ACCURATE EXTRACTION OF TISSUE PARAMETERS FOR MONTE CARLO SIMULATIONS USING MULTI-ENERGY CT

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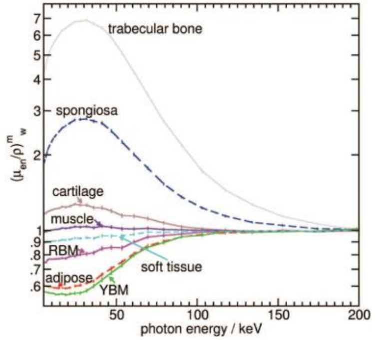
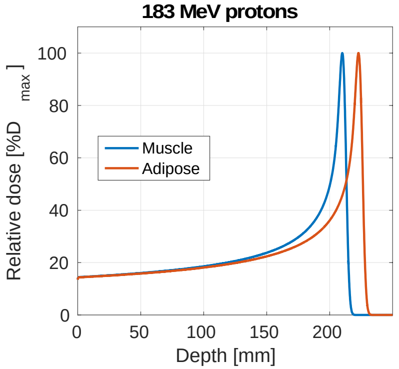
THE IMPORTANCE OF MC IN RT

Monte Carlo **(MC)** simulations offer many advantages over conventional algorithms for dose calculation:

- In **brachytherapy**, dose deposition depends strongly on **Z** due to the dominance of **photoelectric** effect at low photon energies.
- In **particle therapy**, accurate beam **range calculation** is critical for optimal planning and patient safety.





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PATIENT GEOMETRY TO MC INPUTS

- One of the key steps in the preparation of a MC simulation is the creation of the patient geometry, including the assignment of material composition in each voxel.
  - Complete elemental composition and mass density is necessary to calculate the exact cross sections for all interactions considered.

- Great attention must be paid to this step as it influences all results generated by the simulation: *« Rubbish in, Rubbish out ».*

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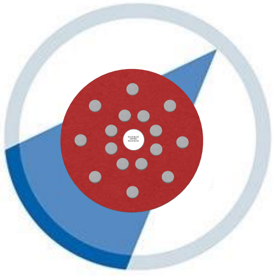
THE SCHNEIDER METHOD

To extract MC inputs from single energy CT (SECT) data, the gold standard is the method of Schneider et al. (2000). The CT is calibrated to construct a segmented look-up table (LUT) that links every possible HU to a certain set of MC inputs.



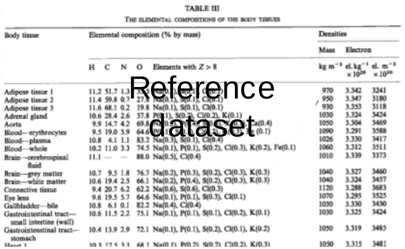
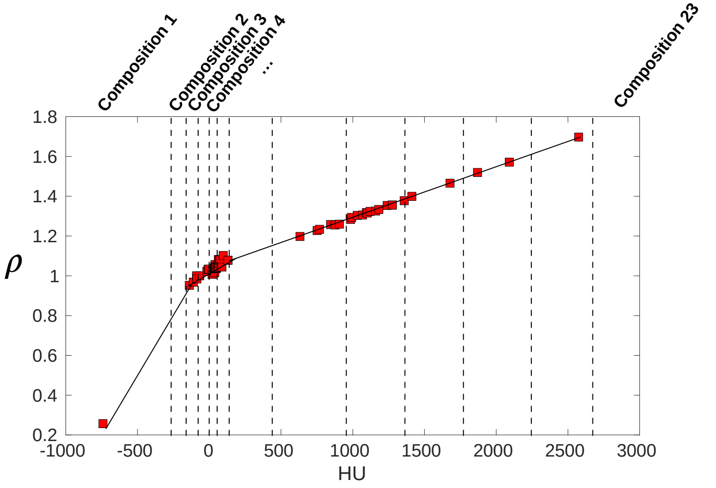


