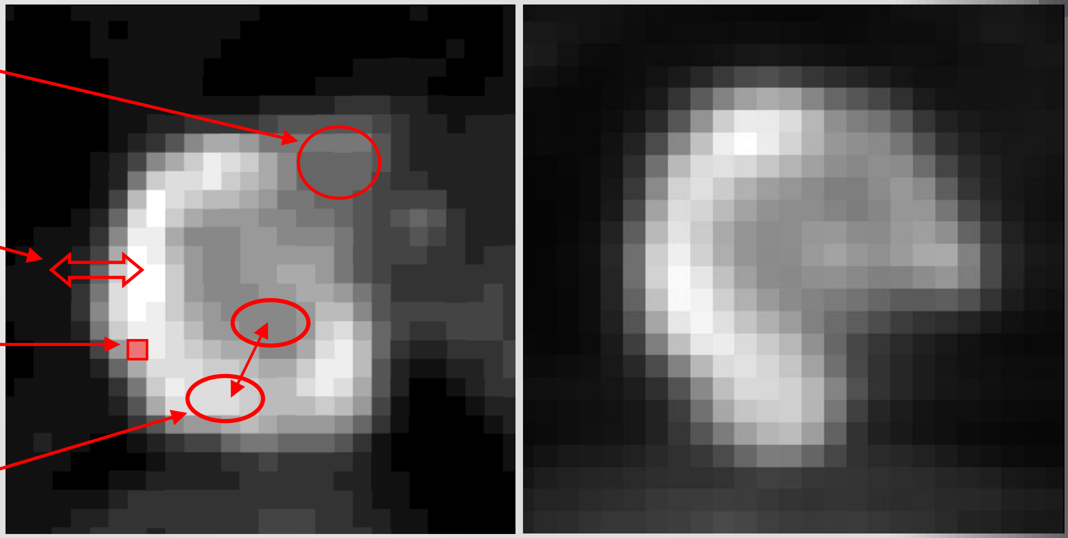
(résolution spatiale ~ 5 mm FWHM)

✓ Echantillonnage spatial

(taille des voxels ~ 2 à 5 mm)

✓ Hétérogénéité

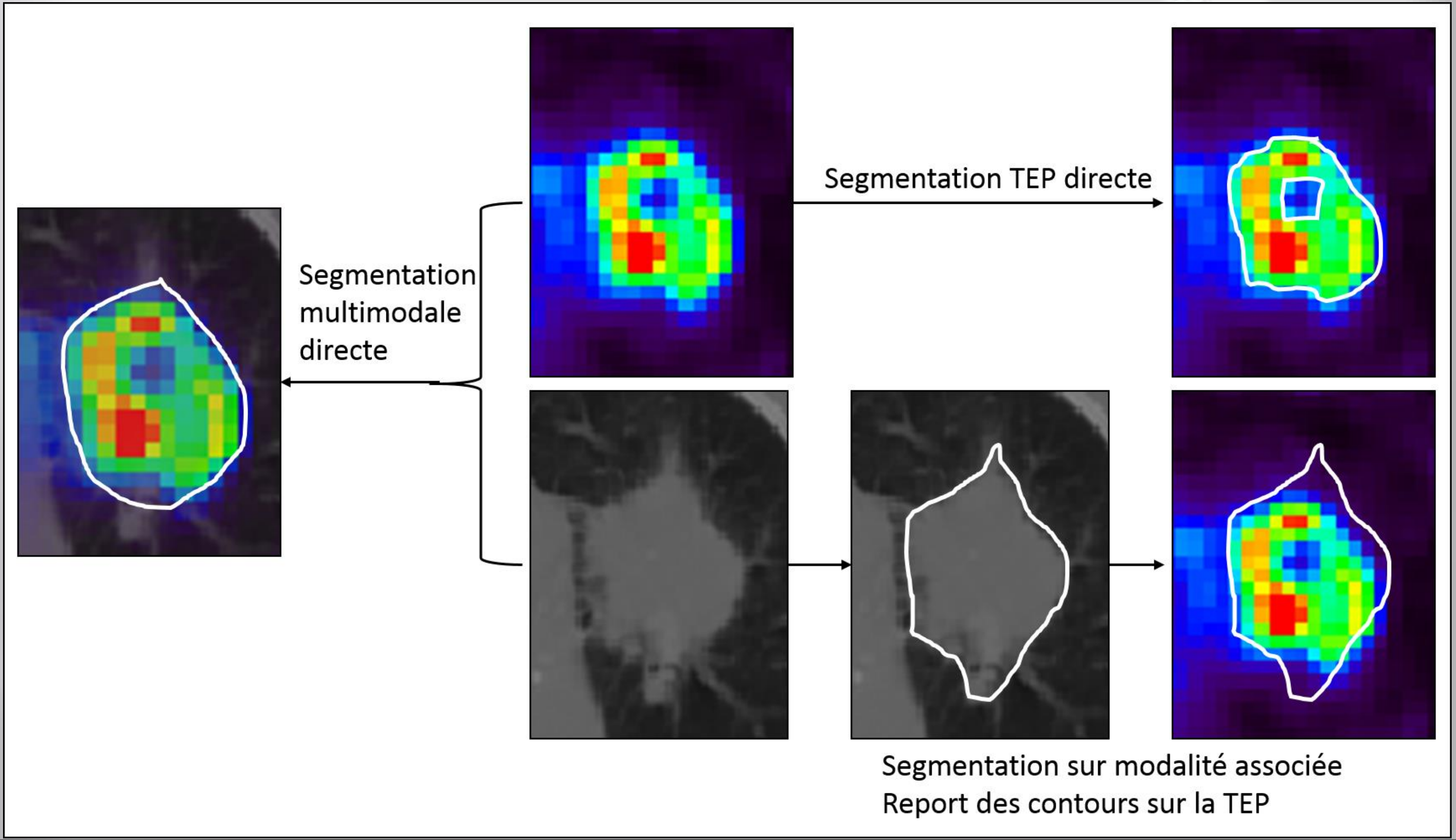
✓ Complexité des formes



→ Segmentation manuelle peu fiable (variabilité intra- & inter- experts)
→ Il n'existe pas de seuil universel
→ Une segmentation binaire n'est souvent pas appropriée

M. Hatt, *et al*. **Metabolically active volumes automatic delineation methodologies in PET imaging: Review and perspectives**. *Cancer Radiother* 2011
J.A. Lee. **Segmentation of positron emission tomography images: some recommendations for target delineation in radiation oncology**. *Radiother Oncol*. 2010

Défis en TEP


Segmentation TEP directe
Segmentation
multimodale
directe
Segmentation sur modalité associée
Report des contours sur la TEP

1997-2007 : l'âge sombre

- Un des premiers articles (conférence)
  - Suggestion d'un seuil fixe à 42% du maximum

Sixth Conference on Radioimmunodetection and Radioimmunotherapy of Cancer

Supplement to ***Cancer***

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

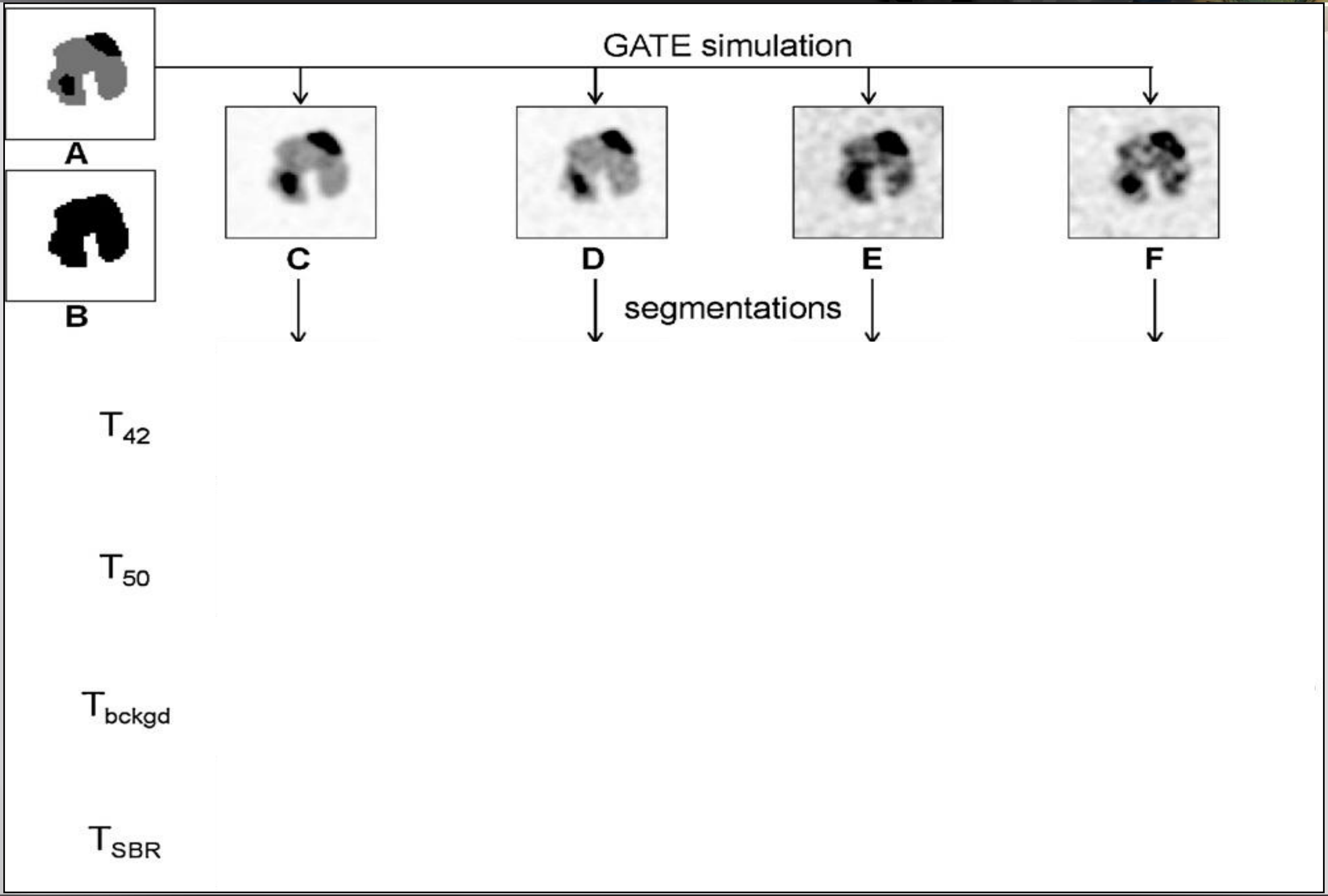
Yusuf E. Erdi, D.Sc.[1]
O. Mawlawi, M.Sc.[2]
Steven M. Larson, M.D.[2]
M. Imbriaco, M.D.[2]
H. Yeung, M.D.[2]
R. Finn, Ph.D.[1]
John L. Humm, Ph.D.[1]

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).

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

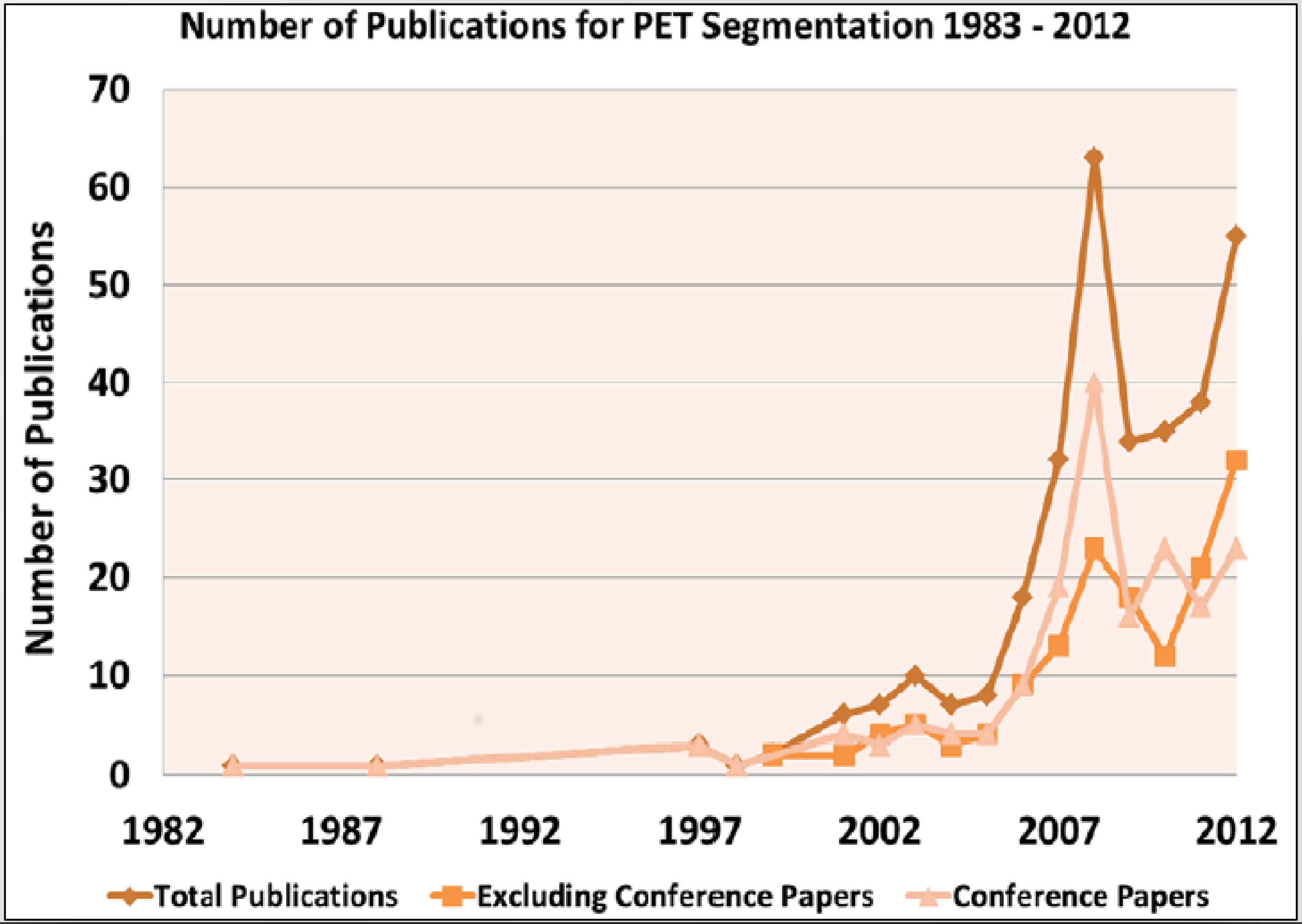
Radiomique en TEP/TDM

Segmentation



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

- 2007 : l’ère de la segmentation d’images



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

AMERICAN ASSOCIATION of PHYSICISTS IN MEDICINE

- Task Group No. 211 - Classification, Advantages and Limitations of the Auto-Segmentation Approaches for PET
- 2011-2016
- Objectifs :
  - Recenser l'état de l'art
  - Evaluer de façon critique les différentes approches
  - Proposer une méthodologie d'évaluation des méthodes
    - Données (synthétiques, simulées, fantômes physiques, cliniques)
    - Métriques de performance (précision, robustesse, reproductibilité)

1. M. Hatt, *et al*. **Report of AAPM TG211: Classification and evaluation strategies of auto-segmentation approaches for PET**. *Med Phys* 2017
2. B. Berthon, *et al*. **Design and Implementation of PETASset: Benchmark Evaluation Software for PET Auto-Segmentation Methods**. *Med Phys* 2017

- Conclusions :
  - Des dizaines de méthodes publiées, niveau de validation très variable (et le plus souvent médiocre)
  - Pas de comparaisons à grande échelle, donc pas de consensus scientifique (à part concernant les seuillages)
  - *A fortiori* pas de consensus industriel et donc implémentation limitée d'outils pour les cliniciens
  - Besoin important de standardisation

Medical Physics
The International Journal of Medical Physics Research and Practice
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Task Group Report

Classification and evaluation strategies of auto-segmentation approaches for PET: Report of AAPM Task Group No. 211

Mathieu Hatt, John Lee, Charles R. Schmidtlein, Issam El Naqa, Curtis Caldwell, Elisabetta De Bernardi, Wei Lu, Shiva Das, Xavier Geets, Vincent Gregoire, Robert Jeraj, Michael P. MacManus, Osama R. Mawlawi, Ursula Nestle, Andrei B. Pugachev, Heiko Schöder, Tony Shepherd, Emiliano Spezi, Dimitris Visvikis, Habib Zaidi, Assen S. Kirov

Medical Physics
The International Journal of Medical Physics Research and Practice
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Research Article

Towards a standard for the evaluation of PET Auto-Segmentation methods: requirements and implementation

Beatrice Berthon, Emiliano Spezi, Paulina Galavis, Tony Shepherd, Aditya Apte, Mathieu Hatt, Hadi Fayad, Elisabetta De Bernardi, Chiara Soffientini, Charles R. Schmidtlein, Issam El Naqa, Robert Jeraj, Wei Lu, Shiva Das, Habib Zaidi, Osama R. Mawlawi, Dimitris Visvikis, John A. Lee, Assen S. Kirov

1. M. Hatt, *et al*. **Report of AAPM TG211: Classification and evaluation strategies of auto-segmentation approaches for PET**. *Med Phys* 2017
2. B. Berthon, *et al*. **Design and Implementation of PETASset: Benchmark Evaluation Software for PET Auto-Segmentation Methods**. *Med Phys* 2017

Benchmark (« banc de test »)

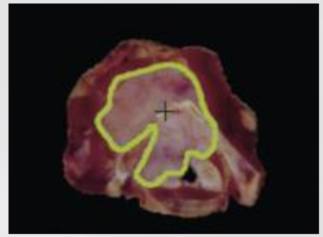
Fiabilité de la vérité terrain

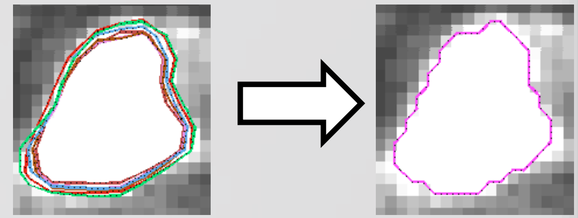
Réalisme

❖ Images cliniques

Vérité approximative

Cas réels

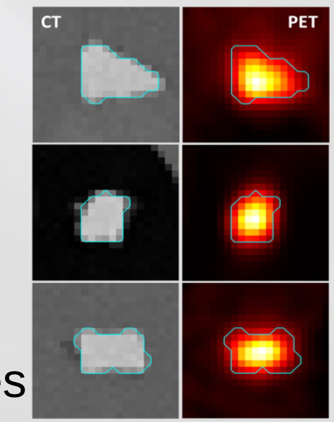




❖ Fantômes physiques

Vérité fiable (avec approximations)

Acquisitions réelles mais objets simplifiés



❖ Simulations numériques

Vérité parfaitement fiable

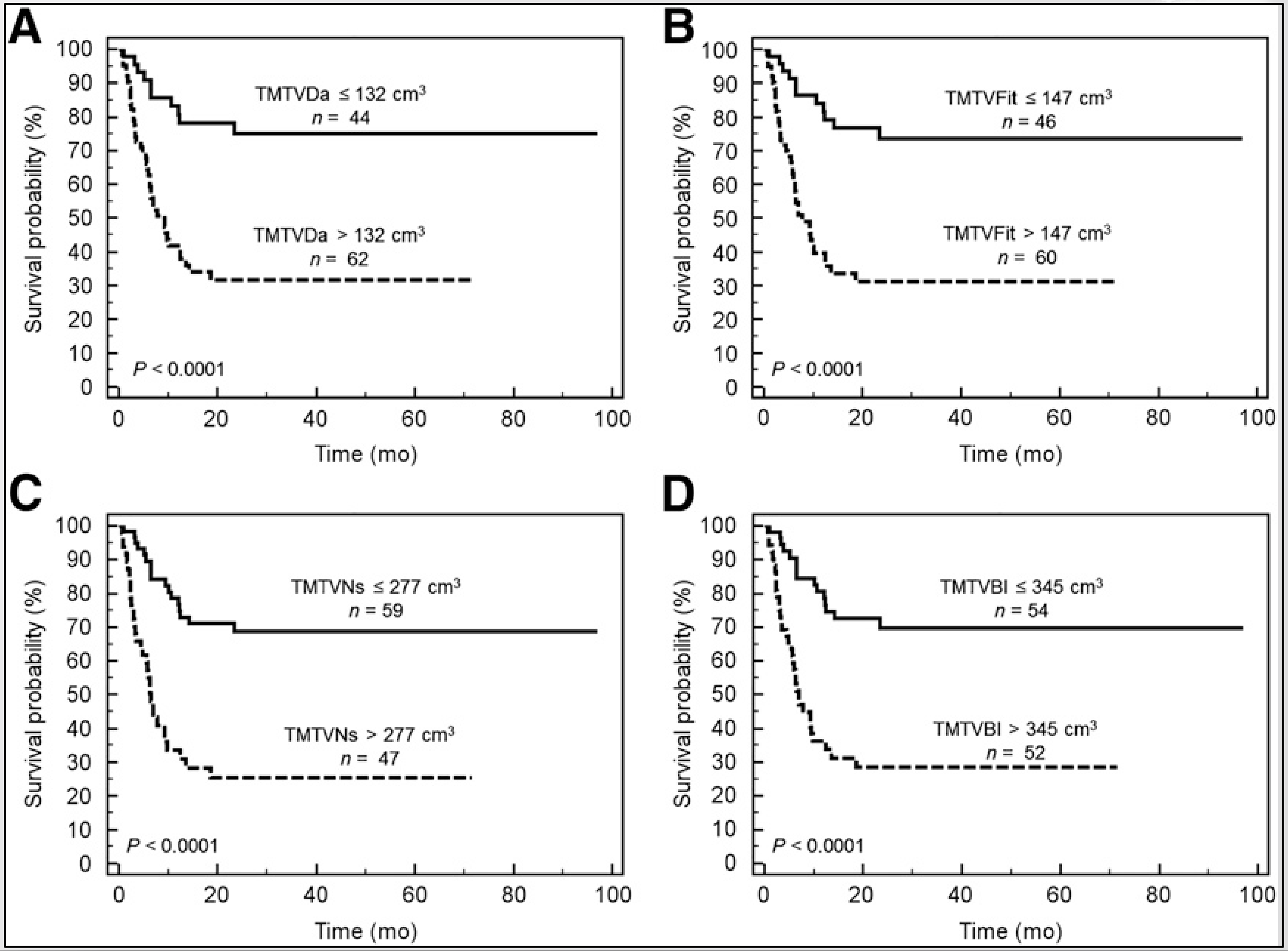
Réalisme variable à la fois dans les caractéristiques d'images et dans les objets

1. M. Hatt, *et al*. **Report of AAPM TG211: Classification and evaluation strategies of auto-segmentation approaches for PET**. *Med Phys* 2017
2. B. Berthon, *et al*. **Design and Implementation of PETASset: Benchmark Evaluation Software for PET Auto-Segmentation Methods**. *Med Phys* 2017

Radiomique en TEP/TDM

Exemple lymphome

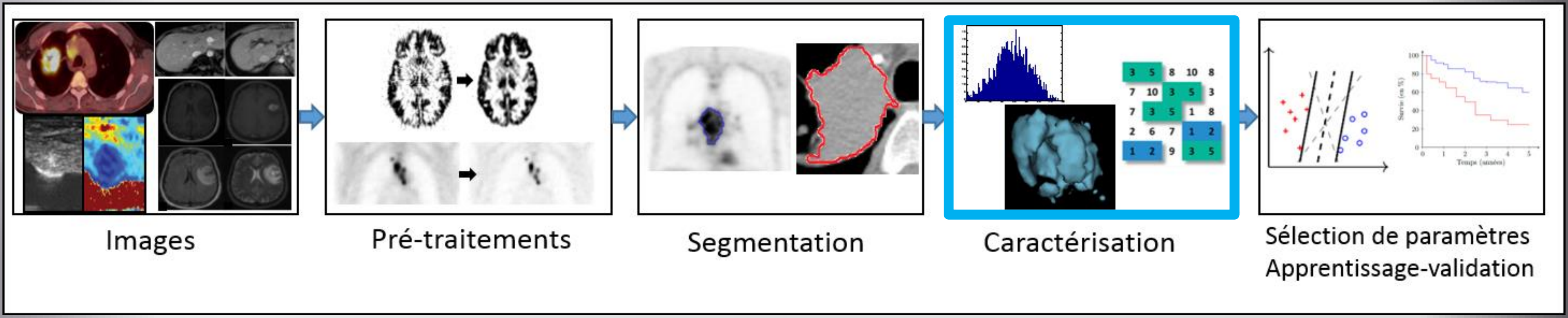
- Variabilité due à la segmentation TEP



A-S. Cottereau, *et al*. **Baseline Total Metabolic Tumor Volume Measured with Fixed or Different Adaptive Thresholding Methods Equally Predicts Outcome in Peripheral T Cell Lymphoma**. *J Nucl Med* 2017

