

Automatic PET-based target delineation: Tentative state of the art

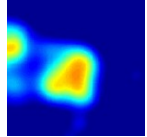
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Volumes cibles biologiques en Radiothérapie, Paris, December 2009.



PET-based target delineation

- Positron emission tomography:
 - Tracer → Isotope → Positron → Photons → Detectors → Sinogram
 - PET image = measurement of a statistical nature
- Typical procedure:
 - PET acquisition
 - PET reconstruction
 - PET delineation
 - PET / CT registration
- Aim: **accurate** delineation
- Main pitfall: the **low resolution** of PET images → 
- Delineation methodology:
 - Manual
 - PET alone (*blur → intra- & inter-observer variability?*)
 - PET/CT or PET/MR fusion (*bias introduced by anatomical modality?*)
 - Automatic
 - ...

Automatic delineation methods

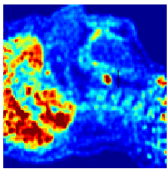
- State of the art to be looked for in
 - Literature
 - Radiation oncology (red/green journals)
 - Nuclear medicine
 - Medical physics
 - Engineering (IEEE journals, etc.)
 - **Many different approaches**
 - Numerous conferences, congresses, symposia, ...
- An exhaustive list of publications is almost impossible to establish
- There are also many
 - Methodological differences
 - Delineation algorithm
 - Validation data (simulated, phantom, or patient images)
 - Application contexts
 - Various PET systems, acquisition & reconstruction protocols
 - Several tumor sites and/or tracers
- There are only a few comparative studies with uniform experimental setup

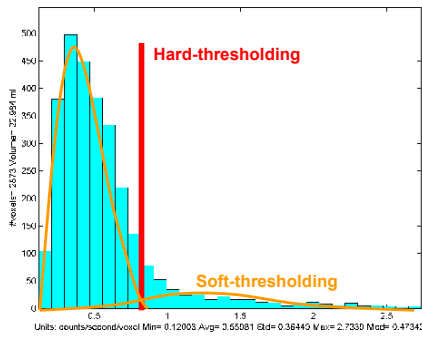
Automatic delineation methods

- Histogram-based
 - Threshold-based
 - Hard thresholding
 - Absolute
 - Relative
 - Soft thresholding
 - Probabilistic modeling (finite mixture of probability distributions)
 - Fuzzy clustering
- Feature-based
 - (Fuzzy) Clustering
 - Clustering of Time Activity Curves
- Image-based
 - Probabilistic modeling (Hidden Markov random fields)
 - Gradient based
 - Active contours, snakes, ...
 - Watersheds

Histogram-based approaches

- Principle:





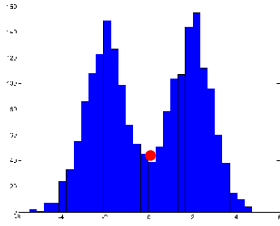
Units: counts/second/voxel Min= 0.12003 Avg= 0.65081 Std= 0.36440 Max= 2.7330 Mod= 0.47342

Directly fix a threshold value

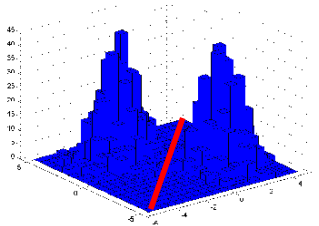
Fit a finite mixture of probability density functions and find Bayesian threshold

Feature-based approaches

- Histogram thresholding is difficult due to mode overlap and badly balanced modes
- Idea: use pixel values and additional 'features'



Pixel uptake ≈ single feature



Two features → reduced mode overlap

Feature-based approaches

- Features can be
 - Transformed pixel values (e.g. filtered values, wavelet components, ...)
 - can involve neighboring pixels
 - allows for taking into account the image structure
 - Time sequences in dynamic PET acquisitions (pixels have several values that are the features)