TABLE III
THE ELEMENTAL COMPOSITIONS OF THE BODY TISSUES

Body tissue	Elemental composition (% by mass)					Densities		
						Mass	Electron	
	H	C	N	O	Elements with $Z > 8$	kg m^{-3}	el. kg^{-1} $\times 10^{26}$	el. m^{-3} $\times 10^{26}$
Adipose tissue 1	11.2	51.7	1.3	[illegible]	[illegible]	970	3.342	3241
Adipose tissue 2	11.4	59.8	0.7	27.8	Na(0.1), S(0.1), Cl(0.1)	950	3.347	3180
Adipose tissue 3	11.6	68.1	0.2	19.8	Na(0.1), S(0.1), Cl(0.1)	930	3.353	3118
Adrenal gland	10.6	28.4	2.6	57.8	P(0.1), S(0.2), Cl(0.2), K(0.1)	1030	3.324	3424
Aorta	9.9	14.7	4.2	69.8	[illegible] Ca(0.4)	1050	3.304	3469
Blood—erythrocytes	9.5	19.0	5.9	64.6	[illegible] Fe (0.1)	1090	3.291	3588
Blood—plasma	10.8	4.1	1.1	83.2	Na(0.3), S(0.1), Cl(0.4)	1026	3.330	3417
Blood—whole	10.2	11.0	3.3	74.5	Na(0.1), P(0.1), S(0.2), Cl(0.3), K(0.2), Fe(0.1)	1060	3.312	3511
Brain—cerebrospinal fluid	11.1	—	—	88.0	Na(0.5), Cl(0.4)	1010	3.339	3373
Brain—grey matter	10.7	9.5	1.8	76.7	Na(0.2), P(0.3), S(0.2), Cl(0.3), K(0.3)	1040	3.327	3460
Brain—white matter	10.6	19.4	2.5	66.1	Na(0.2), P(0.4), S(0.2), Cl(0.3), K(0.3)	1040	3.324	3457
Connective tissue	9.4	20.7	6.2	62.2	Na(0.6), S(0.6), Cl(0.3)	1120	3.288	3683
Eye lens	9.6	19.5	5.7	64.6	Na(0.1), P(0.1), S(0.3), Cl(0.1)	1070	3.295	3525
Gallbladder—bile	10.8	6.1	0.1	82.2	Na(0.4), Cl(0.4)	1030	3.330	3430
Gastrointestinal tract—small intestine (wall)	10.6	11.5	2.2	75.1	Na(0.1), P(0.1), S(0.1), Cl(0.2), K(0.1)	1030	3.325	3424
Gastrointenstinal tract—stomach	10.4	13.9	2.9	72.1	Na(0.1), P(0.1), S(0.2), Cl(0.1), K(0.2)	1050	3.319	3485
Heart 1	10.3	17.5	3.1	68.1	Na(0.1), P(0.2), S(0.2), Cl(0.2), K(0.3)	1050	3.315	3481



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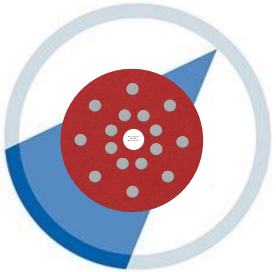