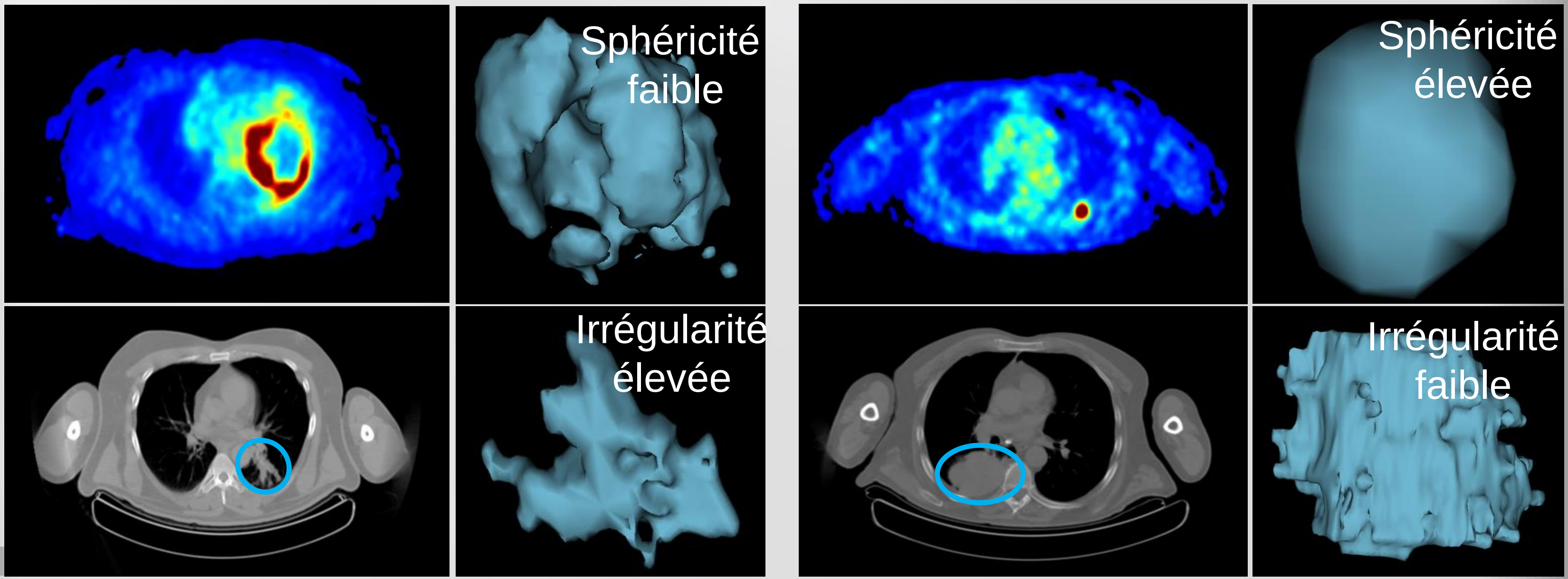
Radiomique en TEP/TDM

Extraction de caractéristiques



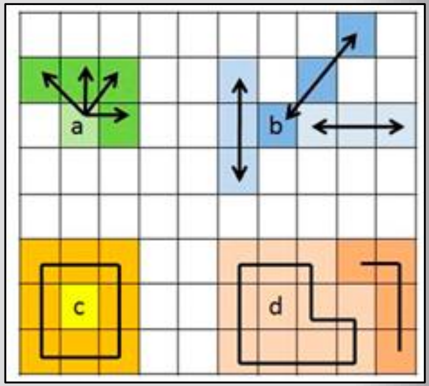
Forme 3D:

- <u>Hypothèse</u> : agressivité, potentiel métastatique…
  - Forme anatomique (TDM, IRM…)
  - Forme fonctionnelle (TEP)
  - Calculs simples avec descripteurs géométriques



Textures

- Technique utilisée depuis les années 70 dans tous les domaines du traitement d'image
- Quantification des motifs et les variations d'intensité et leur arrangement spatial
- Imagerie médicale (TDM IRM >1990[1,2], TEP >2009[3])
  - Quantification d'organes/tissus/tumeurs
  - Segmentation
  - Détection
  - Classification d'images
  - Radiomics (>2012)



1. Schad LR, *et al*. **MR tissue characterization of intracranial tumors by means of texture analysis.** *Magn Reson Imaging* 1993.
2. Mir AH, *et al*. **Texture analysis of CT-images for early detection of liver malignancy.** *Biomed Sci Instrum.* 1995.
3. El Naqa I, *et al*. **Exploring feature-based approaches in PET images for predicting cancer treatment outcomes.** *Pattern Recognit*. 2009

Radiomique en TEP/TDM

Textures

Segmented tumor volume

2. Interpolation

- ❖ Method
  - ❑ Nearest neighbors, B-Spline…

Image with cubic voxels

3. Quantization

- ❖ Method
  - ❑ Uniform, equal, Max-Lloyd, fixed bin size…
  - ❑ Quantization value
  - ❑ Size of bin

Quantized image

1. Segmentation

- ❖ Overall analysis
  - ❑ 2D or 3D
  - ❑ Segmentation tool (gradient, clustering…)
  - ❑ Including low/no uptake areas
  - ❑ Excluding low/no uptake areas

Reconstructed PET image

4. Texture matrices design

- ❖ Co-occurrence matrices
  - ❑ Number of directions
  - ❑ Voxels distance
  - ❑ 1 matrix per direction + averaging / no averaging

Texture matrices

5. Parameters calculation

- ❖ Implementation
  - ❑ Actual formula used

Textural features

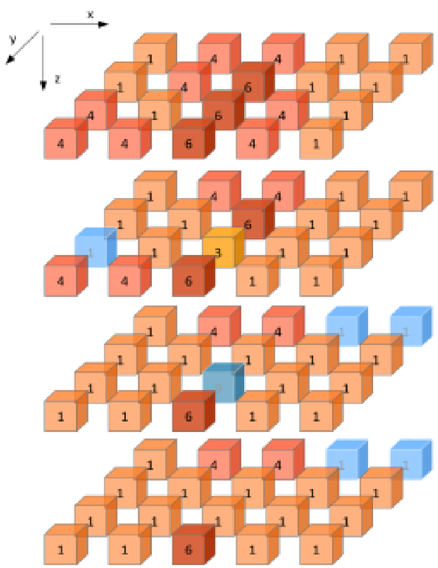
6. Statistical analysis

- ❖ Machine learning
  - ❑ Features selection method
  - ❑ Classifier
- ❖ Selection based on:
  - ❑ Robustness, reproducibility, redundancy, clinical value w.r.t. clinical endpoint

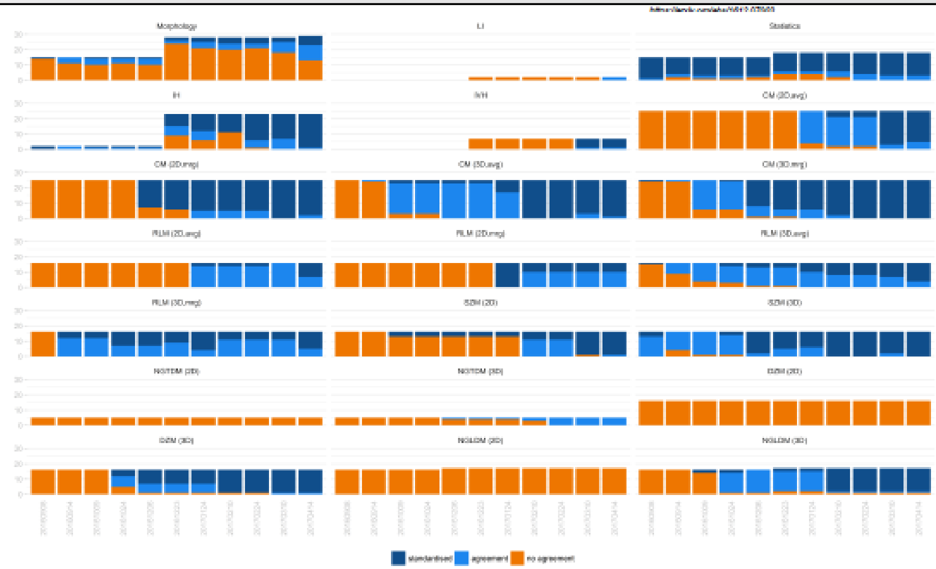
Selected features

M. Hatt, *et al.* **Characterization of PET/CT images using texture analysis: the past, the present… any future?** *Eur J Nucl Med Mol Imaging* 2017

Initiative de standardisation



Digital phantom. Blue voxels lie outside of the region of interest.



Standardisation progress. Height indicates the number of features per family. LI: Local intensity; IH: intensity histogram; IVH: intensity-volume histogram; CM: co-occurrence matrix; RLM: run length matrix; SZM: size zone matrix; NGTDM: neighbourhood grey tone difference matrix; DZM: distance zone matrix; NGLDM: neighbouring grey level difference matrix

Current status:

		current	09-10-16
• no agreement	(< 3 institutions or < 50% identical)	52	192
• agreement	(> 50% identical)	59	85
• standardised	(> 80% identical)	240	25

Conclusions:

- Benchmarking of features is recommended: high initial differences
- Standard values found for most features

Participants

Study leader: *Alex Zwanenburg*

Cardiff University
Philip Whybra, Emiliano Spezi

Dana Farber Cancer Institute and Brigham and Women's Hospital, Harvard University
Andriy Fedorov, Hugo Aerts

Gemelli ART, Università Cattolica del Sacro Cuore
Jacopo Lenkowicz, Luca Boldrini, Nicola Dinapoli, Vincenzo Valentini

German Cancer Research Center (DKFZ)
Michael Götz, Nils Gählert, Fabian Isensee, Klaus H. Maier-Hein

INSERM Brest, University of Brest
Marie-Charlotte Desseroit, Taman Upadhaya, Mathieu Hatt

Leiden University Medical Center
Floris H.P. van Velden

MAASTRO clinic, Maastricht University
Ralph T.H. Leijenaar, Philippe Lambin

McGill University
Martin Vallières, Issam El Naqa

Memorial Sloan Kettering Cancer Center
Aditya Apte

Moffitt Cancer Center
Mahmoud A. Abdalah, Robert Gillies

OncoRay – National Center for Radiation Research in Oncology and NCT Dresden
Alex Zwanenburg, Stefan Leger, Esther Troost, Christian Richter, Steffen Löck

The Netherlands Cancer Institute (NKI)
Joost van Griethuysen, Cuong Viet Dinh, Uulke van der Heide

Universitätsklinikum Tübingen, Eberhard Karls University Tübingen
Jairo Socarras Fernandez, Daniela Thorwarth

University Hospital Zürich, University of Zürich
Marta Bogowicz, Stephanie Tanadini-Lang, Matthias Guckenberger

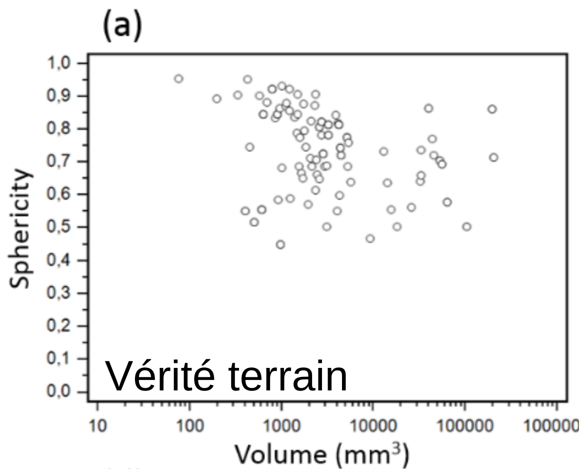
University of Bergen
Are Losnegård

University of California, San Francisco
Olivier Morin

University of Groningen, University Medical Center Groningen
Lisanne V. van Dijk, Jorn Beukinga, Nanna M. Sijtsema, Roel J.H.M. Steenbakkers, Ronald Boellaard

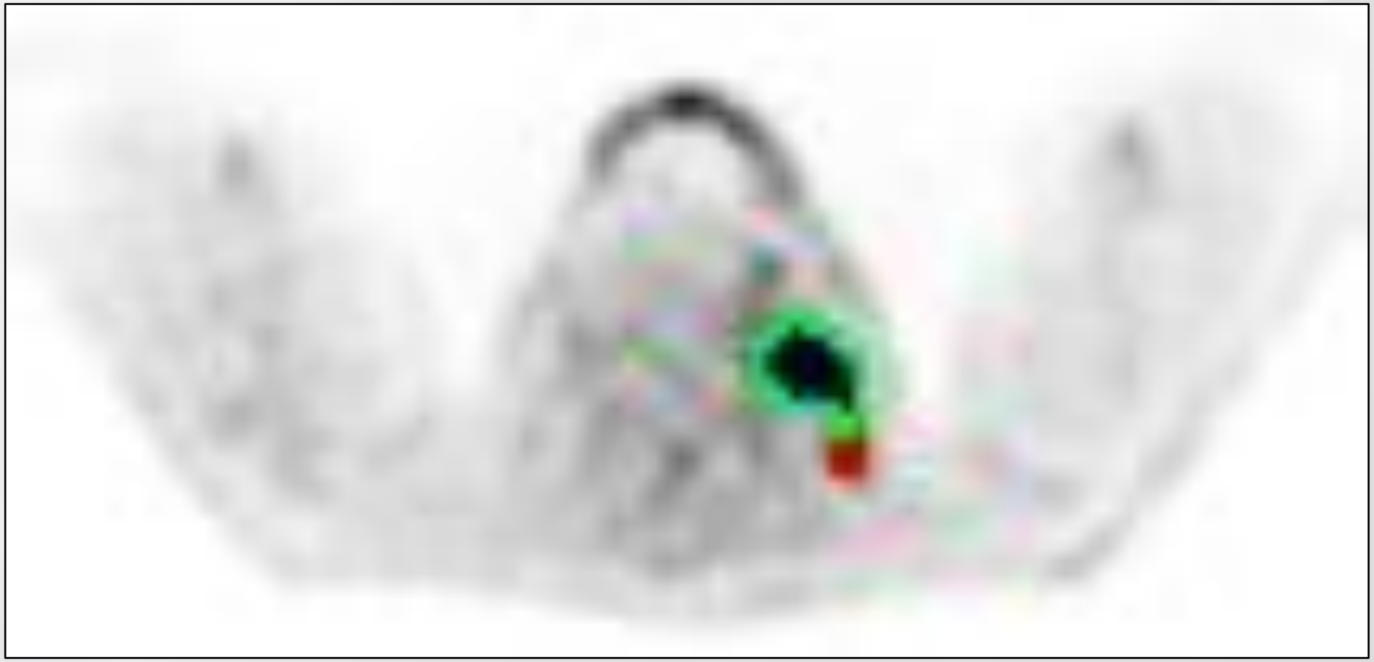
Image Biomarker Standardisation Initiative. **Multicentre initiative for standardization of image biomarkers.** *ESTRO* 2017

Dépendence à la segmentation



Résultats non publiés

Dépendence à la segmentation

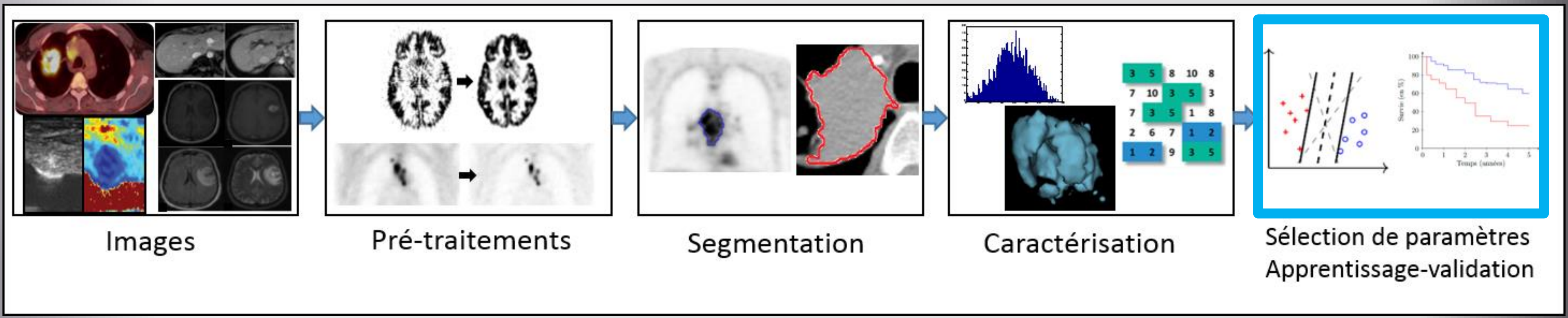


Lésion jugulocarotidienne gauche d'un lymphome du manteau
Rouge : FLAB
Bleu : 40%
Vert : SUV 2.5

Source : T. Carlier

Radiomique en TEP/TDM

Analyse statistique



Radiomique en TEP/TDM

Problèmes et défis

Problèmes dans les analyses statistiques

Table 1. Statistical characteristics of the selected studies divided in three categories: A) Studies with multiple hypotheses testing only, B) studies employing both multiple hypothesis testing and the optimum cut-off approach and C) studies with multiple hypothesis testing, with or without the optimum cut-off approach, but with validation analysis.

Category	Study	Multivariate analysis included volume	Optimum cut-off	Type I error adjustment	Validation dataset	cross correlation reported	Sample size	Hypotheses tested
A	Willaime [19]	Not applicable	No/Mean	No	No	Yes	12	68
	El Naqa [31]	NI*	Not clear	No	No	No	14/9	19
	Tixier [33]	NI	Not clear	No	No	Yes	41	54
	Yip [41]	No	No/Median	Yes[#]	No	No	36	90
B	Miles [30]	No	Yes	No	No	No	48	10
	Goh [32]	No	Yes	No	No	No	39	24
	Cook [29]	No	Yes	No	No	Yes	53	30
	Ganeshan [28]	No	Yes	No	No	Yes	21	15
	Ganeshan [34]	No	Yes	No	No	No	54	8
	Ng [36]	No	Yes	No	No	Yes	55	25
	Zhang [40]	Yes	Yes	No	No	No	72	40
	Cheng [39]	Yes	Yes	No	No	Yes	70	59[‡]
C	Vaidya [35]	Yes	No	No	LOOCV[†]	No	27	102
	Win [37]	No	Yes	No	Yes	No	66	12
	Ravanelli [38]	No	No/Median	No	LOOCV	No	53	16

* No information provided

[#]For multiple hypotheses tested

[†]Leave one out cross validation

[‡] Number is a conservative approximation due to the difficulty establishing the exact number of hypotheses tested

A. Chalkidou, *et al*. **False Discovery Rates in PET and CT Studies with Texture Features: A Systematic Review**. *PLoS One*. 2015

Radiomique en TEP/TDM

Conclusions

- Segmentation TEP
  - Beaucoup de progrès en 10 ans
  - Très nombreuses méthodes, validation médiocre
  - Peu d'outils performants disponibles en clinique
  - Benchmark et standardisation en cours
  - Besoin de précision / robustesse dépendant de l'application et des objectifs
- Segmentation TEP/TDM
  - De nombreuses méthodes déjà publiées
  - Efforts de validation/standardisation pas au niveau de la TEP seule

Radiomique en TEP/TDM

Conclusions

- Radiomique
  - Domaine très dynamique
  - Enormément de difficultés méthodologiques, en particulier sur les textures
  - Pas de standardisation
  - Validation statistique difficile (machine learning)
- Evolutions futures
  - Standardisation (en cours)
  - Grandes études multicentriques prospectives
  - Apprentissage automatique (profond)

Merci pour votre attention

Diapos supplémentaires

2007 : l’ère de la segmentation d’images

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

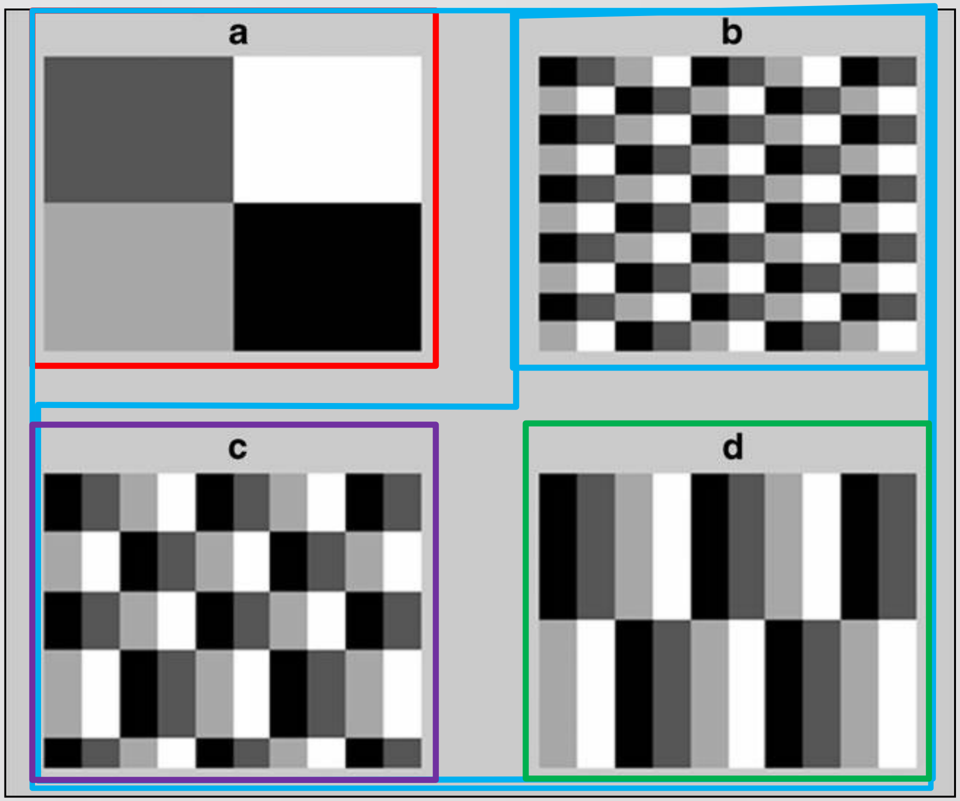
M Hatt[1], F Lamare[1], N Boussion[1], A Turzo[1,2], C Collet[3], F Salzenstein[4], C Roux[1,5], P Jarritt[6], K Carson[6], C Cheze-Le Rest[1,2] and D Visvikis[1]

Potentiel discriminant

1^er ordre
(histogrammes)
a = b = c = d

2^ème ordre
(voisinages)
a # (b = c = d)

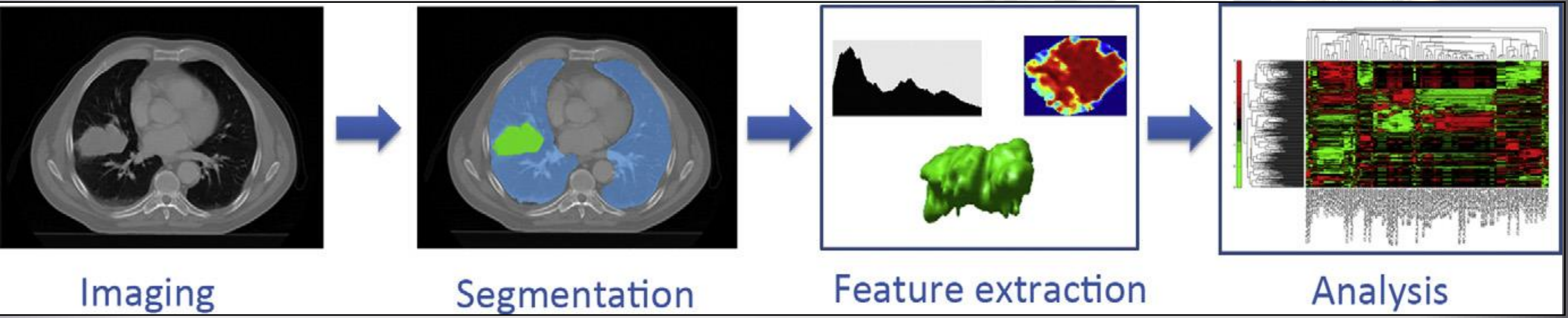
3^ème ordre
(groupes de pixels)
a # b # c # d

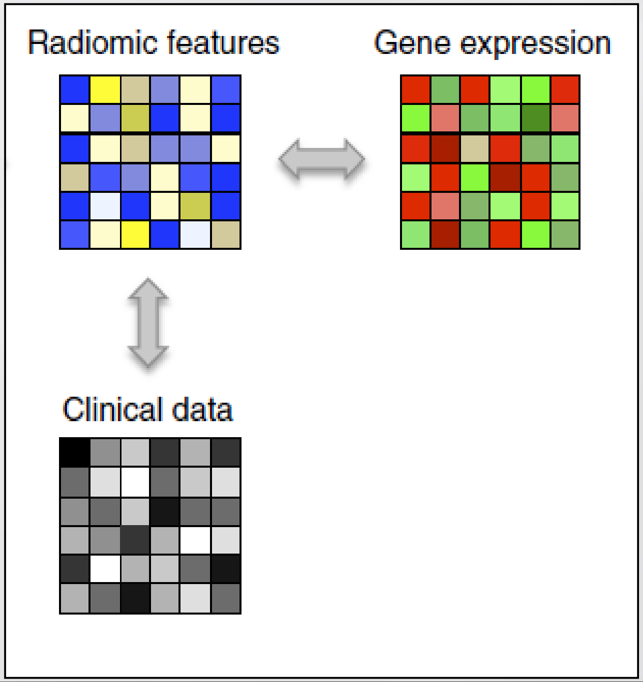


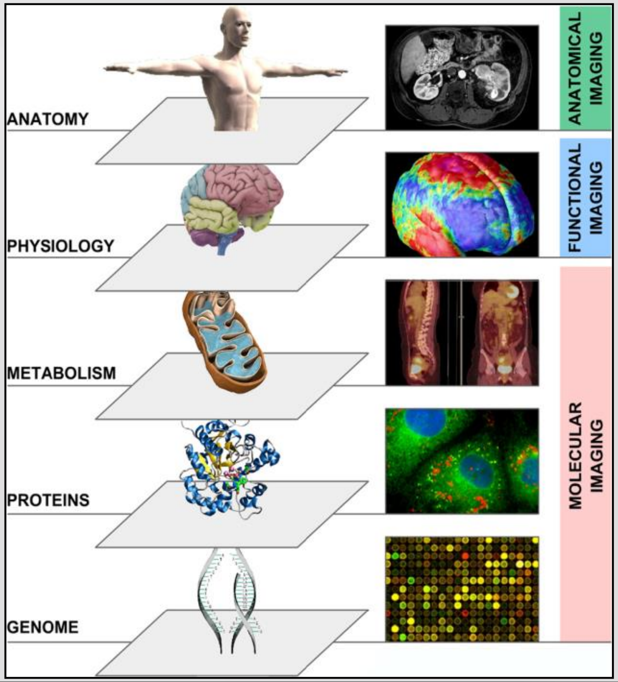
Haralick, et al. Textural Features for Image Classification. IEEE Transactions on Systems, Man and Cybernetics. 1973
The GLCM tutorial page http://www.fp.ucalgary.ca/mhallbey/tutorial.htm