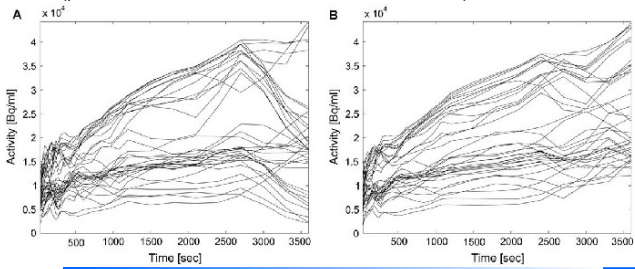
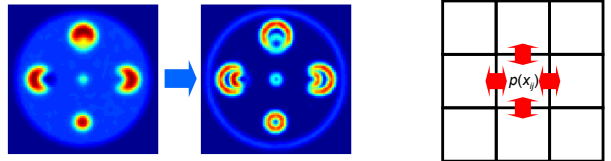
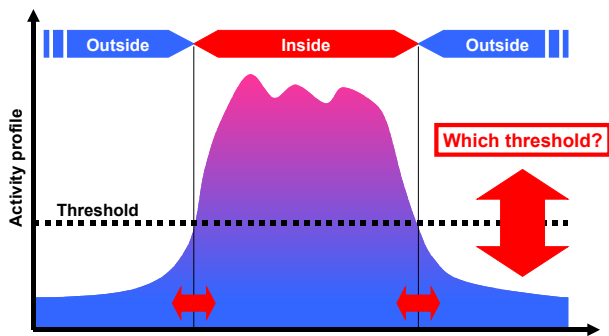


Image-based approaches

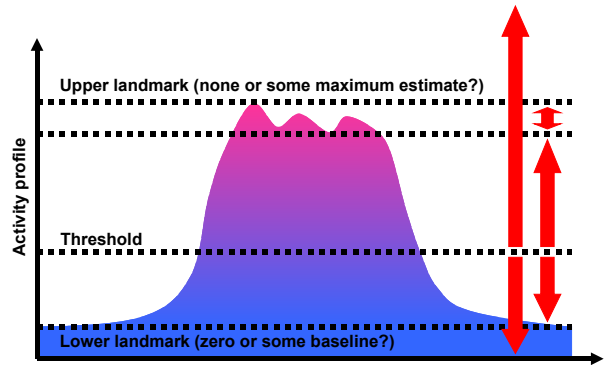
- Motivation
 - Histogram-based and feature-based methods do not (or not explicitly) take into account the image structure
 - Image-based approaches can model the idea that e.g. neighboring pixels are likely to belong to the same region
 - Allows a better control of the contour smoothness, volume connectedness, and similar properties
- Main idea: compare/combine adjacent pixels
- Examples:
 - Gradient & Laplacian operators (profile slope & curvature)
 - Hidden Markov Random Fields



Threshold-based segmentation



Threshold-based segmentation



Which threshold value?

- Examples found in the literature
 - Absolute: 2.5 SUV
 - Relative: ~40% of maximum
 - Adaptive: source-to-background ratio
 - Iterative: intersecting thr.-vol. & vol.-thr. curves
 - ...
- Usual methodology:
 - Calibration with phantom images
 - Validation with
 - Phantom images (often; truth is known!)
 - Patient images (seldom; truth is difficult to measure...)
- Alternative approach: mathematical model...
 - **take into account resolution blur**

Mathematical model

- Work hypotheses (~ Jaszczak phantom)
 - Spherical objects
 - Uniform uptakes in target and background
 - Thin plexiglas wall
 - Resolution is constant in the field of view, with a PSF that is Gaussian and isotropic
- Analytically convolve a sharp image with the PSF...