Introduction

Définition





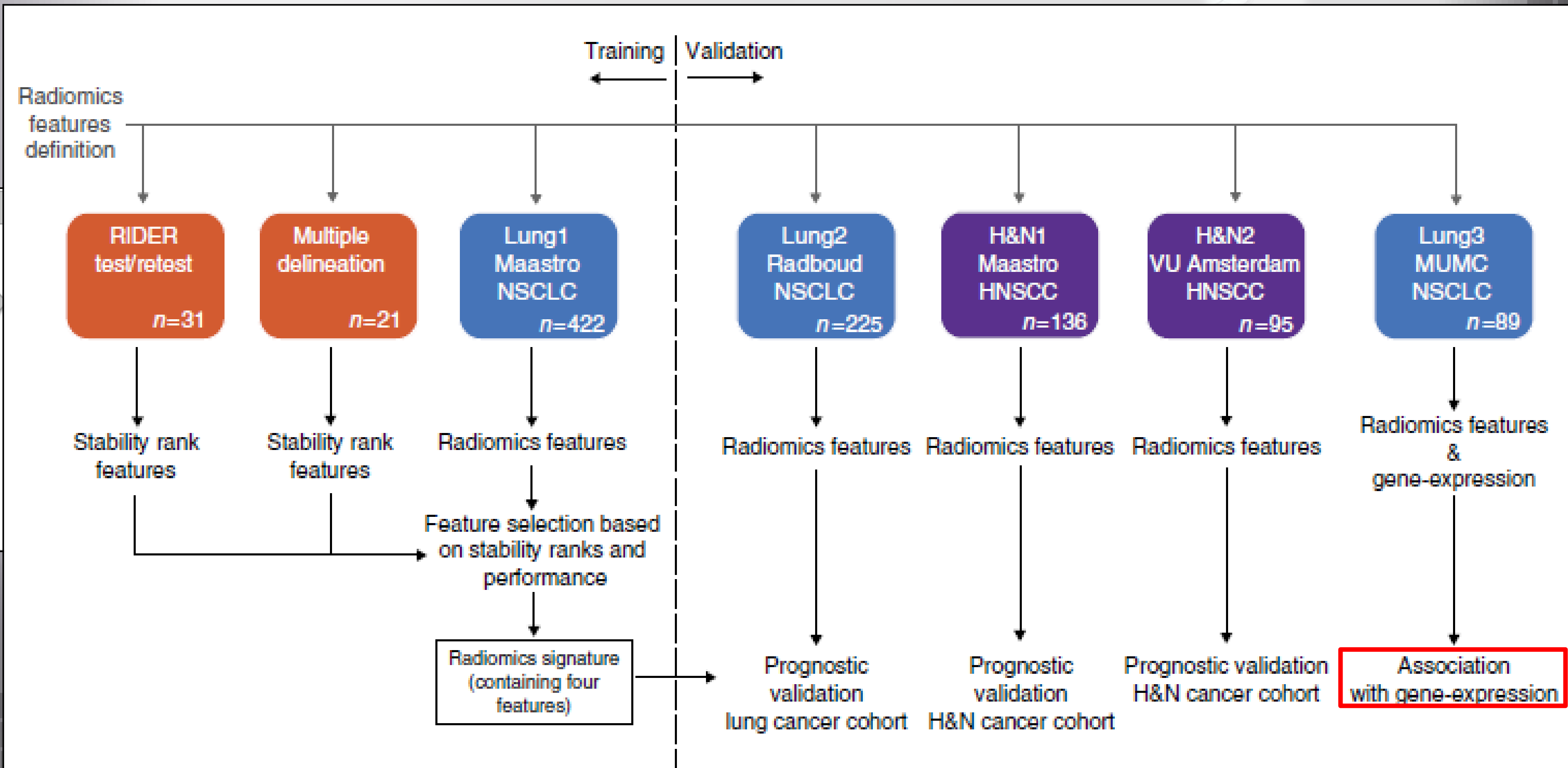


P Lambin, *et al*. **Radiomics: extracting more information from medical images using advanced feature analysis**. *Eur J Cancer* 2012

HJ. Aerts, *et al*. **Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach**. *Nat Commun*. 2014

Introduction

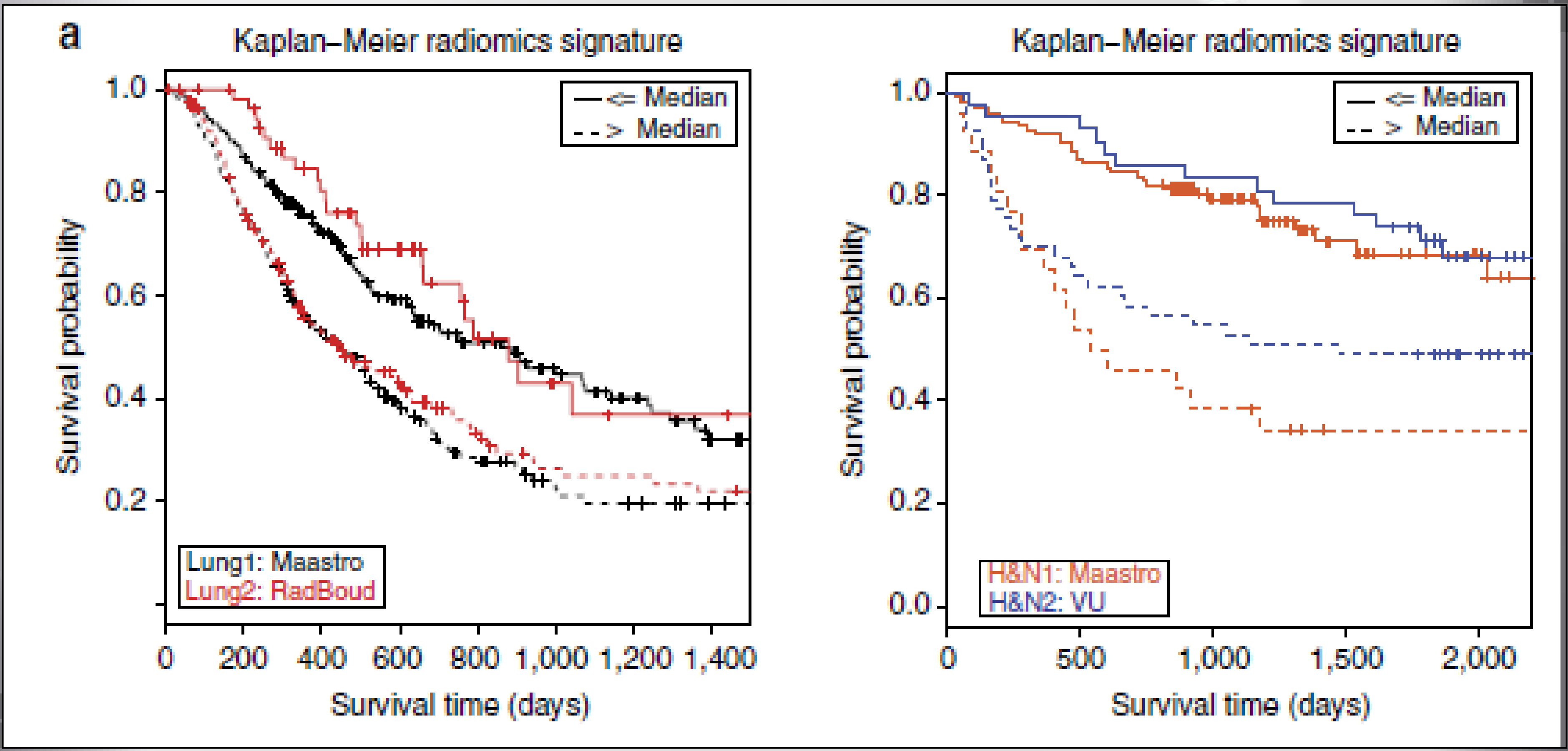
Radiomics



HJ. Aerts, *et al*. **Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach**. *Nat Commun*. 2014

Introduction

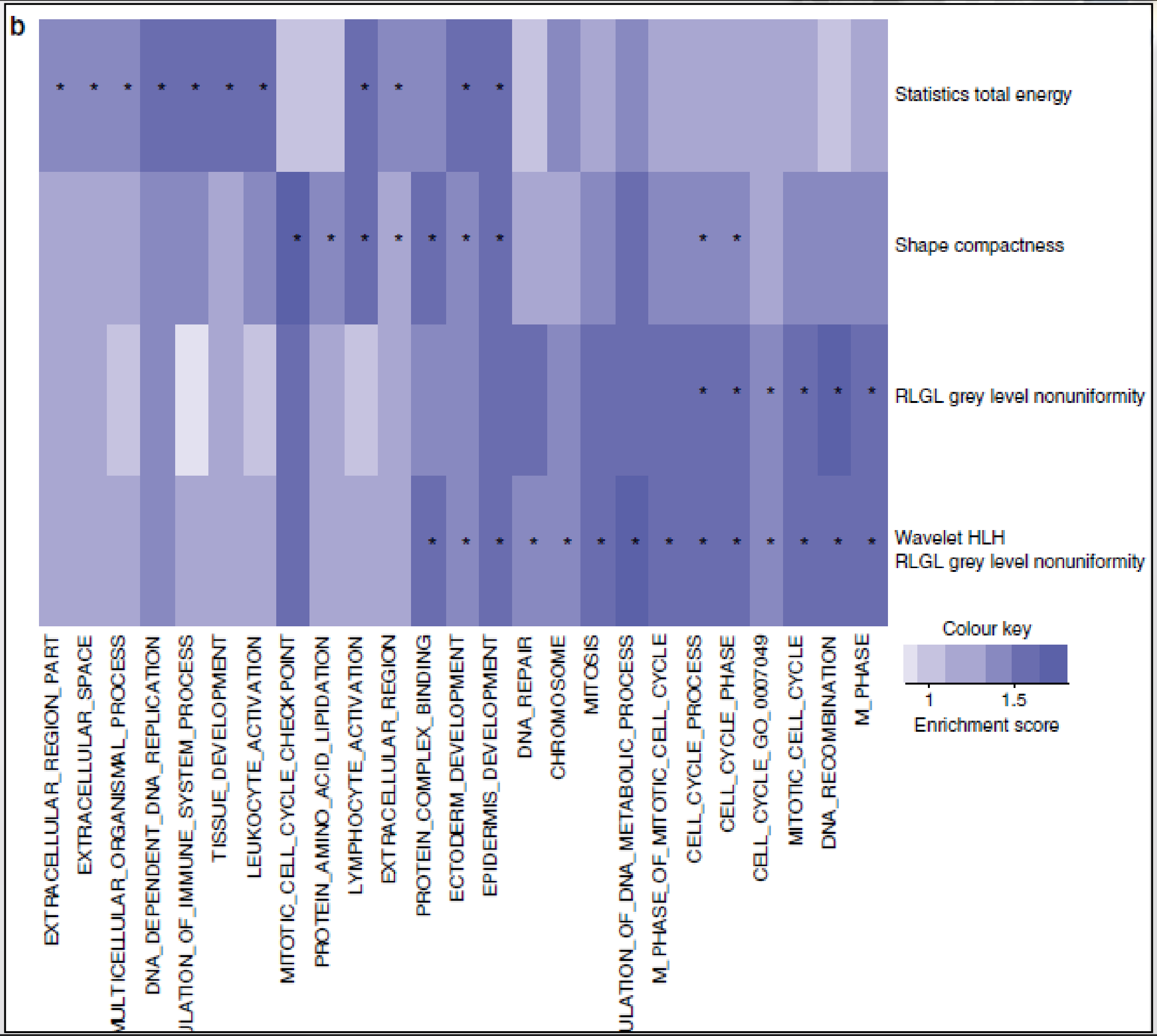
Radiomics



HJ. Aerts, *et al*. **Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach**. *Nat Commun*. 2014

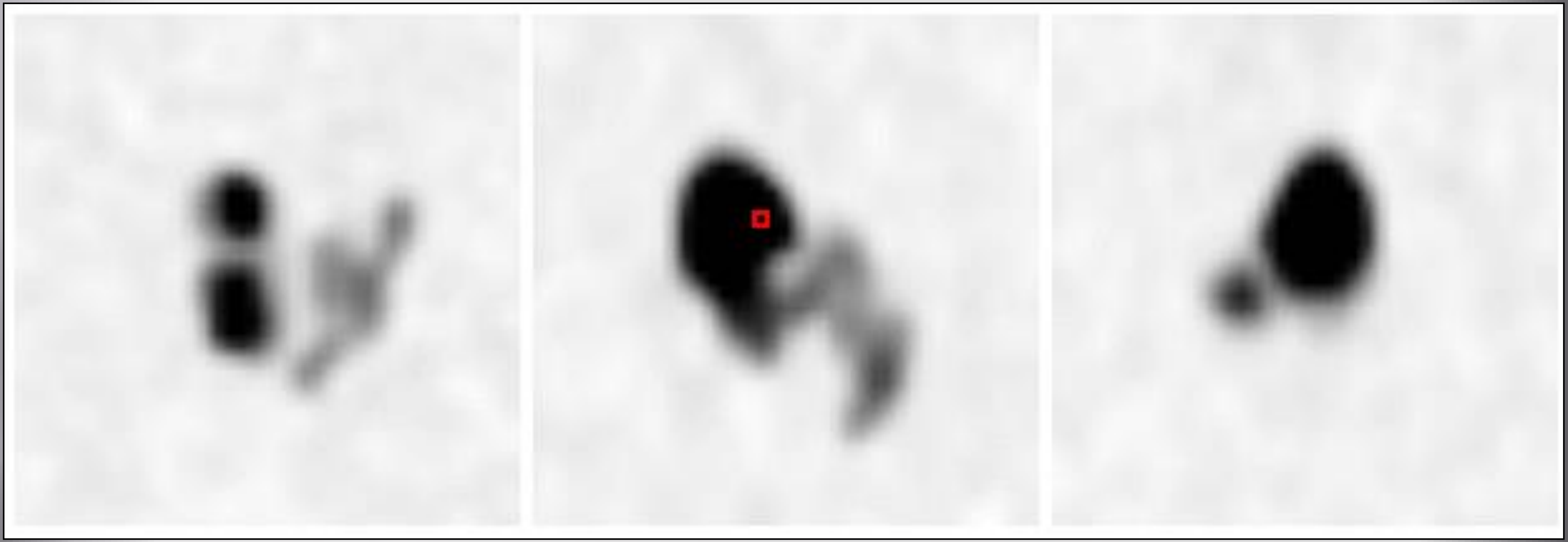
Introduction

Radiomics



HJ. Aerts, *et al*. **Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach**. *Nat Commun*. 2014

Examples: ROVER method

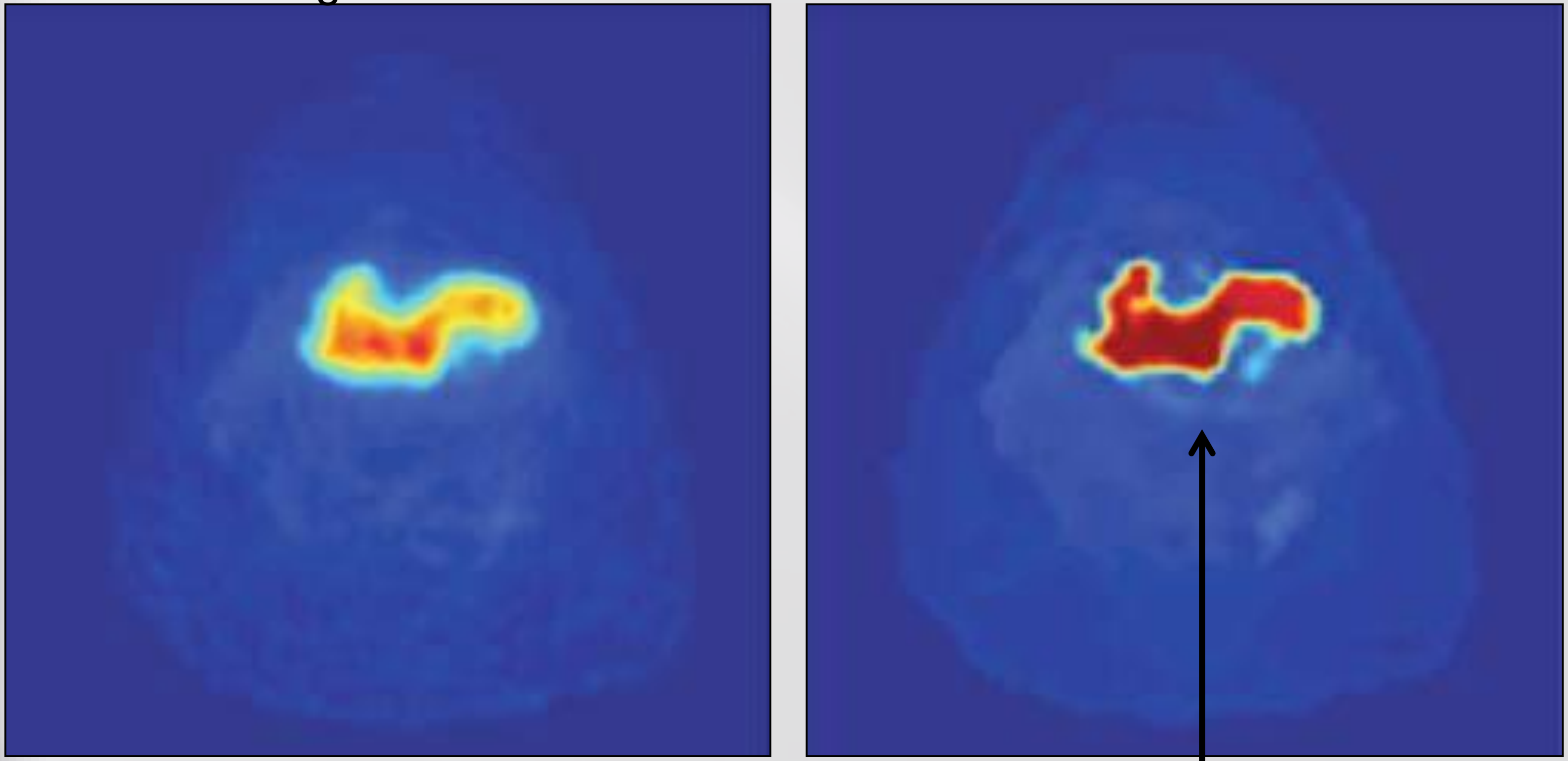


Hofheinz, *et al*. **An automatic method for accurate volume delineation of heterogeneous tumors in PET**. *Med Phys* 2013

Examples: gradient-based

Original PET

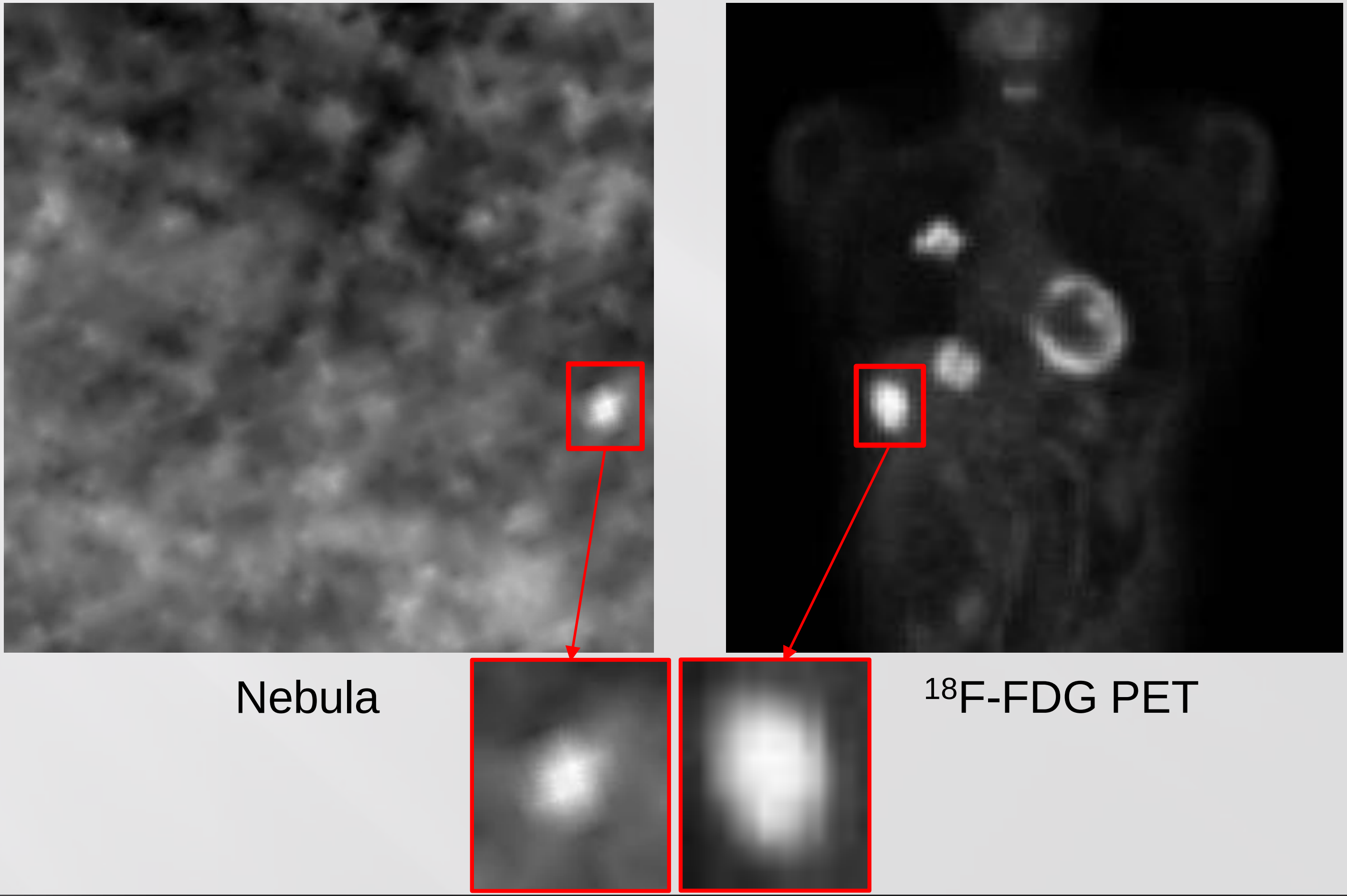
+ bilateral filtering
+ iterative deconvolution



Contours detection

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

Examples: FLAB



Nebula

^{18}F-FDG PET

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

Examples: FLAB

18 clinical NSCLC tumors with histopathology

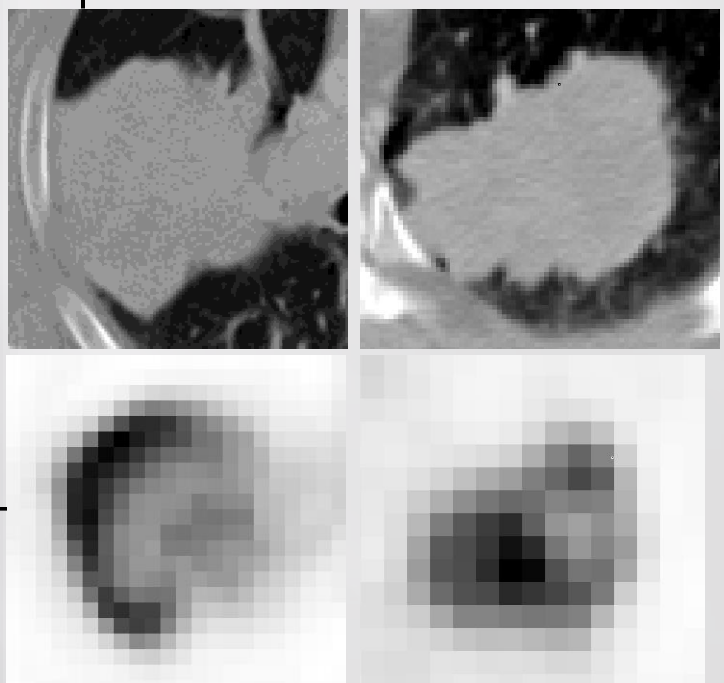
✓ max diameter: 12-90 mm

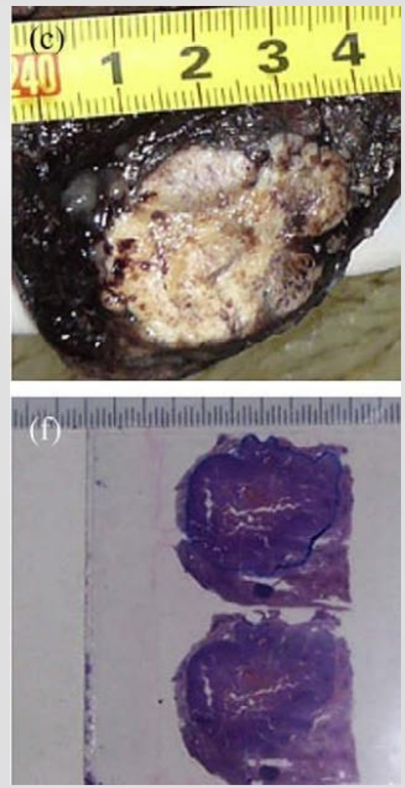
✓ Heterogeneity: variable

✓ Shapes: variable

CT

PET

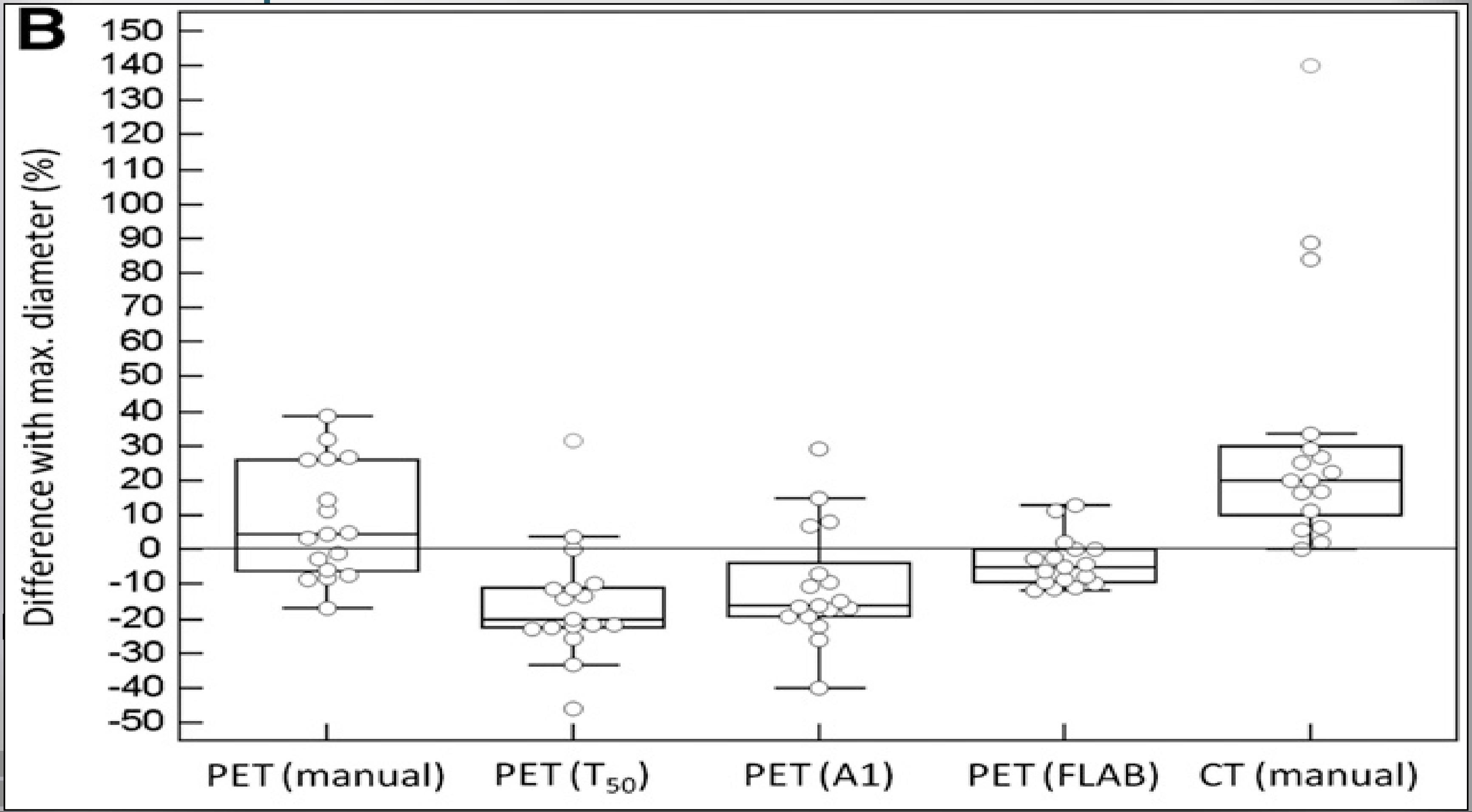




van Baardwijk et al, *International Journal of Radiation Oncology Biology Physics*, 2007

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

Examples: FLAB

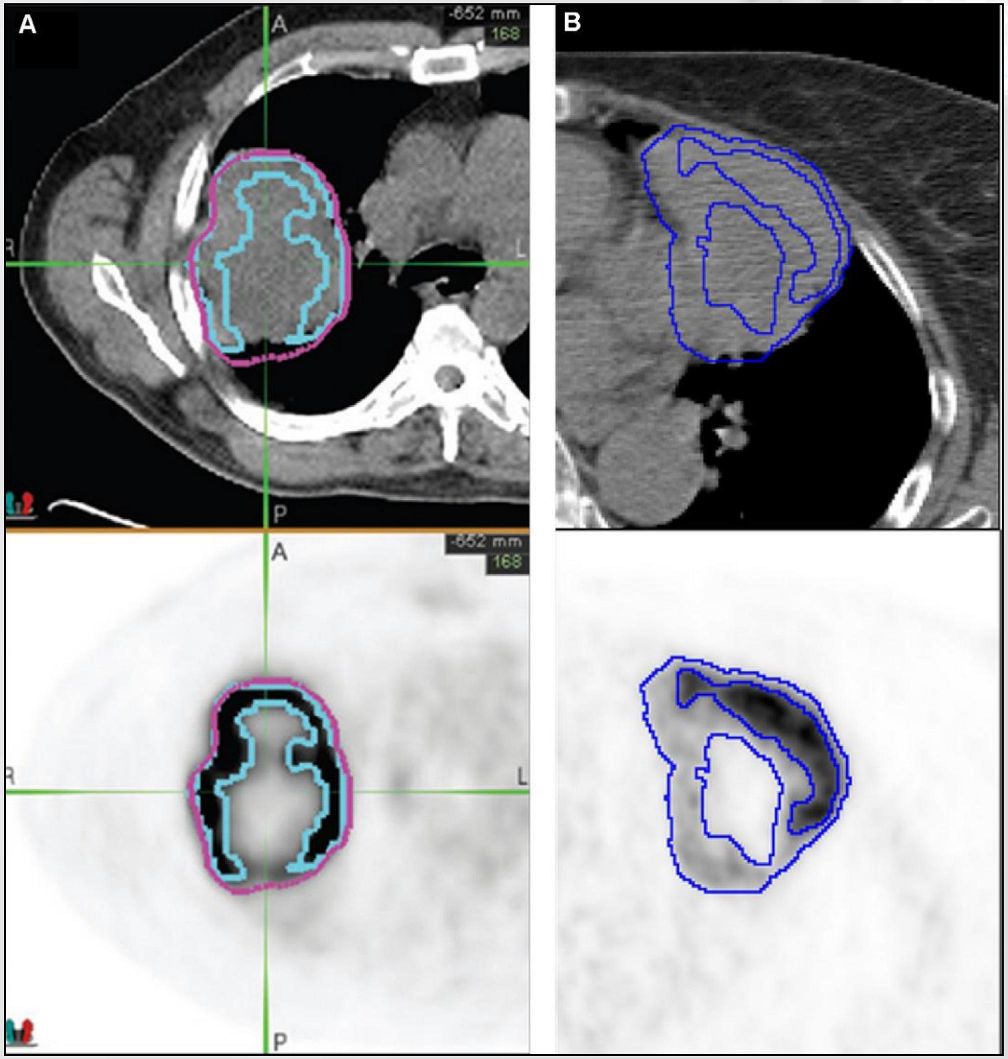


Hatt M, *et al*. **Impact of tumor size and tracer uptake heterogeneity in (18)F-FDG PET and CT non-small cell lung cancer tumor delineation**. *J Nucl Med*. 2011

Radiomics in PET/CT

Segmentation

Comparison between FLAB and gradient-based



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

Problèmes de nomenclature

Parameter	AUC	95% confidence interval
SUV_{max}	0.52	0.32–0.71
Skewness	0.55	0.33–0.75
Kurtosis	0.61	0.39–0.81
SUV_{mean}	0.68	0.48–0.85
Diameter	0.68	0.48–0.85
COV	0.73	0.53–0.88
Volume	0.75	0.55–0.90
TLG	0.79	0.59–0.92

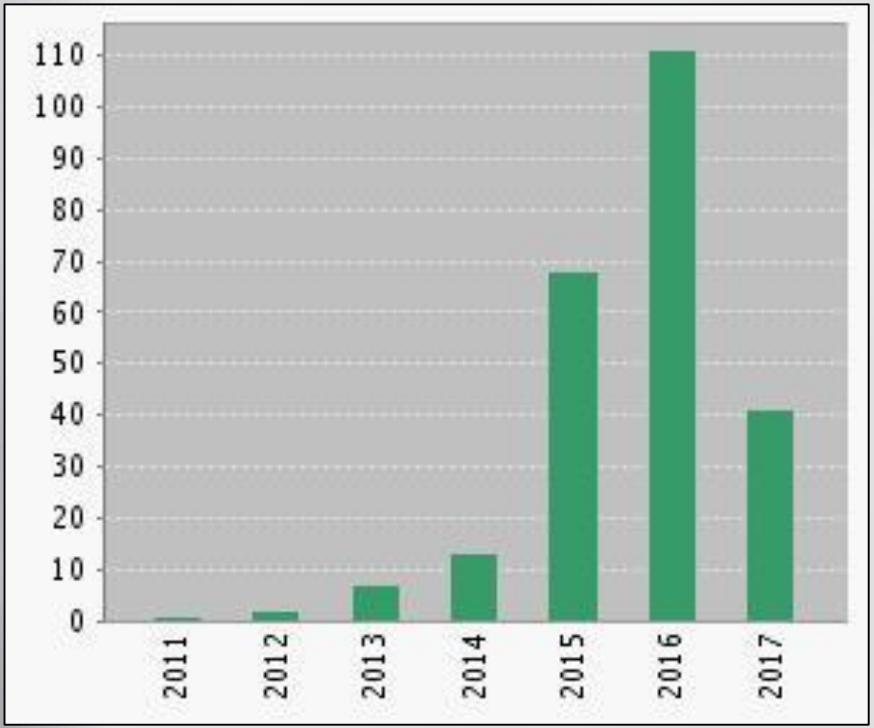
R.A. Bundschuh, *et al*. **Textural Parameters of Tumor Heterogeneity in ^{18}F-FDG PET/CT for Therapy Response Assessment and Prognosis in Patients with Locally Advanced Rectal Cancer**. *J Nucl Med*. 2014

Introduction

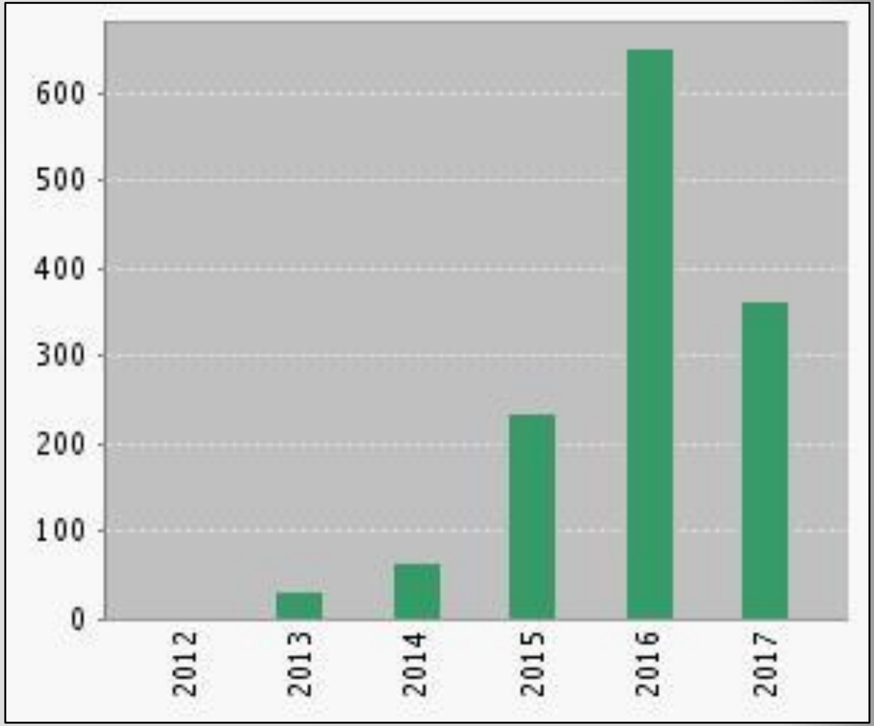
Radiomics depuis 2012

Radiomics : 243 publications recensées au 16/05/2017

Nombre de publications

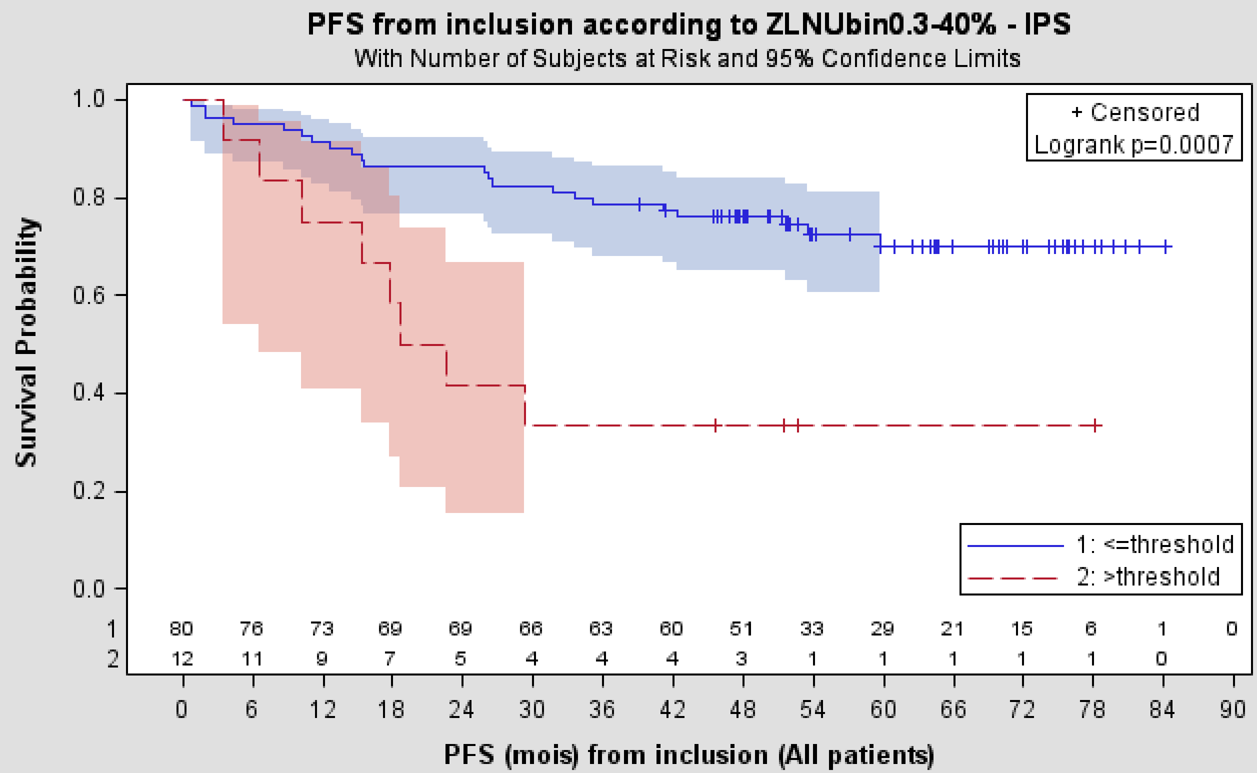


Nombre de citations



Source : web of science

Texture TEP et survie



	No. of Subjects	Event	Censored	Median Survival (95%CL)
<=threshold	80	27.5 % (22)	72.5 % (58)	NA (NA ; NA)
>threshold	12	66.7 % (8)	33.3 % (4)	20.6 (6.5 ; NA)

Threshold is at 378.12

Source : T. Carlier

Radiomics in PET/CT

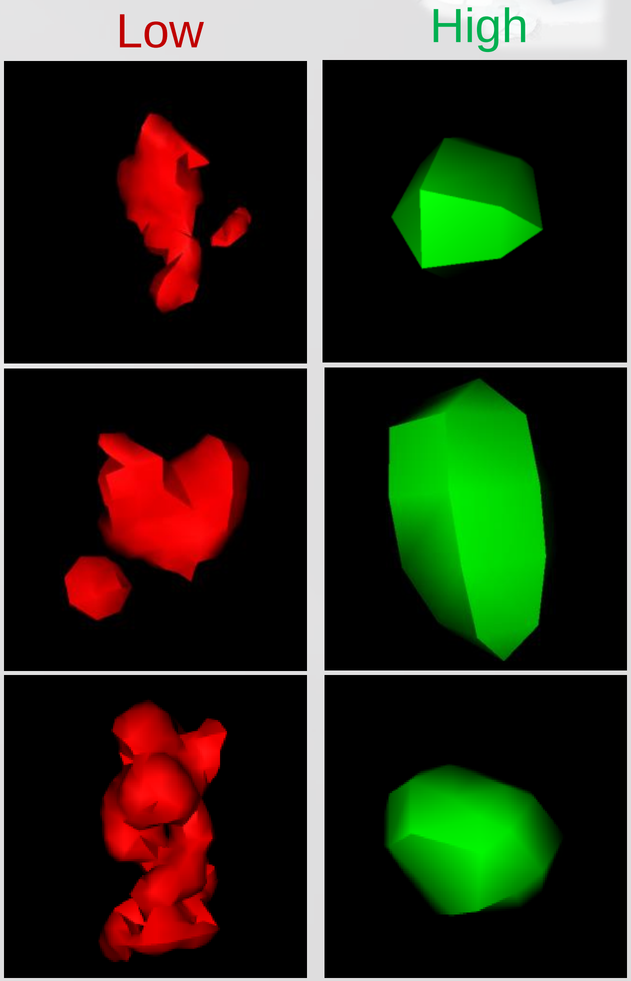
3D geometrical shape

- 3D geometrical shape:

$$Solidity = \frac{Volume}{Convex\ Hull\ volume}$$

$$Rectangularity = \frac{Volume}{Min\ bounding\ box\ volume}$$

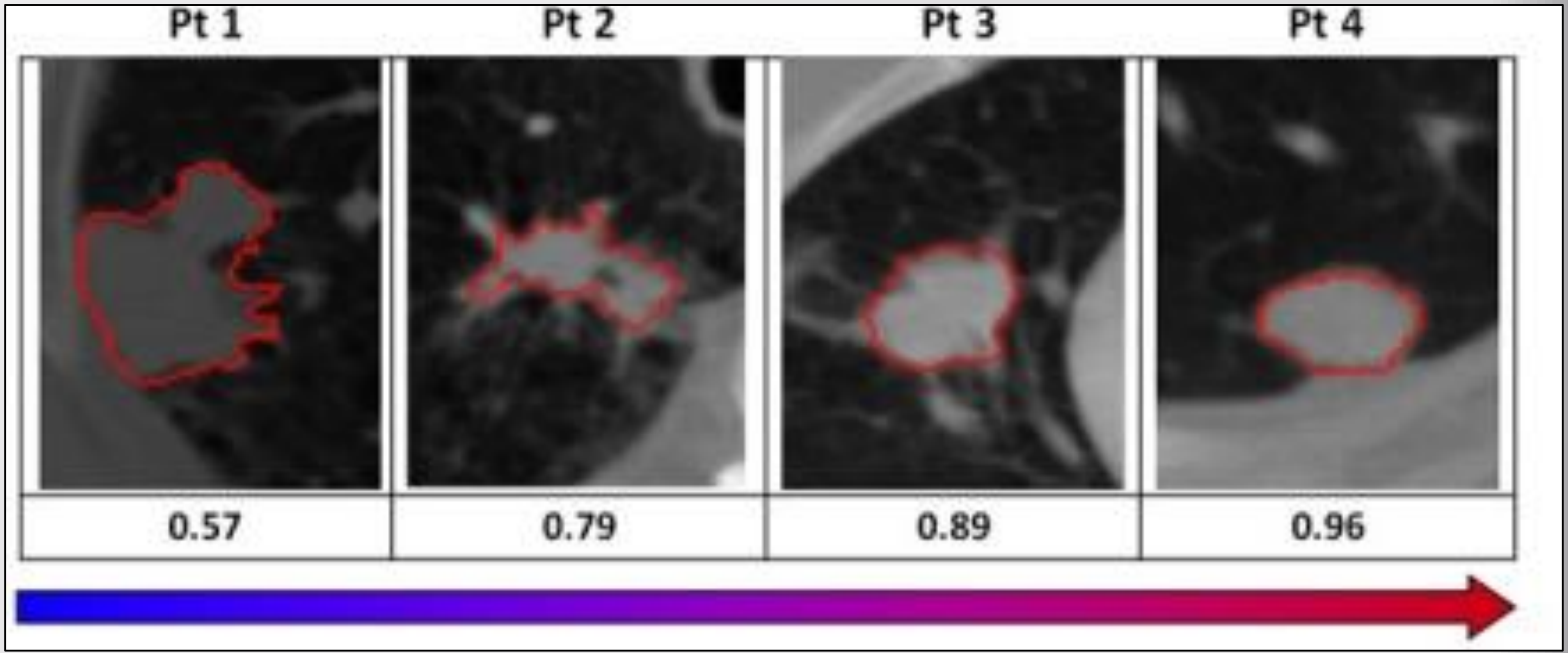
$$Sphericity = \frac{\sqrt[3]{36\,\pi\,Volume^2}}{Surface}$$



El Naqa, *et al*. **Exploring feature-based approaches in PET images for predicting cancer treatment outcomes**. *Pattern Recognit*. 2009

3D geometrical shape:

Images TDM

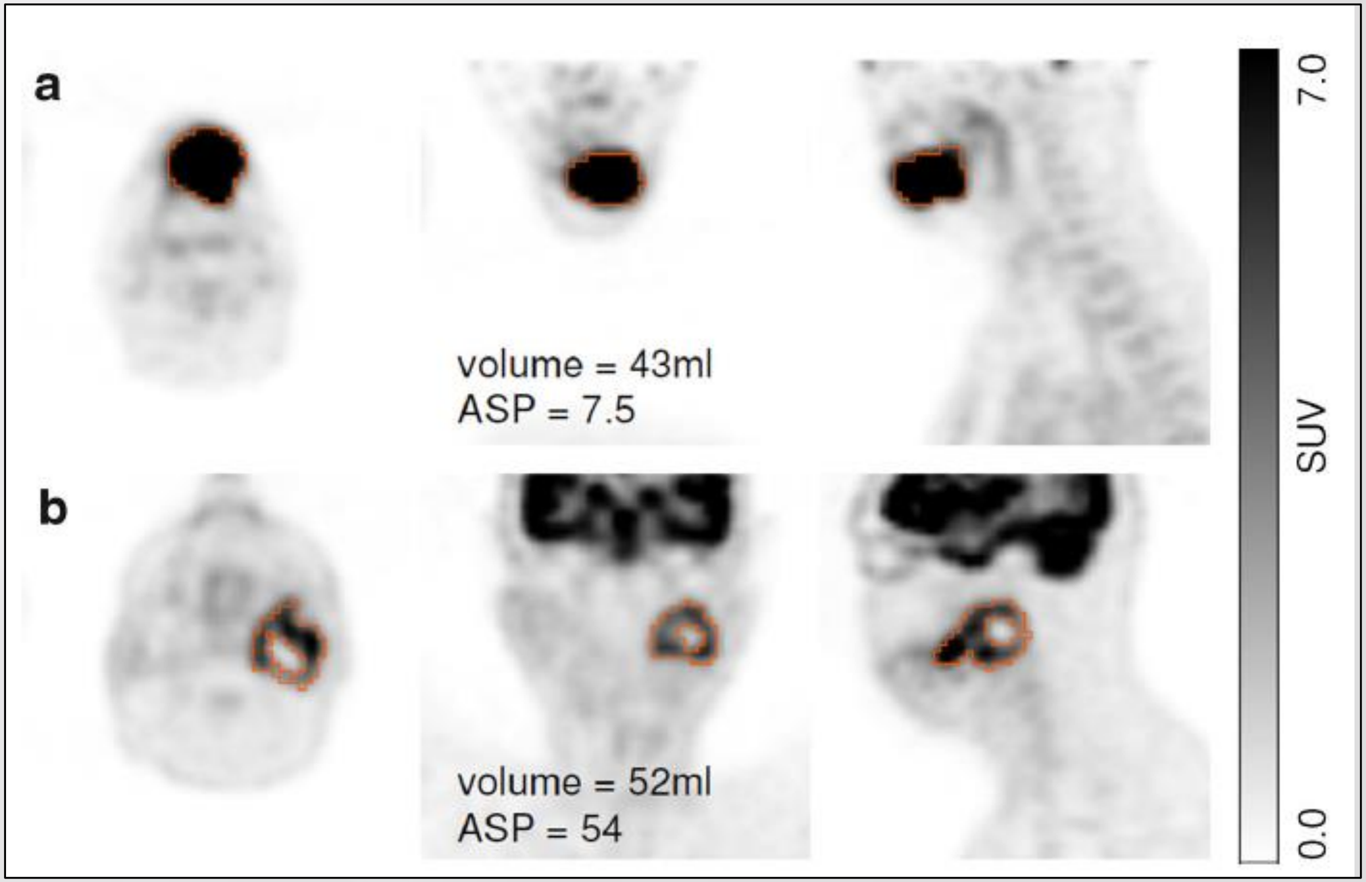


Convexity

O. Grove, *et al*. **Quantitative computed tomographic descriptors associate tumor shape complexity and intratumor heterogeneity with prognosis in lung adenocarcinoma.** *PLOS ONE* 2015

Forme 3D

- Sphéricité



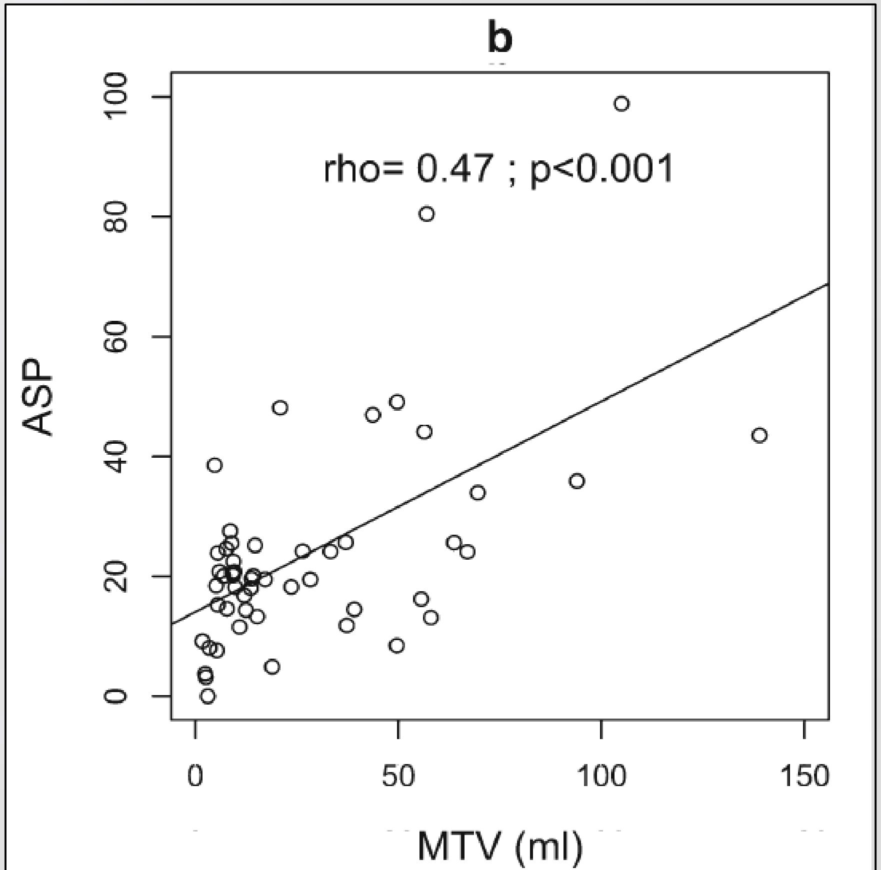
I. Apostolova, *et al*. **Asphericity of pretherapeutic tumour FDG uptake provides independent prognostic value in head-and-neck cancer.** *Eur Radiol*. 2014