Using polar coordinates in the x_2 plane leads to:

$$\begin{aligned}
 f_{Bl}(v) &= \int_{-\pi}^{\pi} \int_{-\sigma\sqrt{2}}^{\sigma\sqrt{2}} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(z-u)^2}{2\sigma^2}\right) \int_{-\pi}^{\pi} \int_0^{R_2} \frac{1}{2\pi\sigma^2} \exp\left(-\frac{r^2}{2\sigma^2}\right) r dr d\theta dz \\
 &= \int_{-\pi}^{\pi} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(z-u)^2}{2\sigma^2}\right) \int_{-\pi}^{\pi} d\theta \int_0^{R_2} \frac{1}{2\pi\sigma^2} \exp\left(-\frac{r^2}{2\sigma^2}\right) r dr dz \\
 &= \int_{-\pi}^{\pi} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(z-u)^2}{2\sigma^2}\right) 2\pi \left[-\frac{1}{2\pi} \exp\left(-\frac{r^2}{2\sigma^2}\right)\right]_0^{R_2} dz \\
 &= \int_{-\pi}^{\pi} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(z-u)^2}{2\sigma^2}\right) \left(1 - \exp\left(-\frac{R_2^2}{2\sigma^2}\right)\right) dz \\
 &= \left[\frac{1}{2} \left(1 + \operatorname{erf}\left(\frac{z-u}{\sigma\sqrt{2}}\right)\right)\right]_{-\pi}^{\pi} \int_{-\pi}^{\pi} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(z-u)^2}{2\sigma^2}\right) dz
 \end{aligned}$$

Mathematical model

The screenshot shows a software interface with a heatmap on the left and two graphs on the right. The heatmap is a circular activity distribution. The 'Sphere profile' graph shows a step-like activity profile. The bottom graph shows relative threshold curves for different parameters.

Mathematical model

- Mathematical analysis says:
 - If**
 - Point-spread function is isotropic
 - Target is spherical
 - Target activity is uniform
 - Background activity is uniform
 - Then**
 - Target contours can be 'exactly' recovered
 - Threshold must be relative to
 - Background activity
 - Maximum target activity
 - Threshold depends on ratio (target_radius/FWHM) → **The problem turns out to be circular!**
 - Otherwise**
 - Contours cannot be accurately recovered with a *single* threshold per target
- Conclusions are already bad in a *simplistic* case
- No need to come up with *real* cases...

Mathematical model

- Sphere wall thickness is not negligible
 - **Threshold calibration with phantoms leads to overestimating tumor volumes**
- Optimal threshold and radius depend on each other
 - **Circularity is broken only with an iterative approach (convergence for non-spherical objects?)**

The graph plots 'optimal RTL' on the y-axis (0% to 90%) against 'sphere diameter, D [mm]' on the x-axis (0 to 100). It shows two curves: 'no wall' (blue) and 'wall thickness = 1mm' (orange), with 'phantom data' points (black dots). Both curves show a sharp drop in RTL as diameter increases from 0 to about 20mm, then level off.

Interest of gradient information

The grid shows 'Raw image' and 'Grad. Int. image' for three different 'Image saturation (window level)' settings. The 'Grad. Int. image' shows sharp boundaries that are independent of the saturation level, unlike the raw images which become more blurred and saturated.

Boundaries do not move for gradient!

Gradient-based segmentation

The graph shows a 'Gradient intensity of Activity profile' on the y-axis. The profile has a central peak labeled 'Inside' and two side peaks labeled 'Crest detection'. The regions are labeled 'Outside' on the left and right. A vertical double-headed arrow indicates 'Steep' (up) and 'Flat' (down) regions.

Gradient-based segmentation

- Naive approach:
 - Smooth image to attenuate noise
 - Apply gradient intensity operator and determine crest

The flowchart shows the process: 'Smoothed image' → 'Gradient image' (via 'Grad. Int.' operator) → 'Crest' → 'True volumes'. A red box notes 'Blur remains an issue!' and a green box notes 'Gradient-based segmentation'.

Gradient-based segmentation

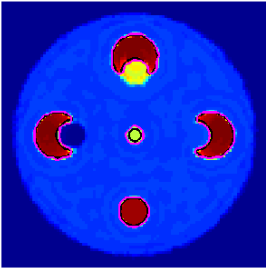
- Principled approach:
 - Reverse PET model
 - Determine gradient crest

~~C Gaussian smoothing~~
Blur!