Radiomique en TEP/TDM

Forme

Forme 3D

- Sphéricité



I. Apostolova, *et al*. **Asphericity of pretherapeutic tumour FDG uptake provides independent prognostic value in head-and-neck cancer.** *Eur Radiol*. 2014

Radiomique en TEP/TDM

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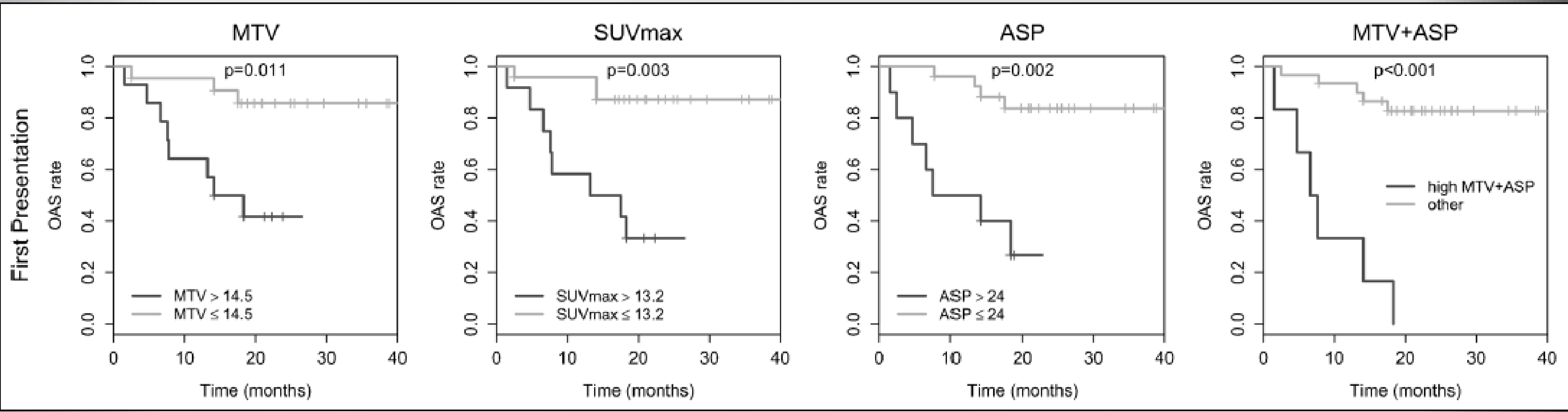


I. Apostolova, *et al*. **Asphericity of pretherapeutic tumour FDG uptake provides independent prognostic value in head-and-neck cancer.** *Eur Radiol*. 2014

Numerous types of features exist

2nd order example: co-occurrence matrix

1. Necessary quantization ($Q = 2^n$, $n = 3,4,5,6,7$)
2. Matrix design and building (direction(s), distance…)
3. Parameters calculation within the matrix

$Q = 2^3 = 8$

5	7	4	5	2
4	6	1	6	4
3	2	3	7	7
5	2	8	5	8
2	3	6	7	3

Direction : $\longrightarrow$

Distance $= 1$

	1	2	3	4	5	6	7	8
1	0	0	0	0	0	2	0	0
2	0	0	3	0	0	0	0	1
3	0	3	0	0	0	1	2	0
4	0	0	0	0	1	2	1	0
5	0	2	0	1	0	0	1	2
6	2	0	1	2	0	0	1	0
7	0	0	2	1	1	1	1	0
8	0	1	0	0	2	0	0	0

$$Entropy = -\sum_{i,j} A(i,j)\log(A(i,j))$$

Jensen. **Introductory Image Processing 3rd ed.** Upper Saddle River, NJ: Prentice-Hall 2005

- Numerous types of features exist

Increasing complexity and difficulty of interpretation

Versatility and potential

Order of textural feature	Description		Examples
First	Grey level frequency distribution from histogram analysis	Global	Minimum, mean and maximum intensity
			Standard deviation
			Skewness
			Kurtosis
Second	From spatial grey level dependence matrices	Local	Entropy
			Energy
			Contrast
			Homogeneity
			Dissimilarity
			Uniformity
			Correlation
Higher	From neighbourhood grey-tone difference matrices	Local	Coarseness
			Contrast
			Busyness
			Complexity
	From voxel alignment matrices	Regional	Run-length and emphasis
			Run-length variability
	From grey level size zone matrices	Regional	Zone emphasis
			Size-zone variability

Histogram analysis
No spatial info

Co-occurrence matrix
Local spatial info

Size-zone matrix
Regional spatial info

Jensen. **Introductory Image Processing 3rd ed**. Upper Saddle River, NJ: Prentice-Hall 2005

Numerous types of features exist

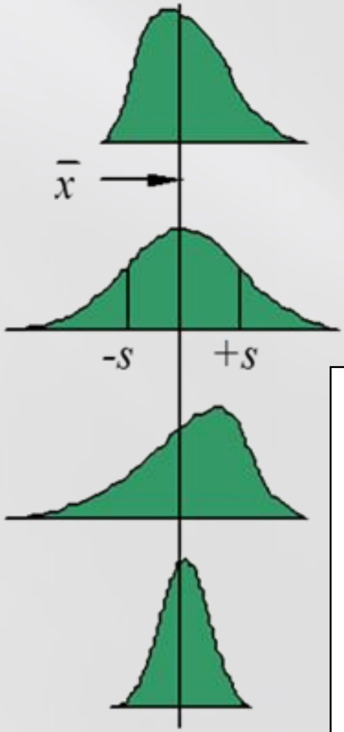
1st order: histogram analysis

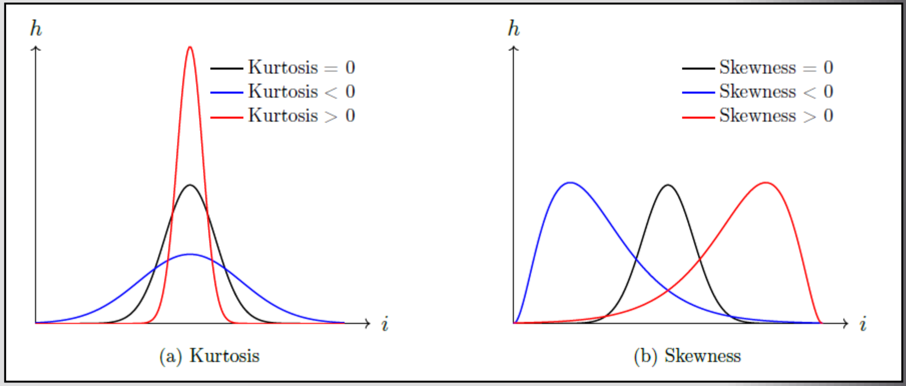
First Moment:
mean - measure of location

Second Moment:
Standard deviation - measure of spread

Third Moment:
skewness - measure of symmetry

Fourth Moment:
kurtosis - measure of peakedness





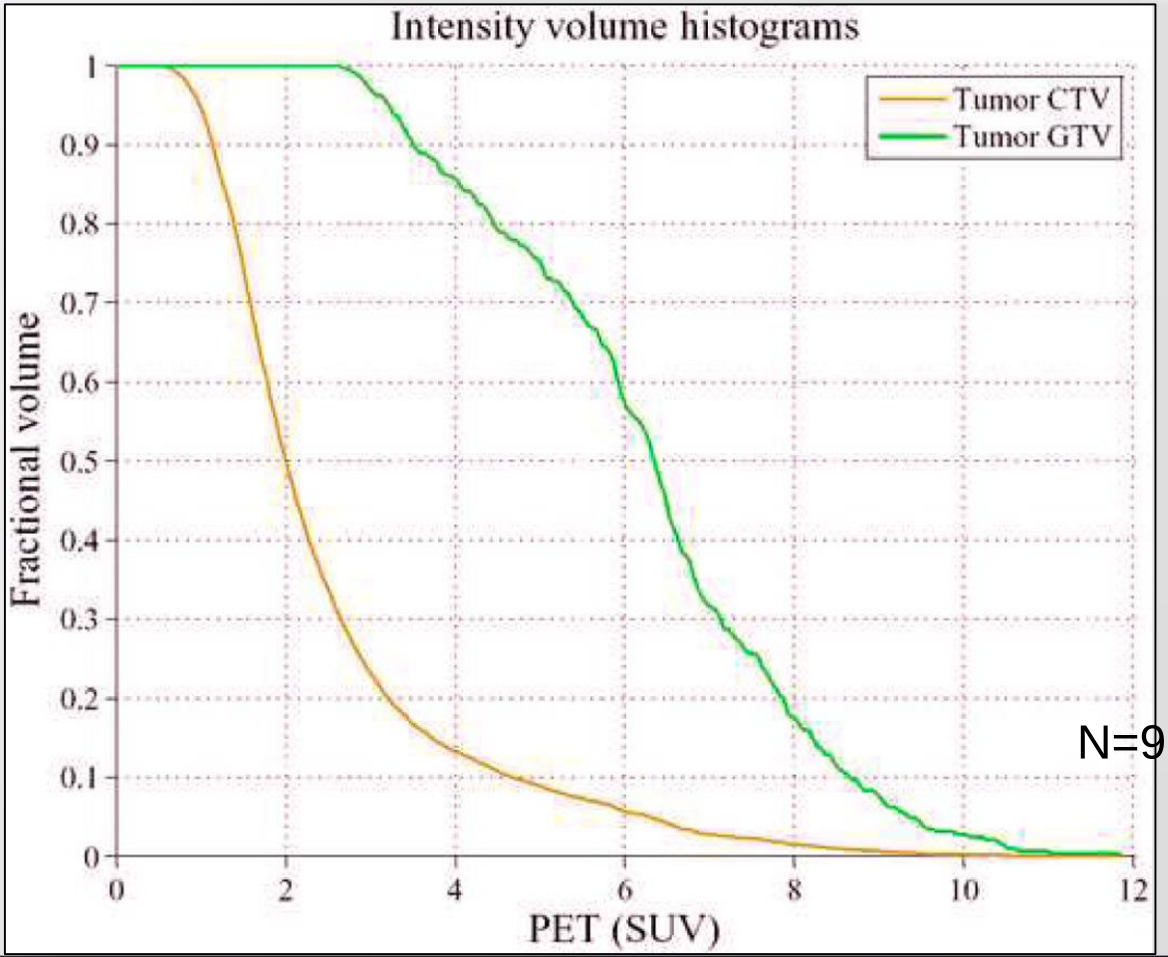
(a) Kurtosis (b) Skewness

Jensen. **Introductory Image Processing 3rd ed**. Upper Saddle River, NJ: Prentice-Hall 2005

Radiomics in PET/CT

The past: the early beginnings

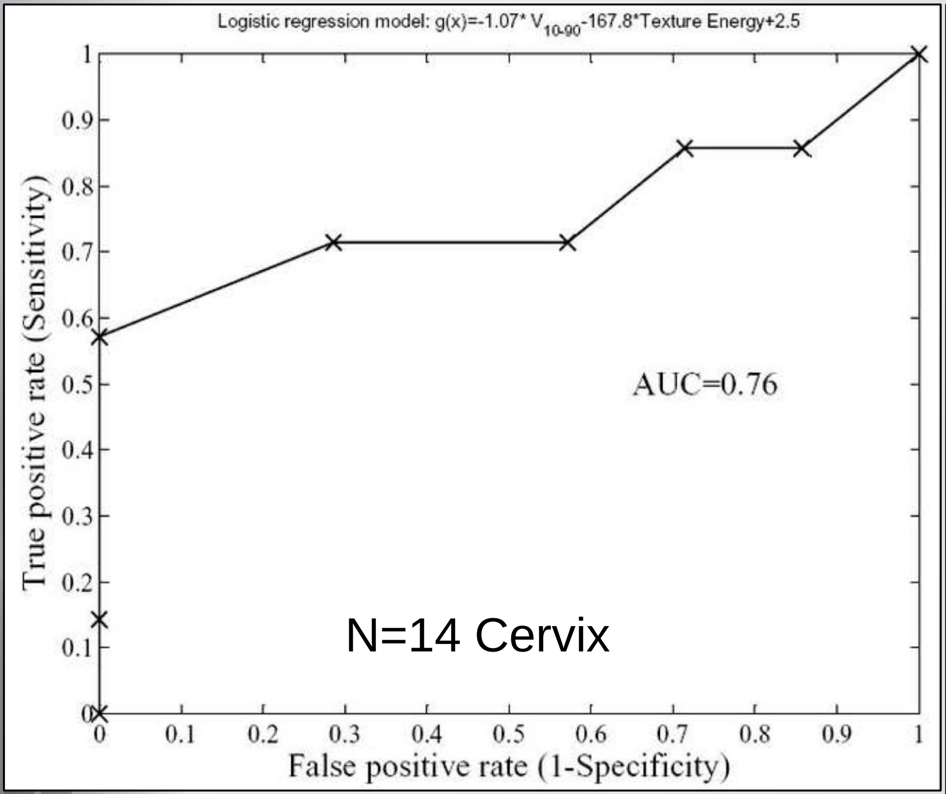
- First papers

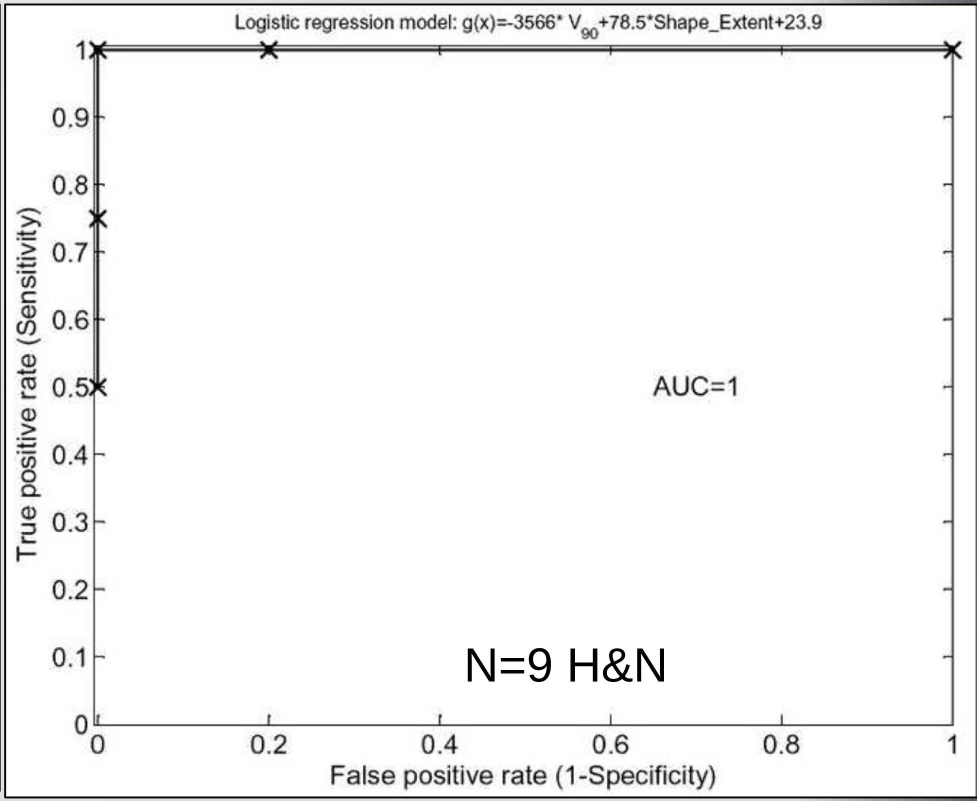


N=9 H&N

El Naqa, *et al*. **Exploring feature-based approaches in PET images for predicting cancer treatment outcomes**. *Pattern Recognit*. 2009

First papers





El Naqa, *et al*. **Exploring feature-based approaches in PET images for predicting cancer treatment outcomes**. *Pattern Recognit*. 2009

Radiomics in PET/CT

The past: the early beginnings

First papers

Image #	Acq. Mode	Grid-Size	Recon. Alg	Iter. number	Post-filter width (mm)	Legend
1	2D	128×128	OSEM	2	3	2D-128-OSEM2-3mm
2	2D	128×128	OSEM	2	5	2D-128-OSEM2-5mm
3	2D	128×128	OSEM	4	5	2D-128-OSEM4-5mm
4	2D	256×256	OSEM	2	3	2D-256-OSEM2-3mm
5	2D	256×256	OSEM	2	5	2D-256-OSEM2-5mm
6	3D	128×128	ITER	2	3	3D-128-ITER2-3mm
7	3D	128×128	ITER	2	6	3D-128-ITER2-6mm
8	3D	128×128	ITER	4	6	3D-128-ITER4-6mm
9	3D	256×256	ITER	2	3	3D-256-ITER2-3mm
10	3D	256×256	ITER	2	6	3D-256-ITER2-6mm

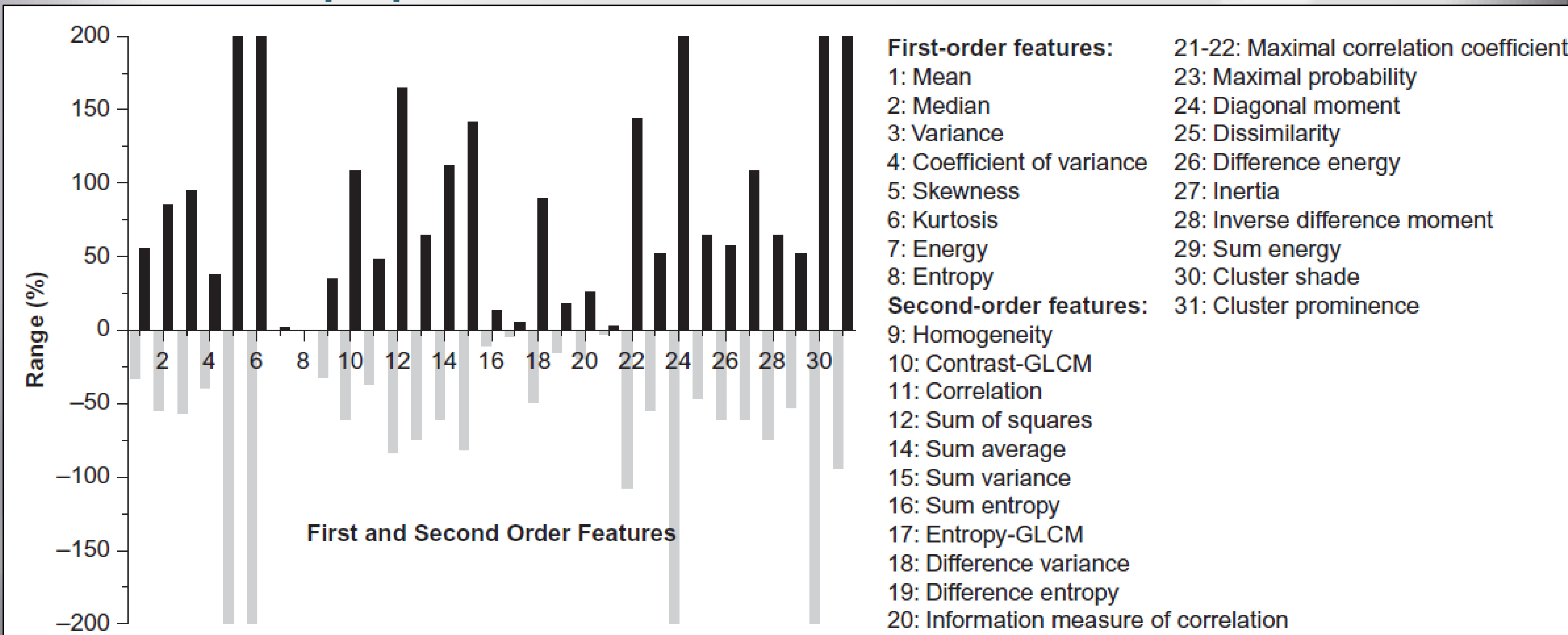
Acq. Mode = acquisition mode; Recon. Alg = reconstruction algorithm; Iter = iteration.

Gavalis, *et al*. **Variability of textural features in FDG PET images due to different acquisition modes and reconstruction parameters**. *Acta Oncol*. 2010

Radiomics in PET/CT

The past: the early beginnings

First papers

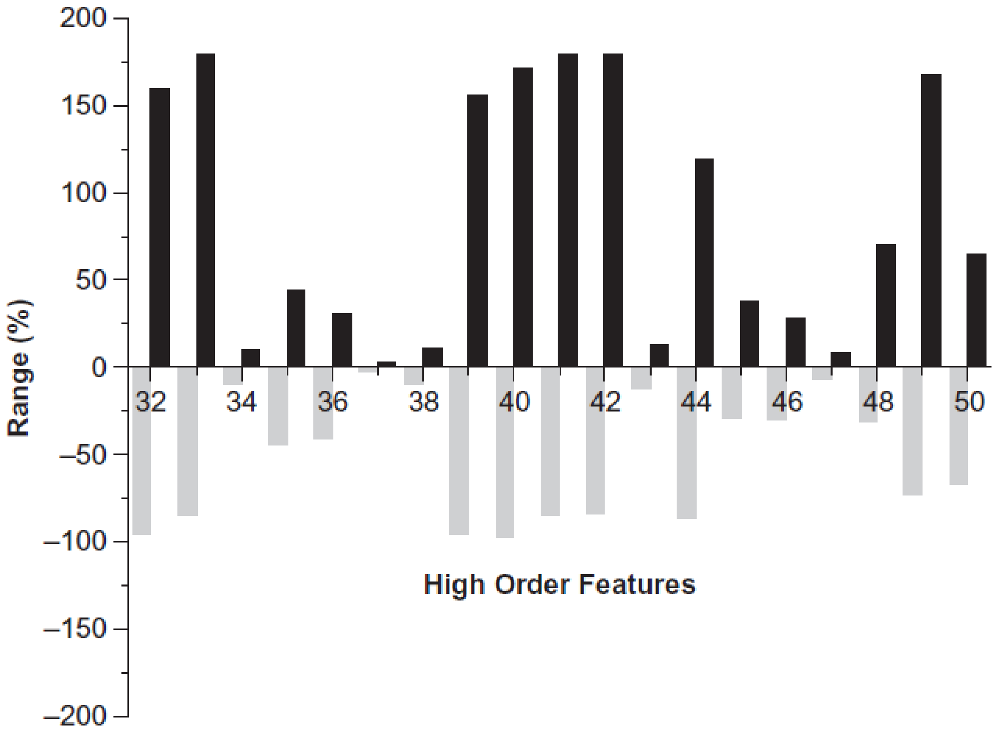


Gavalis, *et al*. **Variability of textural features in FDG PET images due to different acquisition modes and reconstruction parameters**. *Acta Oncol*. 2010

Radiomics in PET/CT

The past: the early beginnings

First papers

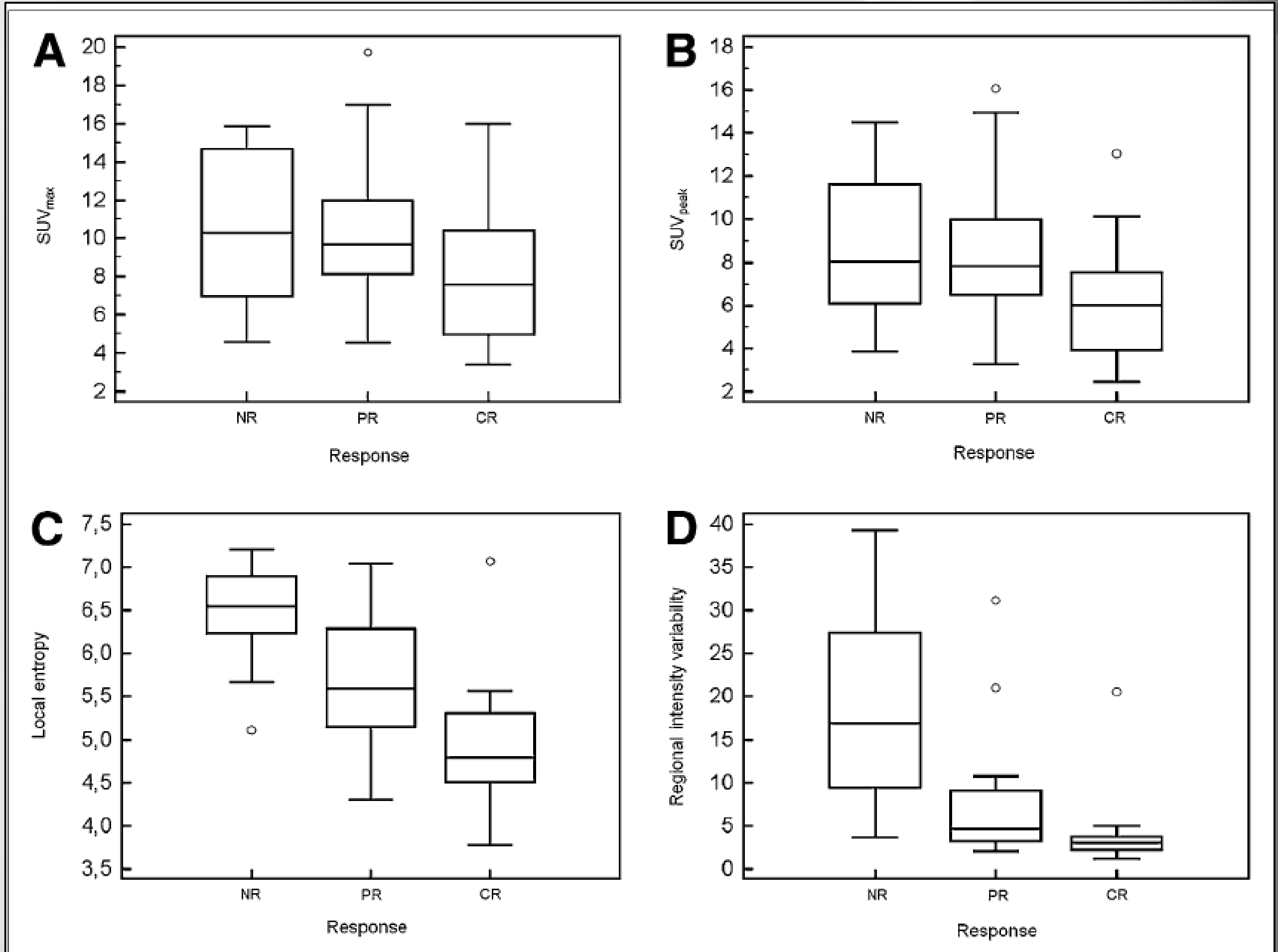


High Order Features (GLRL)
32: Short run emphasis
33: Long run emphasis
34: Gray-level nonuniformity
35: Run length nonuniformity
36: Run Percent
37: Low gray-level run emphasis
38: High gray-level run emphasis
39: Short run low gray-level emphasis
40: Short run high gray-level emphasis
41: Long run low gray-level emphasis
42: Long run high gray-level emphasis
High Order Features (NGL)
43: Small number emphasis
44: Large number emphasis
45: Number nonuniformity
46: Second moment
47: Entropy-NGL
High Order Features (NGTD)
48: Coarseness
49: Contrast-NGL
50: Busyness

Gavalis, *et al*. **Variability of textural features in FDG PET images due to different acquisition modes and reconstruction parameters**. *Acta Oncol*. 2010

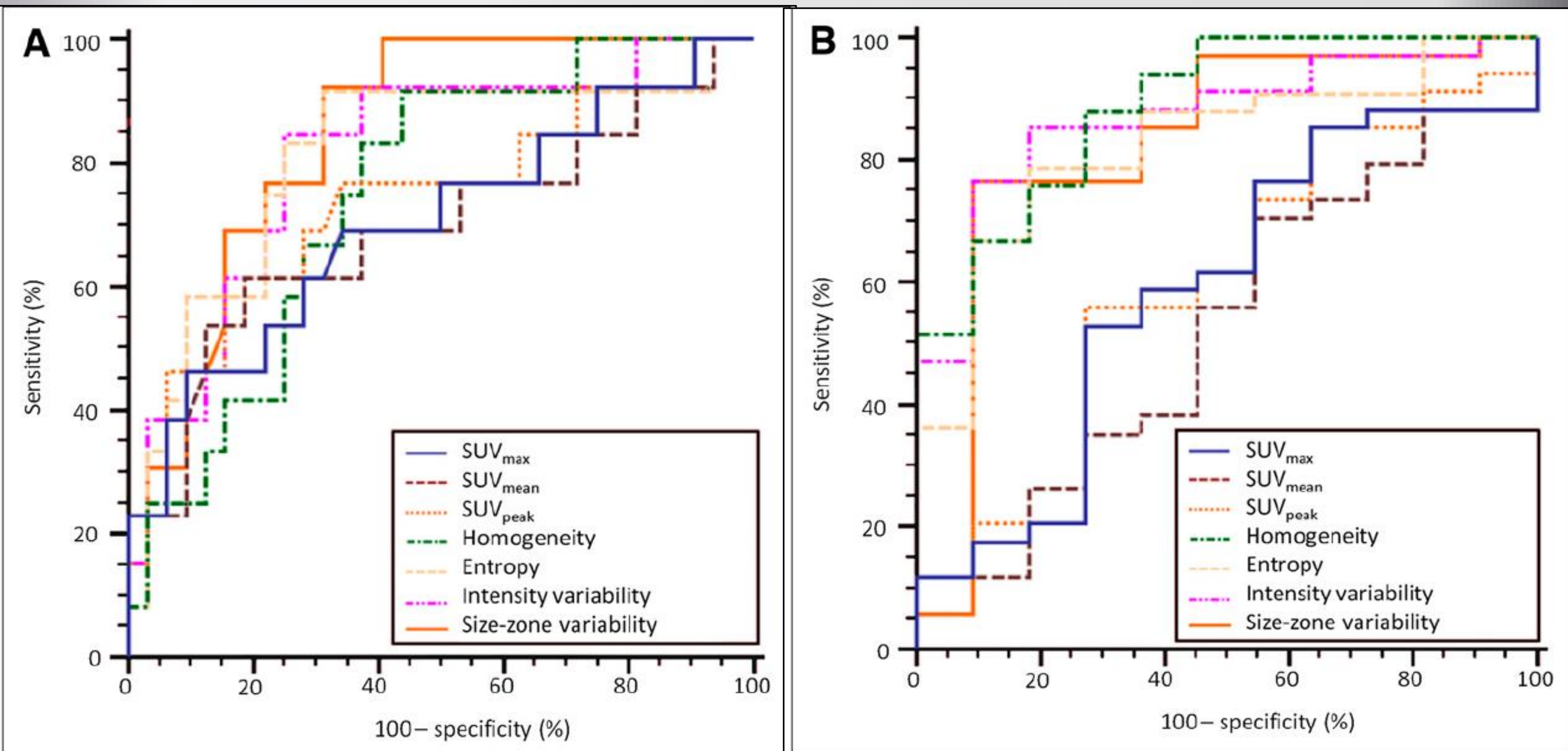
First papers

N=41 esophageal cancer



F. Tixier, *et al*. **Intratumor heterogeneity characterized by textural features on baseline 18F-FDG PET images predicts response to concomitant radiochemotherapy in esophageal cancer**. *J Nucl Med*. 2011 [Highly cited (>200), top 1%]

First papers



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

F. Tixier, *et al*. **Intratumor heterogeneity characterized by textural features on baseline 18F-FDG PET images predicts response to concomitant radiochemotherapy in esophageal cancer**. *J Nucl Med*. 2011 [Highly cited (>200), top 1%]

Radiomics in PET/CT

The past: optimism and naïveté

>2011: numerous other papers

- Dozens, in several pathologies
  - Breast, Lung, Head and neck, rectum, sarcoma, lymphoma…
- Use of textural features or different quantification approaches
  - Different types of textural features
  - Area under the curve of the cumulative histogram
  - Simpler metrics (heterogeneity factor, SUV_{COV} or SUV_{SD})
- As many issues as there are papers…
  - Small cohorts, no external validation
  - Use of unreliable/unreproducible features
  - Lack of rigorous statistical analysis
  - Lack of redundancy analysis
  - …

Radiomics in PET/CT

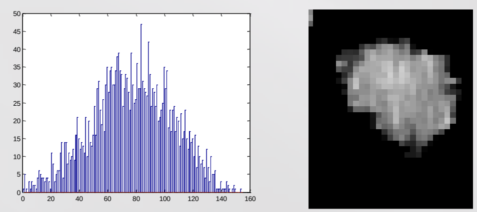
The present: criticism and doubts

- Did we go too fast? [1,2]
  - No thorough technical validation
  - Little to no consideration of volume interaction, and redundancy among features
  - (Very) small cohorts
  - Loose statistical analysis, only surrogate of endpoints/outcome, no gold-standard
  - Use of unreliable features, no acknowledgment of previous publications
  - …

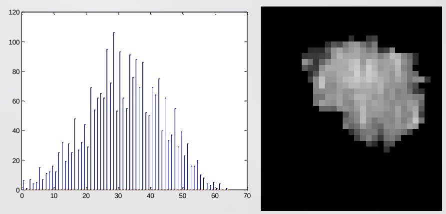
1. Cheng NM, *et al.* **The promise and limits of PET texture analysis**. *Ann Nucl Med*. 2013
2. Brooks FJ. **On some misconceptions about tumor heterogeneity quantification**. *Eur J Nucl Med Mol Imaging*. 2013

Quantization

- A largery ignored and underestimated problem before 2014
- Required for 2nd and 3rd order features calculations
- Huge impact on resulting features

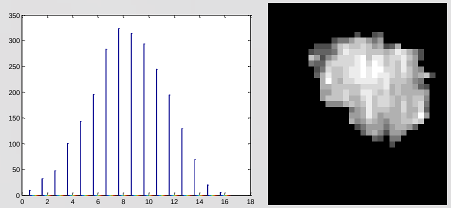


Linear transform[1]



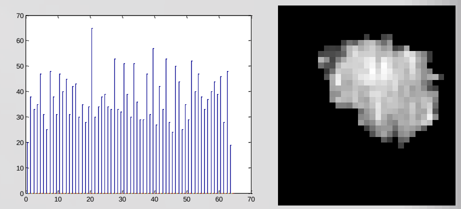
$$I_L(p) = 1 + (N-1) * \frac{I(p) - I_{min}}{I_{max} - I_{min}}$$

Regular bins[2]



$$I_F(p) = 1 + E\left[\frac{I(p) - I_{min}}{F}\right]$$

Histogram equalization



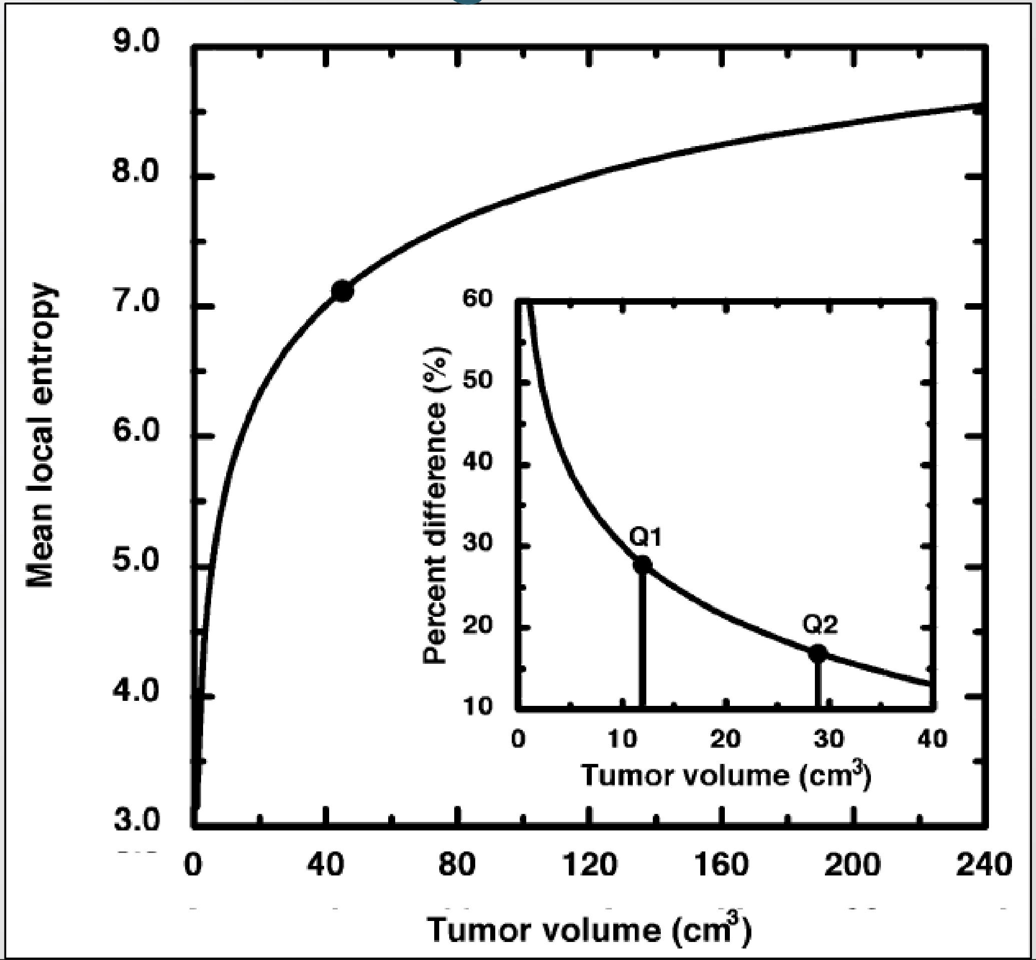
$$I_E(p) = 1 + (N-1) * hic(p)$$

1. Tixier F, *et al.* **Reproducibility of tumor uptake heterogeneity characterization through textural feature analysis in 18 FDG PET**. *J Nucl Med* 2012
2. Leijenaar RTH, *et al*. **The effect of SUV discretization in quantitative FDG-PET Radiomics: the need for standardized methodology in tumor texture analysis**. *Acta Oncol* 2013

Radiomics in PET/CT

The present: criticism and doubts

- Volume confounding effect



FJ. Brooks, *et al*. **The effect of small tumor volumes on studies of intratumoral heterogeneity of tracer uptake**. *J Nucl Med.* 2014

Volume confounding effect

Example Heterogeneity Statistic

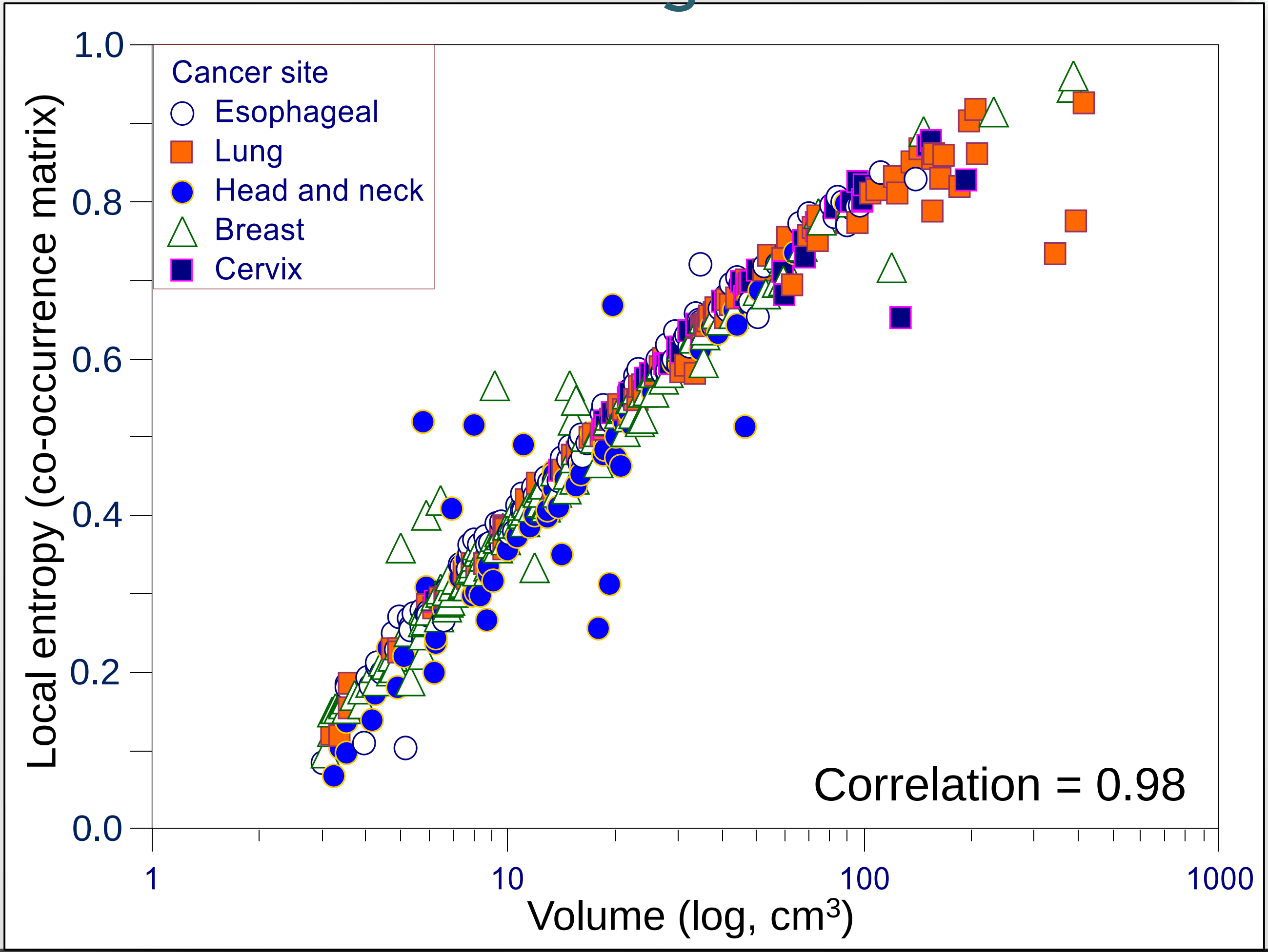
We computed the local information entropy of a 2-dimensional image as described by Haralick et al. (*13*). In brief, the cooccurrence matrix describes the probability p that a pixel of a shade i occurs next to a pixel of shade j. This matrix can be computed for various directions, pixel separations, and bit depths. We computed the horizontal and vertical cooccurrence matrices for the nearest pixel neighbors of 8-bit gray-scale images. From each of these matrices, the local entropy

$$h = -\sum_{j=103}^{255} \sum_{i=103}^{255} p(i,j) \, \ln p(i,j) \qquad \text{Eq. 1}$$

was computed for each direction and then root-mean-square–averaged to obtain a single local entropy value. The limits on the summations reflect the 40% clinical threshold within the 8-bit (0–255) color scale.

FJ. Brooks, *et al*. **The effect of small tumor volumes on studies of intratumoral heterogeneity of tracer uptake**. *J Nucl Med.* 2014

Volume confounding effect

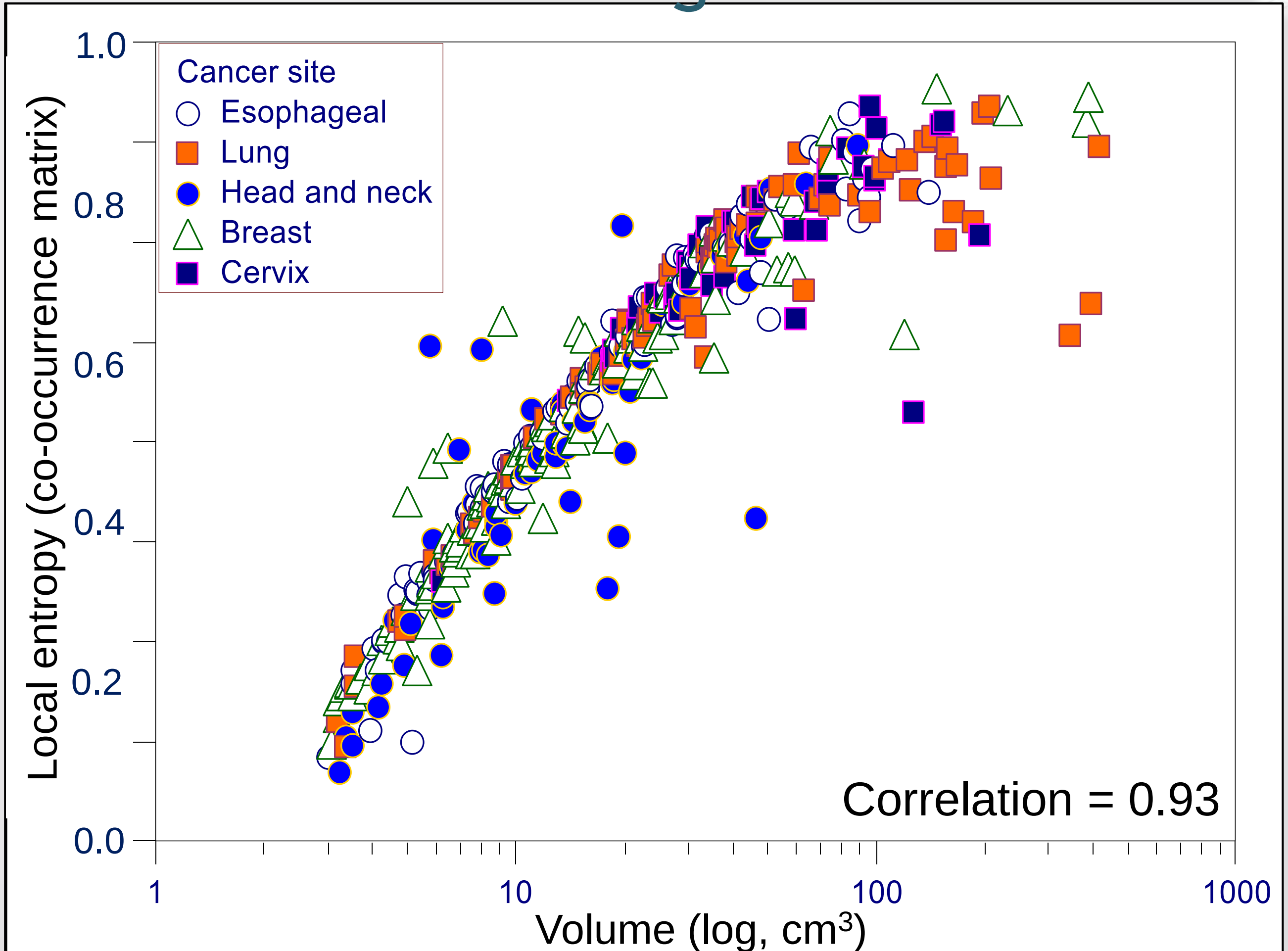


Quantization = 128

13 matrices + averaging

M. Hatt, *et al*. **18F-FDG PET uptake characterization through texture analysis: investigating the complementary nature of heterogeneity and functional tumor volume in a multi-cancer site patient cohort.** *J Nucl Med 2015*

Volume confounding effect



Quantization = 64

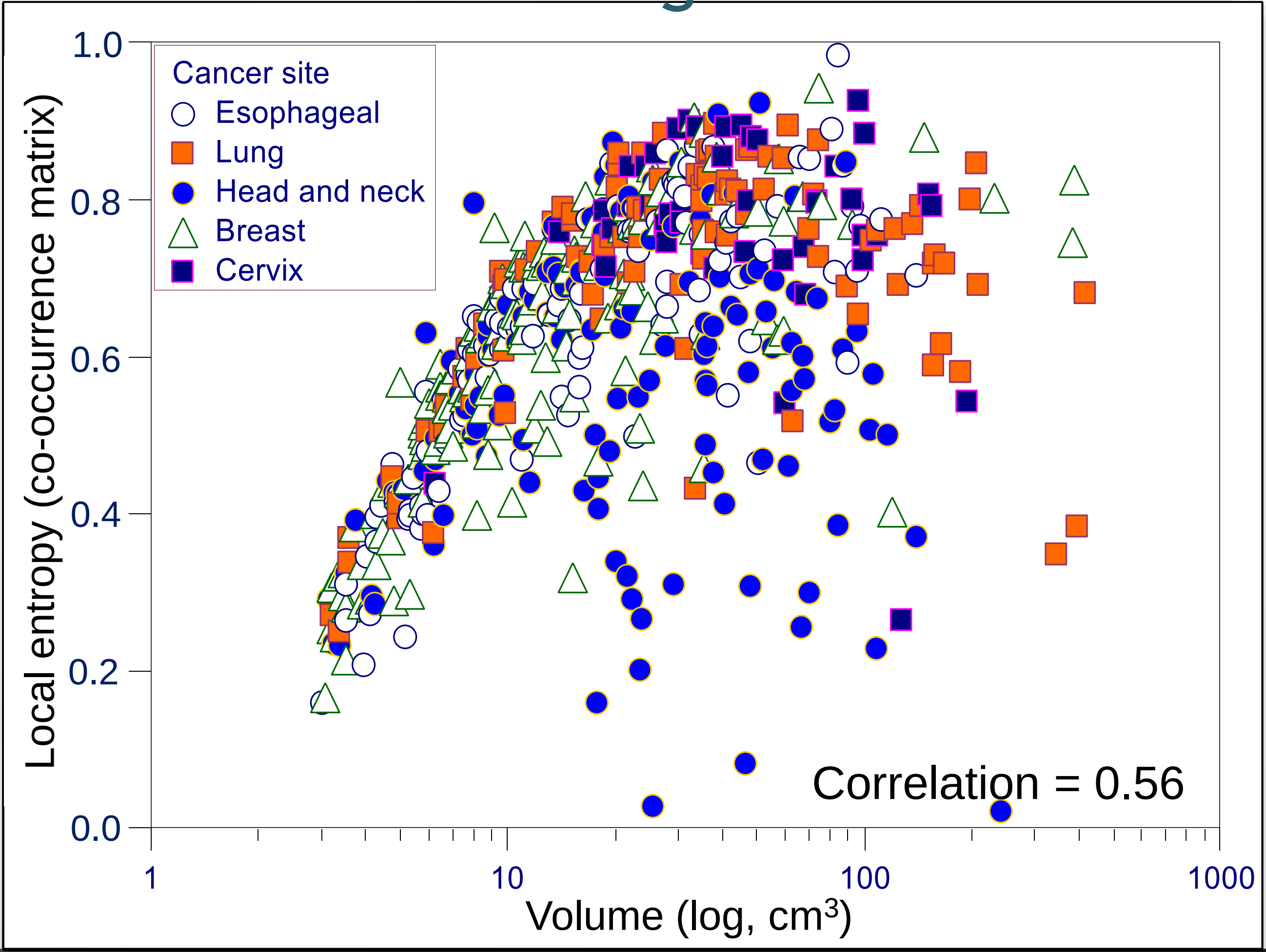
13 matrices + averaging

M. Hatt, *et al*. **18F-FDG PET uptake characterization through texture analysis: investigating the complementary nature of heterogeneity and functional tumor volume in a multi-cancer site patient cohort.** *J Nucl Med 2015*