Bilateral filter

~~Iterative deconvolution~~
Artefacts!

Constrained iterative deconvolution



Deblurring

PSF

Blurred image

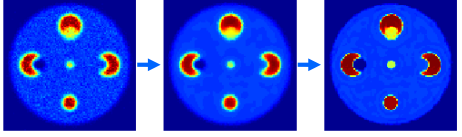
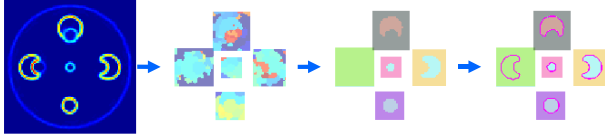
Noise

Real image

Gradient-based PET segmentation

- Image processing
 - Denoising (edge-preserving filter)
 - Bilateral filter for Poisson noise
 - Denoise without smoothing edges
 - Deblurring (edge enhancement)
 - Iterative deconvolution to roll back PSF-induced blur
 - Min & Max local constraints prevents ringing artifacts
- Gradient-based segmentation
 - Gradient-intensity image (\approx derivative)
 - Plains & Plateaus \rightarrow Mountain chains & Valleys
 - Crest detection (Watershed Transform)
 - Detect mountain crests \rightarrow Compute watersheds
 - Practically: flooding simulation
 - Cluster analysis (hierarchical Ward's clustering)

Gradient-based PET segmentation

- Image processing
 
- Gradient-based segmentation
 

Methodological issues

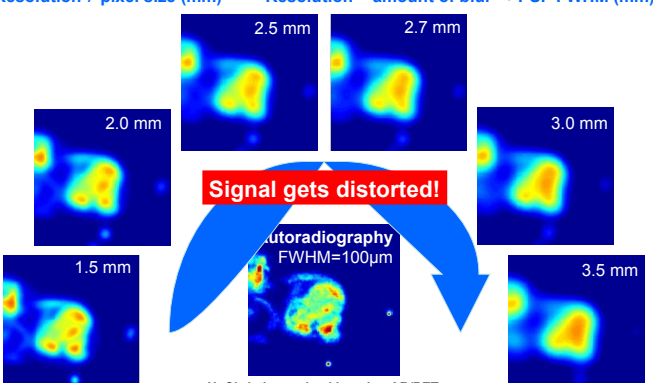
- Experimental conditions are too different
 - Acquisition hardware
 - Reconstruction software
 - Segmentation technique
 - Specific patient / disease sets
- Validation sets are
 - Too small and difficult to build (**ground truth is difficult to observe**)
 - Rarely exchanged
- There are too many empirical studies:
 - Pick a random segmentation method
 - Adjust its parameters with some data
 - evidence-based strategies are effective in medicine, not in engineering**
- Key questions are often neglected
 - How can we model the shortcomings of PET images?
 - How can we compensate for them with delineation in mind?
 - What is the best attainable accuracy?

Methodological issues

- PET segmentation is complex because multidisciplinary (dialog between physicists/engineers/physicians is tedious) (learning curves are rather flat)
- There is a tendency toward YAPETISM (Yet Another PET Image Segmentation Method)
 - It is easier and fancier to design new methods
 - This is more cost-effective in terms of publications
 - Analogy with a regression problem:
 - Learn Y as a function of X with some regression model
 - If the model is complex enough, if the learning and validation sets are small and similar, then some parameter tuning suffices to obtain good results
 - But generalization to other data sets will be poor
- The quality of PET images is low
 - Automatic PET delineation is a difficult problem
 - Can we circumvent the problem with dose painting?
 - No! Resolution remains an issue...**

Resolution blur: illustration

Resolution \neq pixel size (mm) Resolution = amount of blur \rightarrow PSF FWHM (mm)