Radiomics in PET/CT

The present: criticism and doubts

Volume confounding effect



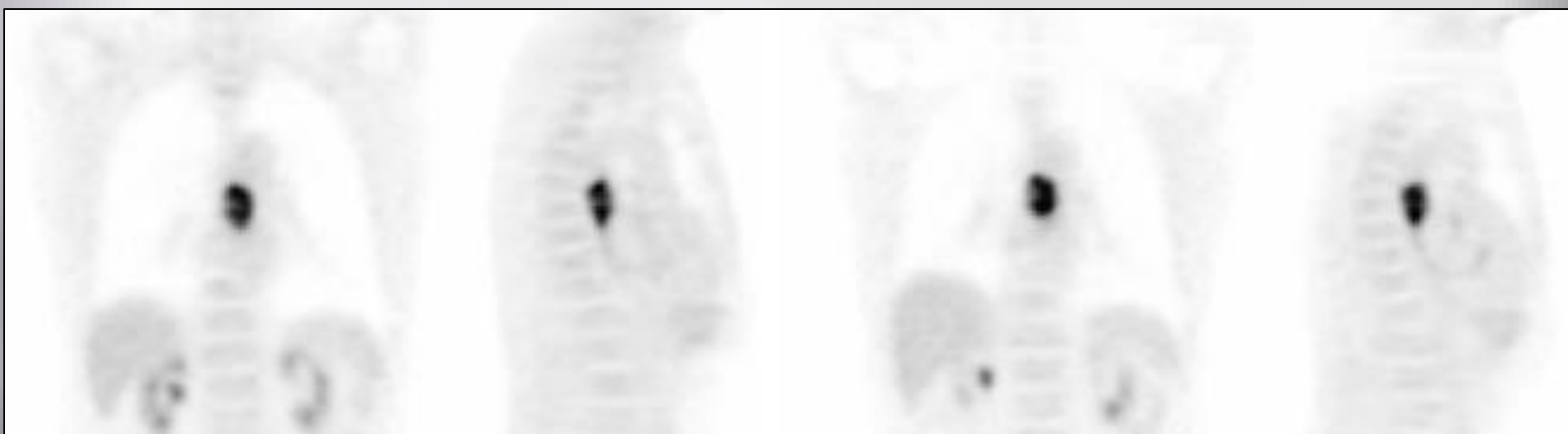
Quantization = 64

1 matrix

M. Hatt, *et al*. **18F-FDG PET uptake characterization through texture analysis: investigating the complementary nature of heterogeneity and functional tumor volume in a multi-cancer site patient cohort.** *J Nucl Med 2015*

Selection and validation of parameters

- Before investigating any potential clinical value
- Evaluate their repeatability
  - Test-retest (double baseline) images[1,2,3]



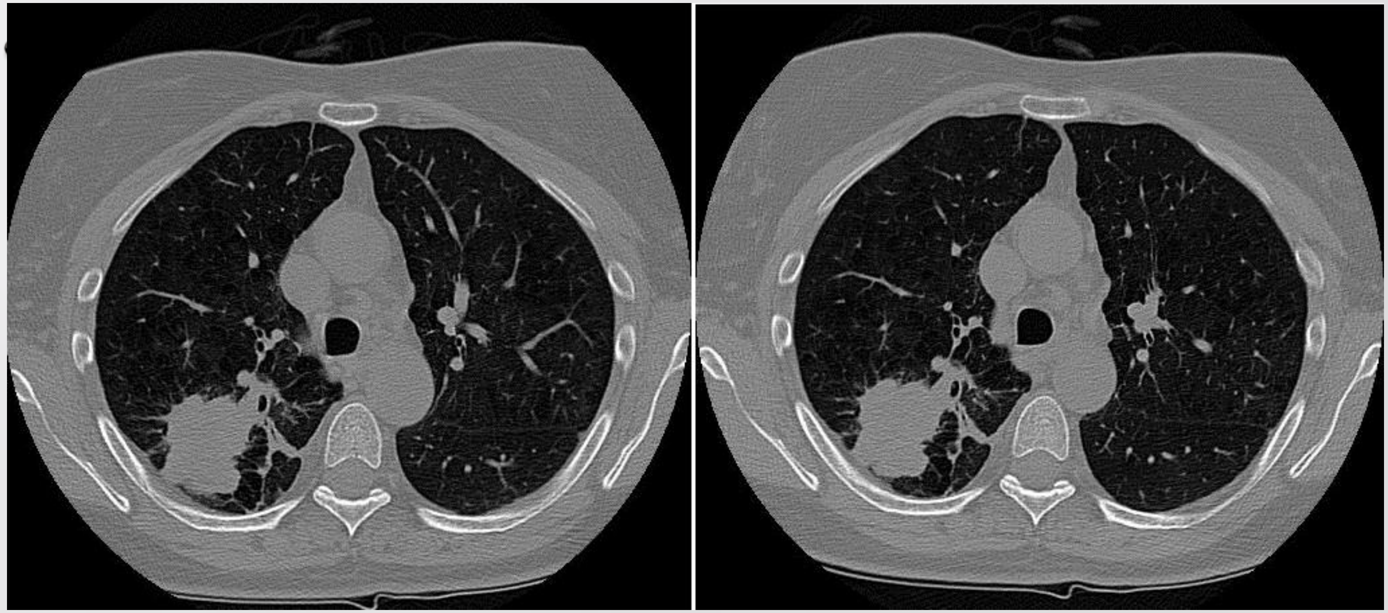
1. Tixier F, *et al.* **Reproducibility of Tumor Uptake Heterogeneity Characterization Through Textural Feature Analysis in 18F-FDG PET.** *J Nucl Med* 2012
2. Leijenaar RT, *et al.* **Stability of FDG-PET Radiomics features: an integrated analysis of test-retest and inter-observer variability.** *Acta Oncol* 2014
3. Fried DV, *et al.* **Prognostic value and reproducibility of pretreatment CT texture features in stage III non-small cell lung cancer.** *Int J Radiat Oncol Biol Phys.* 2014
4. Galavis P, *et al.* **Variability of textural features in FDG PET images due to different acquisition modes and reconstruction parameters.** *Acta Oncol* 2010
5. Hatt M, *et al.* **Robustness of intra-tumor ^{18}F-FDG PET uptake heterogeneity quantification for therapy response prediction in esophageal carcinoma.** *Eur J Nuc Med* 2013

Radiomics in PET/CT

The present: technical and practical issues

Selection and validation of parameters

- Before investigating any potential clinical value
- Evaluate their repeatability
  - Test-retest (double baseline) images[1,2,3]



1. Tixier F, *et al*. **Reproducibility of Tumor Uptake Heterogeneity Characterization Through Textural Feature Analysis in 18F-FDG PET.** *J Nucl Med* 2012
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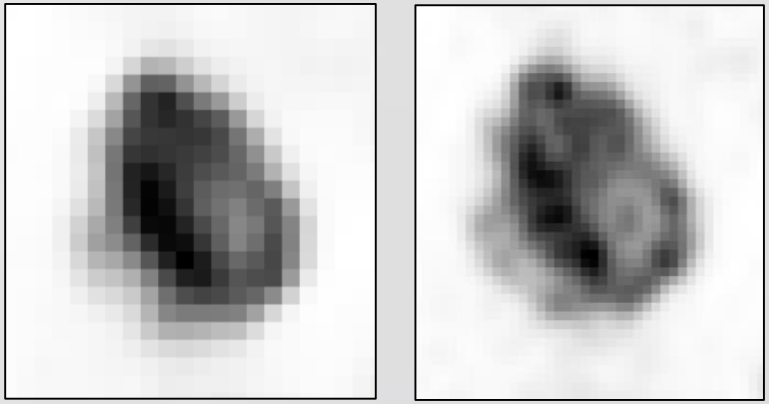
3. Fried DV, *et al*. **Prognostic value and reproducibility of pretreatment CT texture features in stage III non-small cell lung cancer.** *Int J Radiat Oncol Biol Phys.* 2014

4. Galavis PE, *et al*. **Variability of textural features in FDG PET images due to different acquisition modes and reconstruction parameters.** *Acta Oncol* 2010
5. Hatt M, *et al*. **Robustness of intra-tumor ^{18}F-FDG PET uptake heterogeneity quantification for therapy response prediction in esophageal carcinoma.** *Eur J Nuc Med* 2013

Selection and validation of parameters

- Before investigating any potential clinical value
- Evaluate their repeatability
  - Test-retest (double baseline) images[1,2,3]
- Evaluate their robustness
  - Reconstruction algorithms and parameters[4]
  - Processing and analysis workflow[5]

4×4×4 mm^3



2×2×2 mm^3

1. Tixier F, *et al*. **Reproducibility of tumor uptake heterogeneity characterization through textural feature analysis in 18F-FDG PET.** *J Nucl Med* 2012
2. Leijenaar RT, *et al*. **Stability of FDG-PET Radiomics features: an integrated analysis of test-retest and inter-observer variability.** *Acta Oncol* 2014
3. Fried DV, *et al*. **Prognostic value and reproducibility of pretreatment CT texture features in stage III non-small cell lung cancer.** *Int J Radiat Oncol Biol Phys* 2014
4. Galavis PE, *et al*. **Variability of textural features in FDG PET images due to different acquisition modes and reconstruction parameters.** *Acta Oncol* 2010
5. Hatt M, *et al*. **Robustness of intra-tumor ^{18}F-FDG PET uptake heterogeneity quantification for therapy response prediction in esophageal carcinoma.** *Eur J Nuc Med* 2013

Radiomics in PET/CT

The present: technical and practical issues

Selection and validation of parameters

- Before investigating any potential clinical value
- Evaluate their repeatability
  - Test-retest (double baseline) images[1,2,3]
- Evaluate their robustness
  - Reconstruction algorithms and parameters[4]
  - Processing and analysis workflow[5]

❑ Features very sensitive to small intensity variations
❑ Features quantifying regions of small size and/or low intensity
→ Not robust / reproducible

→ Among dozens of parameters, only a handful are sufficiently reliable (robust+reproducible)

1. Tixier F, *et al*. **Reproducibility of tumor uptake heterogeneity characterization through textural feature analysis in 18F-FDG PET.** *J Nucl Med* 2012
2. Leijenaar RT, *et al*. **Stability of FDG-PET Radiomics features: an integrated analysis of test-retest and inter-observer variability.** *Acta Oncol* 2014
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5. Hatt M, *et al*. **Robustness of intra-tumor ^{18}F-FDG PET uptake heterogeneity quantification for therapy response prediction in esophageal carcinoma.** *Eur J Nuc Med* 2013

Radiomics in PET/CT

The present: technical and practical issues

Repeatability & robustness

TABLE 3
Reproducibility Results for All Image-Derived Parameters, Including SUVs and Textural Features (Calculated Using Downsampling Range of 64 Values)

Texture	Feature	Mean ± SD	95% CI	LRL	95% CI for LRL	URL	95% CI for URL
Global	Minimum SUV	6.3 ± 26.5	−7.8 to 20.4	−45.6	−70.2 to −20.9	58.2	33.6 to 82.8
	SUV_{max}	4.7 ± 19.5	−5.7 to 15.0	−33.5	−51.7 to −15.4	42.9	24.7 to 61.0
	SUV_{mean}	5.5 ± 21.2	−5.8 to 16.8	−36.1	−55.8 to 16.4	47.1	27.3 to 66.8
	SD	1.2 ± 23.2	−11.1 to 13.6	−44.18	−65.7 to −22.6	46.6	25.1 to 68.2
	Skewness	−0.3 ± 27.5	−15.0 to 14.3	−54.2	−79.8 to −28.6	53.6	28.0 to 79.2
	Kurtosis	2.1 ± 18.0	−7.4 to 11.7	−33.1	−49.8 to −16.4	37.3	20.6 to 54.0
	Mean/SD	4.1 ± 24.1	−8.8 to 16.9	−43.2	−65.6 to −20.7	51.3	28.9 to 73.7
Local	Second angular moment	10.9 ± 26.4	−3.2 to 25.0	−40.9	−65.5 to −16.3	62.7	38.1 to 87.3
	Contrast (inertia)	5.4 ± 24.0	−18.1 to 7.4	−52.3	−74.6 to −30.0	41.6	19.3 to 63.9
	Entropy	−2.0 ± 5.4	−4.9 to 0.9	−12.6	−17.7 to −7.6	8.7	3.6 to 13.8
	Correlation	−0.6 ± 27.7	−15.3 to 14.1	−54.8	−15.3 to 14.1	53.6	27.9 to 79.3
	Homogeneity	1.8 ± 11.5	−4.4 to 7.9	−20.8	−31.5 to −10.1	24.4	13.6 to 35.1
	Dissimilarity	−2.1 ± 13.0	−9.0 to 4.9	−27.6	−39.7 to −15.5	23.5	11.4 to 35.6
Regional	Small-area emphasis	−6.0 ± 54.3	−35.0 to 22.9	−112.5	−163.0 to −62.0	100.4	49.9 to 150.9
	Large-area emphasis	3.6 ± 30.0	−12.4 to 19.6	−55.2	−83.1 to −27.3	62.4	34.5 to 90.3
	Intensity variability	−9.7 ± 24.0	−22.5 to 3.1	−56.7	−79.0 to −34.4	37.3	15.0 to 59.6
	Size–zone variability	11.2 ± 23.1	−1.1 to 23.5	−34.1	−55.6 to −12.6	56.5	35.0 to 78.0
	Zone percentage	−2.7 ± 16.9	−11.7 to 6.2	−35.8	−51.5 to −20.1	30.3	14.6 to 46.0
	Low-intensity emphasis	−4.0 ± 55.3	−33.5 to 25.4	−112.4	−163.9 to −61.0	104.4	525.9 to 155.8
	High-intensity emphasis	3.9 ± 20.4	−7.0 to 14.8	−36.1	−55.1 to −17.1	44.0	24.9 to 63.0
	Low-intensity small-area emphasis	−7.0 ± 67.6	−43.1 to 29.0	−139.5	−202.4 to −76.6	125.4	62.5 to 188.3
	High-intensity small-area emphasis	1.0 ± 31.2	−15.6 to 17.6	−60.1	−89.1 to −31.1	62.0	33.0 to 91.0
	Low-intensity large-area emphasis	1.8 ± 28.9	−13.6 to 17.2	−54.9	−81.8 to 28.0	58.5	31.6 to 85.4
	High-intensity large-area emphasis	3.5 ± 35.8	−15.6 to 22.6	−66.7	−100.1 to −33.4	73.7	40.4 to 107.1

LRL and URL = lower and upper reproducibility limits, respectively.

F. Tixier, *et al*. **Reproducibility of tumor uptake heterogeneity characterization through textural feature analysis in 18F-FDG PET.** *J Nucl Med 2012*

Radiomics in PET/CT

The present: technical and practical issues

Repeatability & robustness

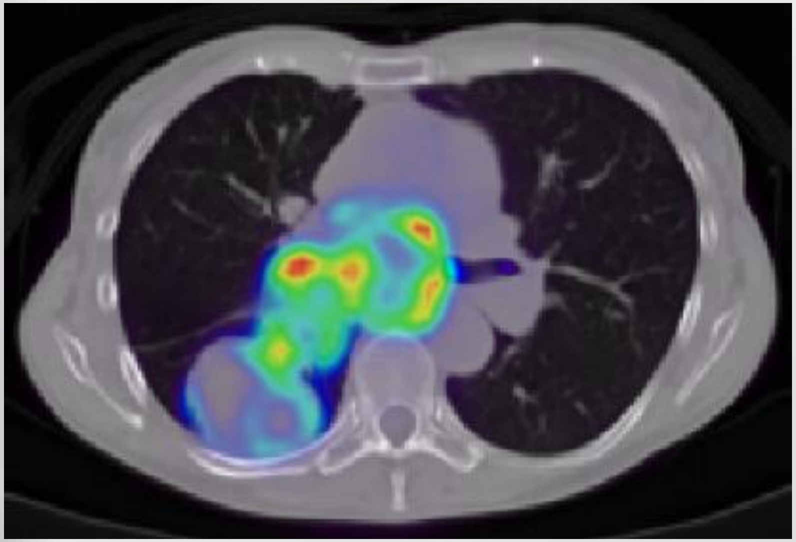
Study	Modality	# of patients	Features evaluated
Tixier, *J Nucl Med* 2012	FDG PET	16	1st-order, textural
Leijenaar, *Acta Oncol* 2013	FDG PET	11	Shape, 1st-order, textural
Willaime, *Phys Med Biol* 2013	FLT PET	11	1st-order, textural
Fried, *Int J Radiat Oncol Biol Phys* 2014	CT + CE-CT	20, 13	1st-order, textural
Aerts, *Nat Commun* 2014	CT	31	Shape, 1st-order, textural
Yang, *Comput Med Imaging Graph* 2015	CE-CT	8	Shape, 1st-order, textural
Fave, *Med Phys* 2015	CBCT	10	1st-order, textural
Desseroit, *Eur J Nucl Med Mol Imaging* 2016	CT	31	1st-order, textural
Van Velden, *Mol Imaging Biol* 2016	FDG PET	11	Shape, 1st-order, textural

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

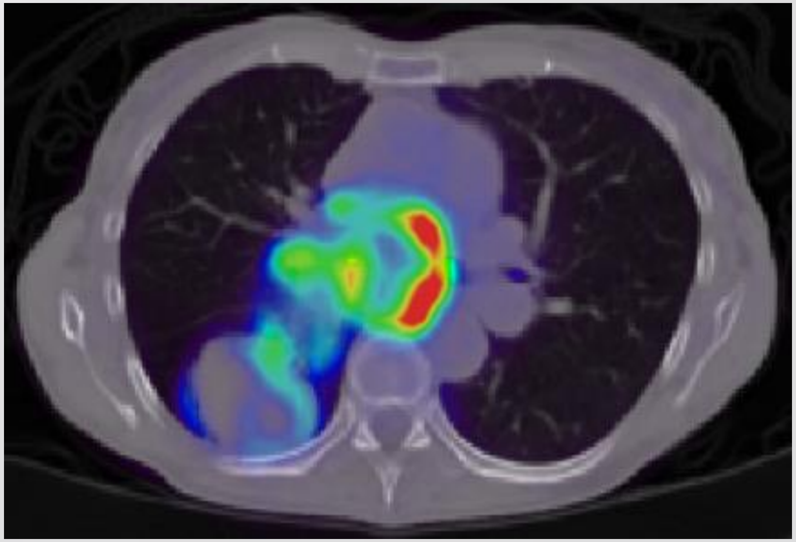
M-C. Desseroit, *et al*. **Reliability of PET/CT shape and heterogeneity features in functional and morphological components of Non-Small Cell Lung Cancer tumors: a repeatability analysis in a prospective multi-center cohort.** *J Nucl Med 2017*

Repeatability & robustness

- N = 74 NSCLC stage III-IV, prospective inclusion in 31 sites
  - Merck (n = 40, 17 sites Europe + Asia)
  - American College of Radiology Imaging Network (ACRIN) 6678 (n = 34, 14 sites USA)
  - Test and re-test acquisitions performed within 1 week



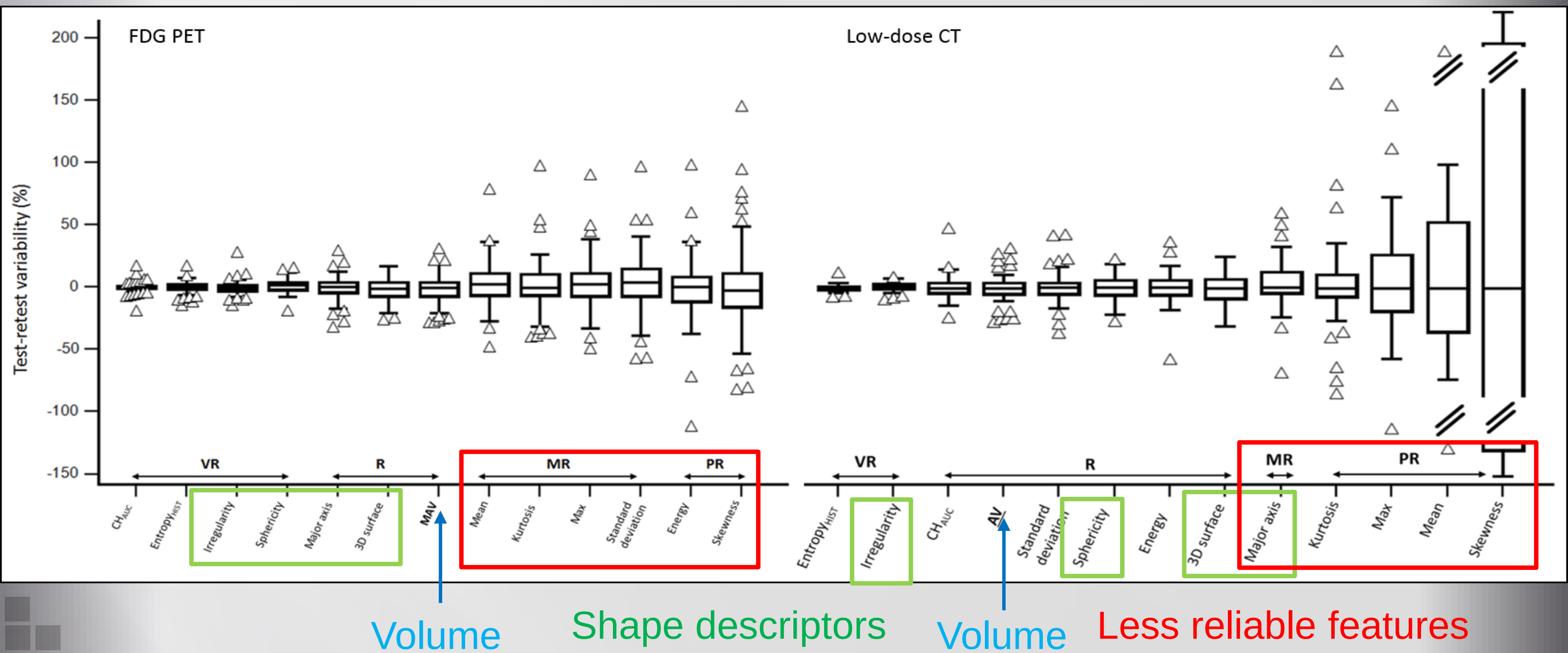
Test PET/CT



Re-test PET/CT

Weber, *et al*. **Repeatability of 18F-FDG PET/CT in Advanced Non-Small Cell Lung Cancer: Prospective Assessment in 2 Multicenter Trials**. *J Nucl Med*. 2015

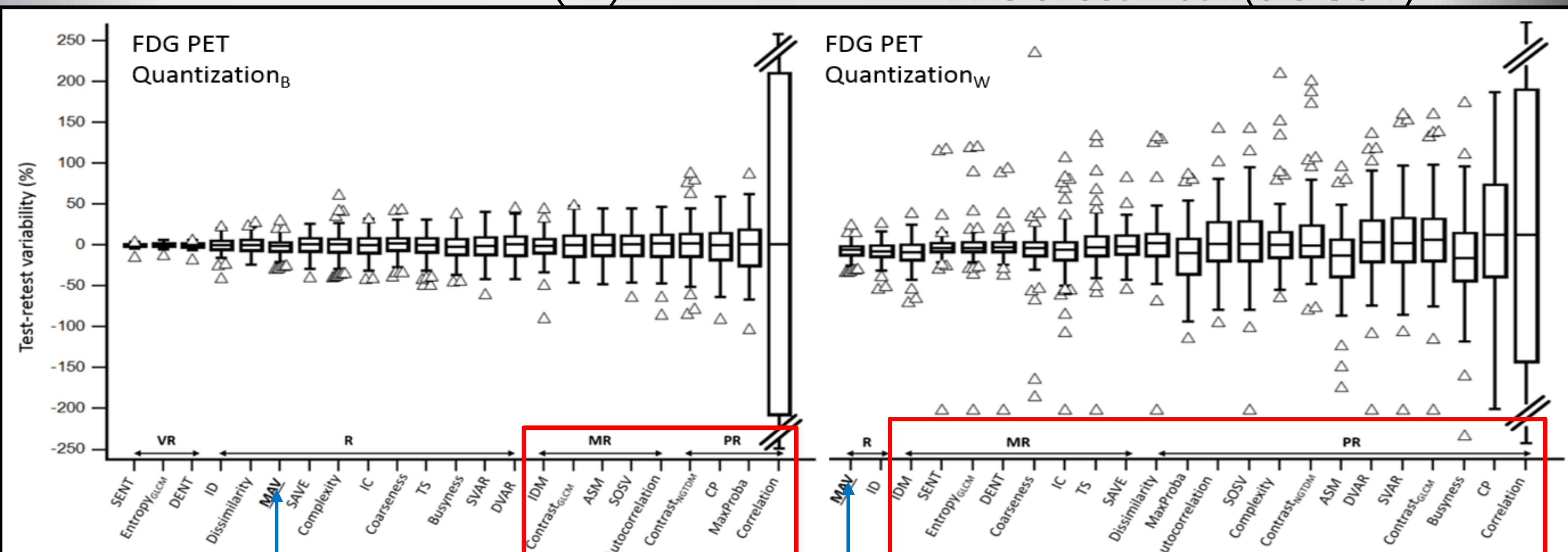
Repeatability & robustness



M-C. Desseroit, *et al*. **Reliability of PET/CT shape and heterogeneity features in functional and morphological components of Non-Small Cell Lung Cancer tumors: a repeatability analysis in a prospective multi-center cohort.** *J Nucl Med 2017*

Repeatability & robustness

Set number of bins (64) | Bins of set width (0.5 SUV)