N. Christian: animal imaging AR/PET

Conclusions

- Resolution is the main bottleneck of PET-based for target delineation
- Threshold-based segmentation
 - Relies on questionable assumptions
 - Uniform background and target
 - Spherical target
 - Is intrinsically inaccurate (except in unrealistic conditions)
- Other segmentation paradigms
 - Can handle more complex cases
 - But still critically depends on careful image reconstruction and processing
- Candidate take-home messages
 - Target delineation ≠ target detection ≠ quantification !
 - PET-based target delineation is a difficult problem with
 - No simple solution
 - Specific requirements w.r.t. acquisition & reconstruction
 - Develop your acquisition and reconstruction protocols hand-in-hand with the nuclear medicine department
 - Pick a segmentation method that accounts for the shortcomings of PET (resolution, noise) in a simple and principled way

Literature

- Key paper
 - **Partial-Volume Effect in PET Tumor Imaging**
M. Soret, S.L. Bacharach, and I. Buvat
JNM 48 (9): 522, (2007)
- Comparison papers
 - **Comparison of Different Methods for Delineation of 18F-FDG PET-Positive Tissue for Target Volume Definition in Radiotherapy of Patients with Non-Small Cell Lung Cancer**
U. Nestle, S. Kramp, A. Schaefer-Schuler, Ch. Sebastian-Welsch, D. Hellwig, Ch. Rube, and C.-M. Kirsch
JNM 46 (9): 1342, (2005)
 - **Comparison of five segmentation tools for 18F-fluoro-deoxy-glucose-positron emission tomography-based target volume definition in head and neck cancer**
D.A. Schniag, W.V. Vogel, A.L. Hoffmann, J.A. van Dalen, W.J. Oyen, J.H. Kaanders
Int J Radiat Oncol Biol Phys 69: 1282, (2007)
 - **Assessment of various strategies for 18F-PET PET-guided delineation of target volumes in high-grade glioma patients**
H. Vees, S. Sierthamschelvan, R. Miralbell, D.C. Weber, O. Raab, and H. Zaid
Eur J Nucl Med Mol Imaging 36: 182, (2009)
- Iterative thresholding
 - **Iterative threshold segmentation for PET target volume delineation**
L. Drever, W. Rog, A. McEwan, and D. Robinson
Med Phys 34: 1253, (2007)
 - **Development of a generic thresholding algorithm for the delineation of 18FDG-PET-positive tissue: application to the comparison of three thresholding models**
S. Vascini, K. Doreux, S. Hagegey, A. Edel-Sanson, P. Vera, and I. Gardin
Phys Med Biol 54 5901, (2009)
 - **Segmentation of PET volumes by iterative image thresholding**
W. Gunter, L. Freudenberg, E.G. Essing, M. Heinze, W. Brandau, and A. Bockisch
JNM 48: 108, (2007)
 - **A novel iterative method for lesion delineation and volumetric quantification with FDG PET**
J.A. van Dalen, A.L. Hoffmann, V. Dicken, W.V. Vogel, B. Wiering, T.J. Ruers, N. Karssenmeijer, and W.J.G. Oyen
Nucl Med Comm 28: 485, (2007)
- Gradient-based segmentation
 - **A gradient-based method for segmenting FDG-PET images: methodology and validation**
X. Geets, J.A. Lee, A. Bol, M. Lonneux, and V. Gregoire
Eur J Nucl Med Mol Imaging 34: 1427, (2007)

Thank you for your attention!

If you have any question...

Resolution: convolution

- Abstract mathematical operation (close to 'times')
- How it can model resolution blur:
 - (blurred image) = (sharp image) * PSF
 - Convolution:
 - Decompose the neat image into a sum of point sources
 - Spread each source (replace each source with the scaled PSF)
 - Sum everything back to obtain the blurred image
 - Dual interpretation: weighted average of neighbors

Resolution: convolution

Resolution blur *distorts* the image:
curved edges and region boundaries look displaced!
 Segmentation will be problematic...