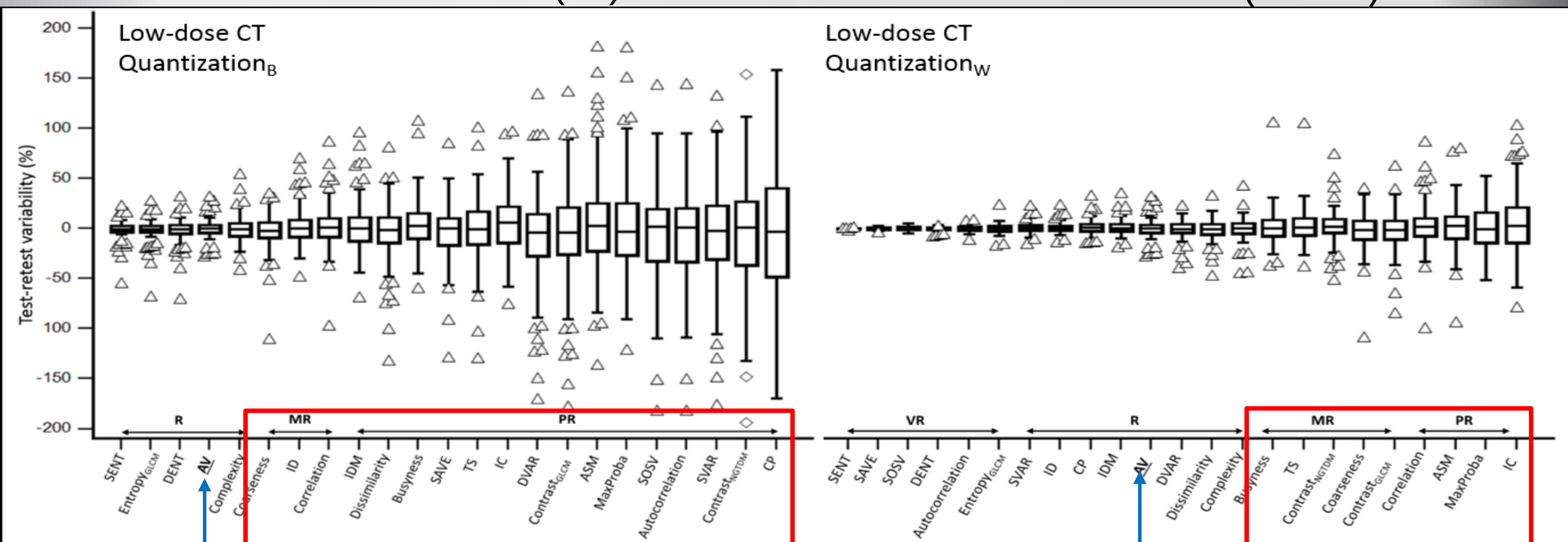
Volume | Volume | Less reliable features

M-C. Desseroit, *et al*. **Reliability of PET/CT shape and heterogeneity features in functional and morphological components of Non-Small Cell Lung Cancer tumors: a repeatability analysis in a prospective multi-center cohort.** *J Nucl Med 2017*

Repeatability & robustness

Set number of bins (64)

Bins of set width (10 HU)



Volume

Less reliable features

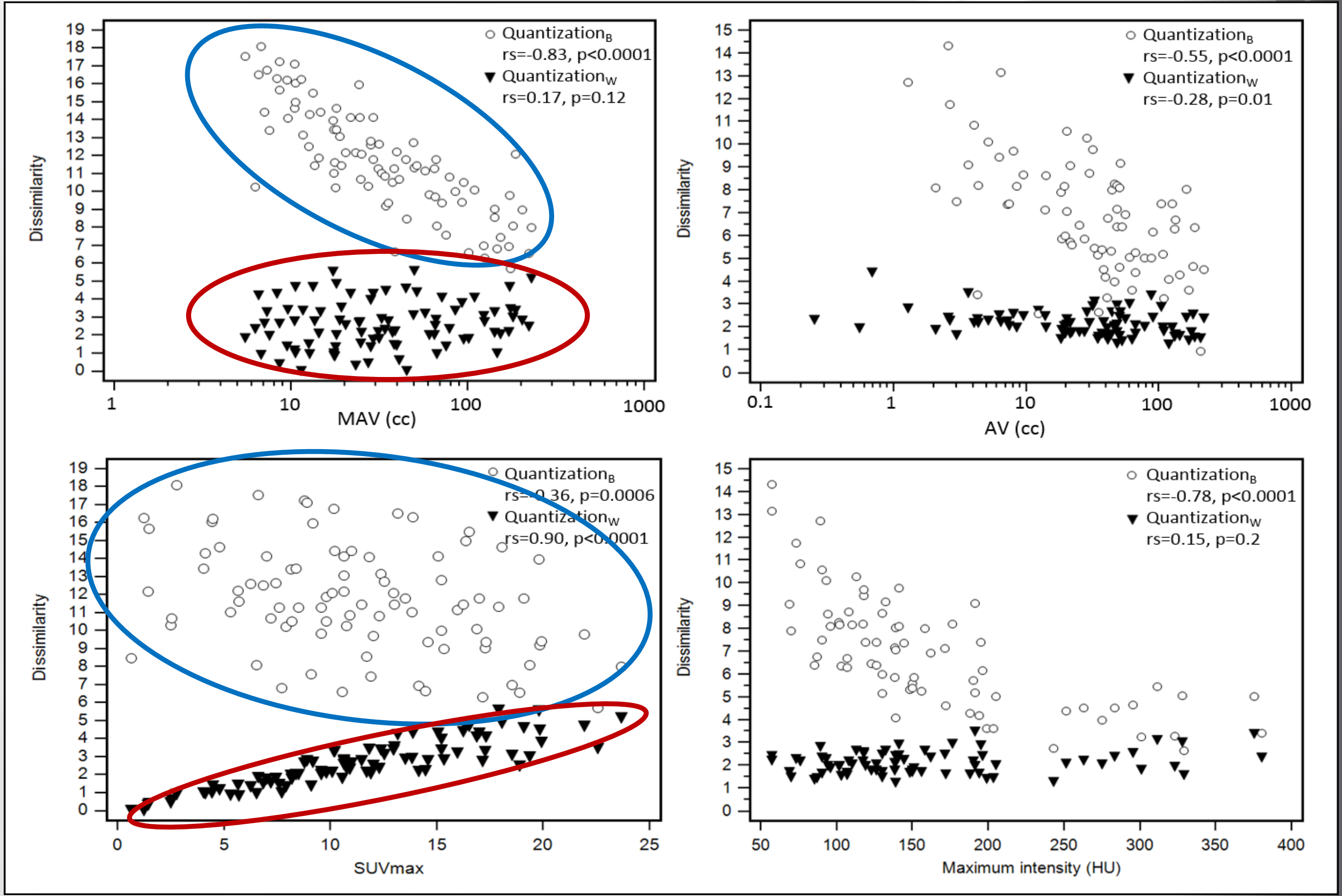
Volume

M-C. Desseroit, *et al*. **Reliability of PET/CT shape and heterogeneity features in functional and morphological components of Non-Small Cell Lung Cancer tumors: a repeatability analysis in a prospective multi-center cohort.** *J Nucl Med 2017*

Repeatability & robustness

Set number of bins (64)
Quantization$_B$

Bins of set width (0.5 SUV)
Quantization$_W$



M-C. Desseroit, *et al*. **Reliability of PET/CT shape and heterogeneity features in functional and morphological components of Non-Small Cell Lung Cancer tumors: a repeatability analysis in a prospective multi-center cohort.** *J Nucl Med 2017*

Reproducibility/variability/robustness

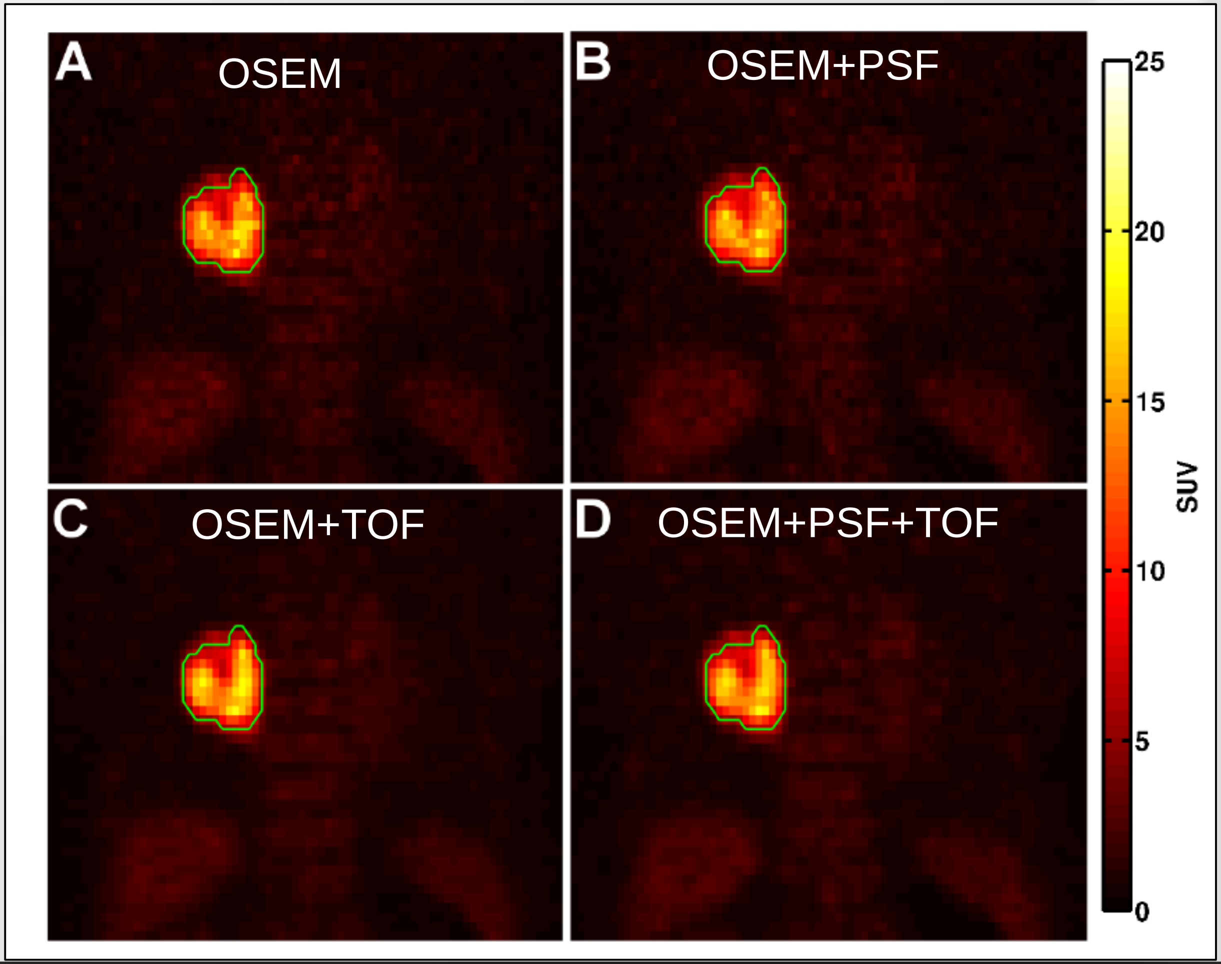
TABLE 1

List of reconstruction settings

Reconstruction algorithm	**Variation over the default reconstruction settings**	**Impact of iteration number on image features** FWHM: 2.5 mm; Grid size: 256 × 256	**Impact of FWHM on image features** iteration: 2; Grid size: 256 × 256	**Impact of grid size on image features** iteration: 2; FWHM: 2.5mm
OSEM	iteration: 2 FWHM: 2.5 mm; Grid size: 256 × 256	iteration: 1, 2, 3	FWHM: 2.5, 3.5, 4.5, 5.5 mm;	Grid size: 256 × 256 128 × 128
OSEM+PSF	iteration: 2 FWHM: 2.5 mm; Grid size: 256 × 256	iteration: 1, 2, 3	FWHM: 2.5, 3.5, 4.5, 5.5 mm;	Grid size: 256 × 256 128 × 128
OSEM+TOF	iteration: 2 FWHM: 2.5 mm; Grid size: 256 × 256	iteration: 1, 2, 3	FWHM: 2.5, 3.5, 4.5, 5.5 mm;	Grid size: 256 × 256 128 × 128
OSEM+PSF+TOF	iteration: 2 FWHM: 2.5 mm; Grid size: 256 × 256	iteration: 1, 2, 3	FWHM: 2.5, 3.5, 4.5, 5.5 mm;	Grid size: 256 × 256 128 × 128

J. Yan, *et al*. **Impact of Image Reconstruction Settings on Texture Features in 18F-FDG PET.** *J Nucl Med* 2015

Reproducibility/variability/robustness



J. Yan, *et al*. **Impact of Image Reconstruction Settings on Texture Features in 18F-FDG PET.** *J Nucl Med* 2015

Radiomics in PET/CT

The present: technical and practical issues

Reproducibility/variability/robustness

TABLE 2

Change of image features over the default reconstruction settings

	COV≤5%	5%<COV≤10%	10%<COV≤20%	COV>20%
SUV	SUVmean, SUVpeak	SUVmax		
FOS	Entropy	COV, Kurtosis, Energy	Variance	Skewness
GLCM	Dissimilarity, Energy, Entropy, ID,SE, DE, IMC, IDM, IDMN, DM, SDN	Contrast, Correlation, Homogeneity, MP, SA, DV	Autocorrelation, SOS, SV	CS
GLRLM	GLNr, RP,LGRE, HGRE		SRE, LRE, RLN, SRLGE, SRHGE, LRLGE, LRHGE	
GLSZM	GLNz, LGZE	ZLN, HGZE, WVGLZ_S	SZE, LZE, SZLGE, SZHGE, LZLGE, LZHGE, WVGLZ_N	ZP
NGLDM	Entropy	SNE, NN, SM	LNE	
NGTDM		Coarseness, Busyness, Complexity, TS	Contrast	
				Busyness, Complexity, TS

J. Yan, *et al*. **Impact of Image Reconstruction Settings on Texture Features in 18F-FDG PET.** *J Nucl Med* 2015

Reproducibility/variability/robustness

TABLE 5

Impact of grid size on image features

	COV≤5%	5%<COV≤10%	10%<COV≤20%	COV>20%
SUV		SUVmean, SUVpeak	SUVmax	
FOS	Entropy		Kurtosis, Variance, COV, Energy	Skewness
GLCM	DE, IDM, IDMN	SA, SE	Autocorrelation, Entropy, ID, SOS, SV	Contrast, Correlation, CS, Dissimilarity, Energy, Homogeneity, MP, DV, IMC, DM, SDN
GLRLM	LGRE, HGRE			LRE, SRE, GLNr, RLN, RP, SRLGE, SRHGE , LRLGE ,LRHGE
GLSZM	LGZE		SZE, LZE, LZLGE, HGZE, SZLGE, LZHGE	GLNz, ZLN, ZP, SZHGE, WVGLZ_N, WVGLZ_S
NGLDM			SNE	LNE, NN, SM, Entropy
NGTDM				Coarseness, Contrast, Busyness, Complexity, TS

J. Yan, *et al*. **Impact of Image Reconstruction Settings on Texture Features in 18F-FDG PET.** *J Nucl Med* 2015

Challenges

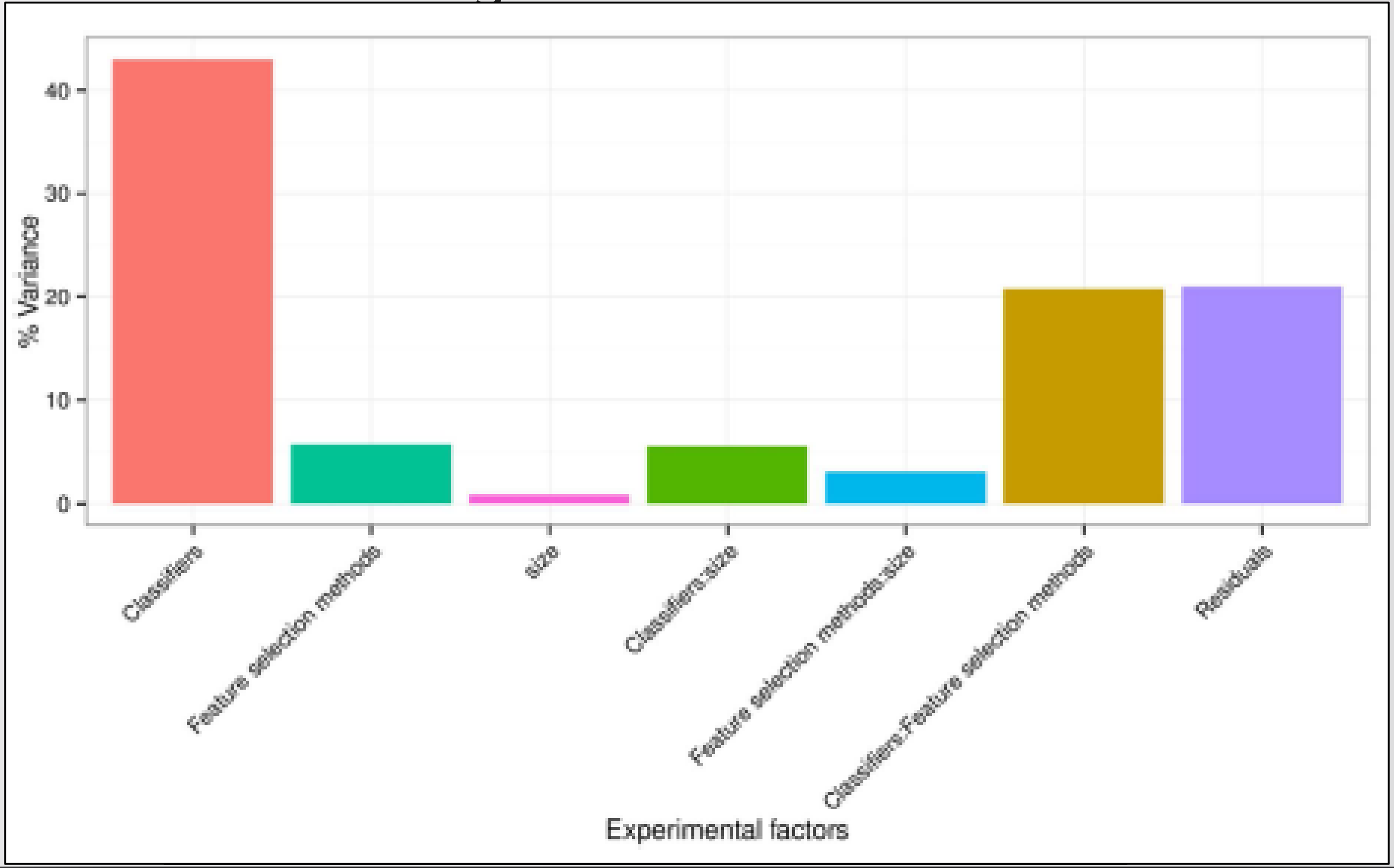
- Machine learning

Classification method acronym	Classification method name	Feature Selection method acronym	Feature selection method name
Nnet	Neural network	RELF	Relief
DT	Decision Tree	FSCR	Fisher score
BST	Boosting	GINI	Gini index
BY	Bayesian	CHSQ	Chi-square score
BAG	Bagging	JMI	Joint mutual information
RF	Random Forset	CIFE	Conditional infomax feature extraction
MARS	Multi adaptive regression splines	DISR	Double input symmetric relevance
SVM	Support vector machines	MIM	Mutual information maximization
DA	Discriminant analysis	CMIM	Conditional mutual information maximization
NN	Neirest neighbour	ICAP	Interaction capping
GLM	Generalized linear models	TSCR	T-test score
PLSR	Partial least squares and prinicipal componenet regression	MRMR	Minimum redundancy maximum relevance
—	—	MIFS	Mutual information feature selection
—	—	WLCX	Wilcoxon

C. Parmar, *et al*. **Machine Learning methods for Quantitative Radiomic Biomarkers**. *Sci Rep.* 2015

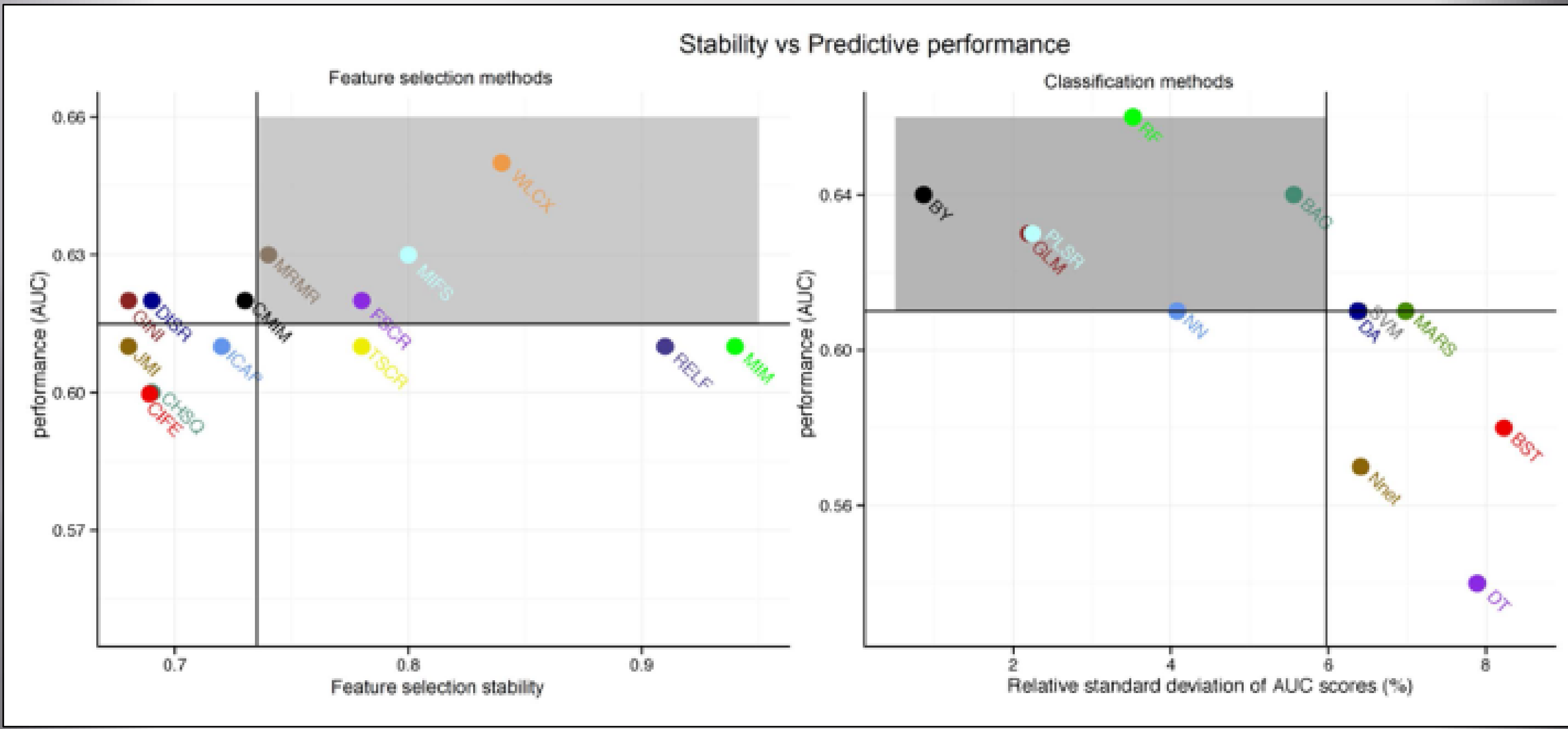
Challenges

- Machine learning



C. Parmar, *et al*. **Machine Learning methods for Quantitative Radiomic Biomarkers**. *Sci Rep.* 2015

Apprentissage automatique (machine learning)

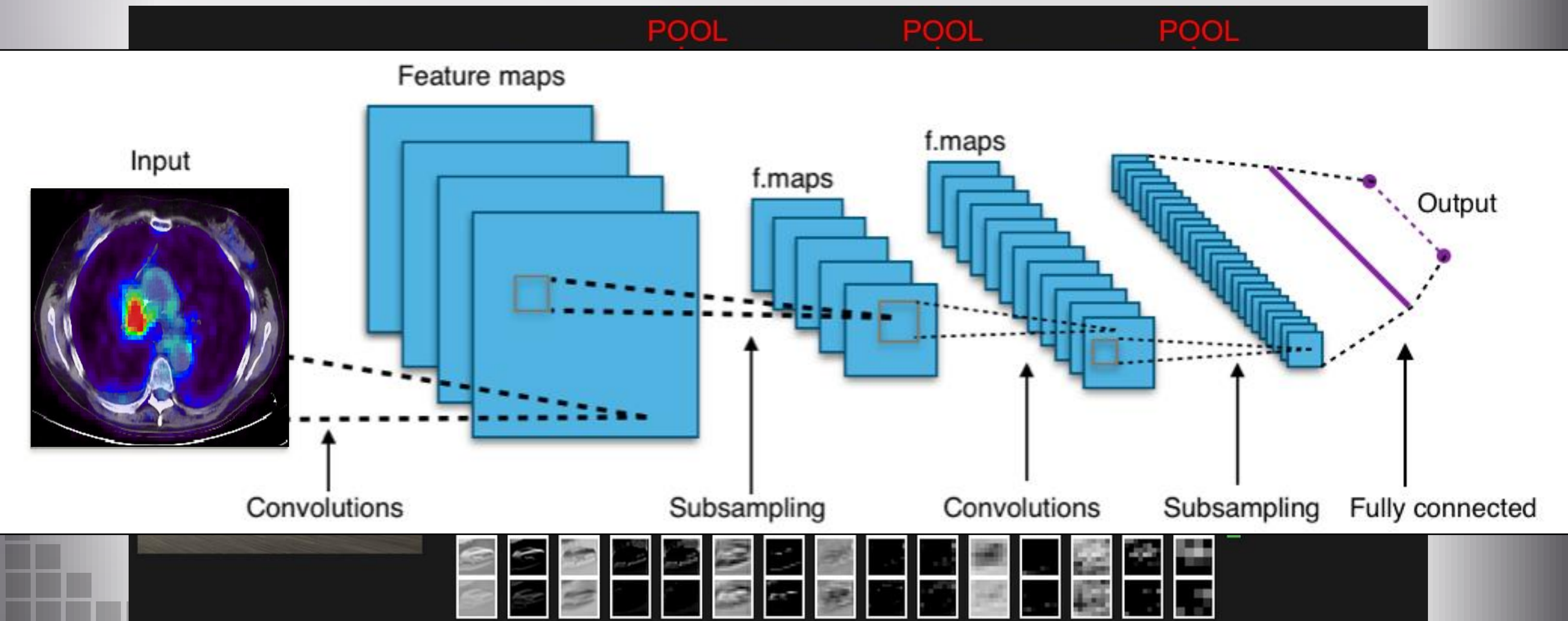


C. Parmar, *et al*. **Machine Learning methods for Quantitative Radiomic Biomarkers**. *Sci Rep.* 2015

Radiomique en TEP/TDM

Evolution future

- Apprentissage profond (deep learning)
  - Evolution récente des réseaux de neurones
  - Performances impressionnantes



Y. Lecun, *et al*. **Deep Learning**. *Nature.* 2015

Deep learning