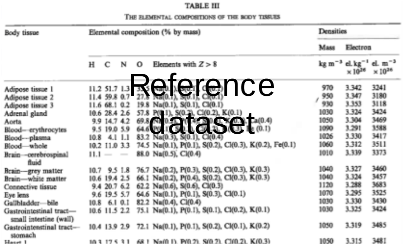

Reference dataset

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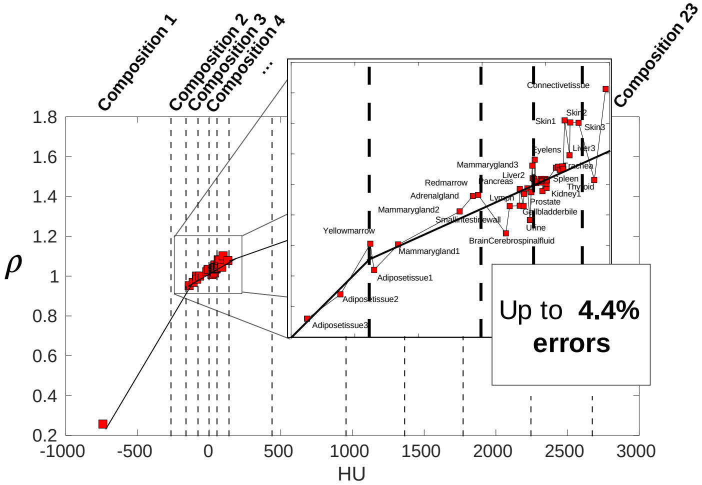

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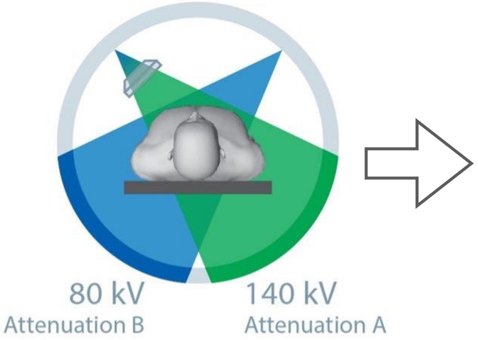
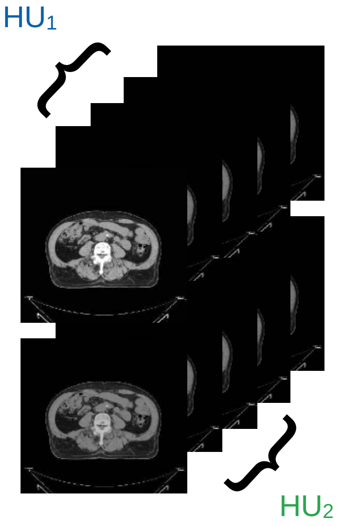
DUAL AND MULTI-ENERGY CT

- With dual- or multi-energy CT, empirical LUT are obsolete, as more information can be extracted directly from MECT data

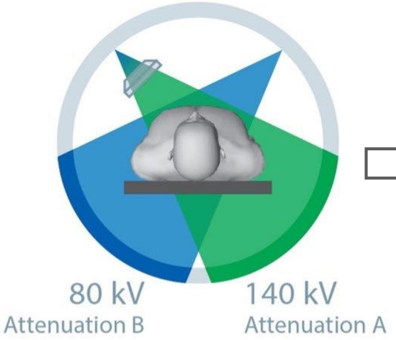


http://www.healthcare.siemens.com/.



DUAL AND MULTI-ENERGY CT

- With dual- or multi-energy CT, empirical LUT are obsolete, as more information can be extracted directly from MECT data
  - Still not enough information to derive directly MC inputs
- How can we use optimally the added information to improve the quality of MC inputs?



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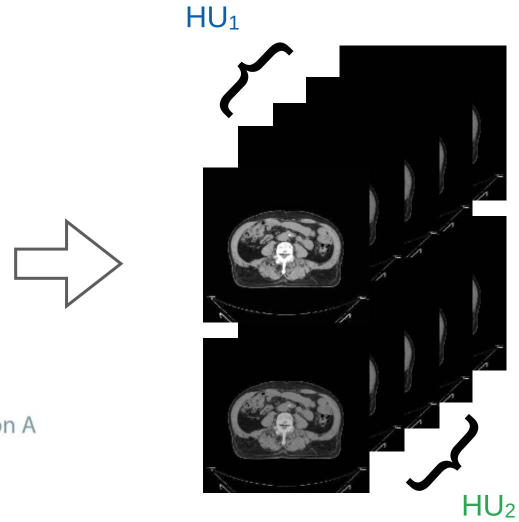

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CT DATA TO MONTE CARLO INPUTS

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  - Tissue characterization for Monte Carlo dose calculation from CT data is an underdetermined problem

- We propose to use principal component analysis (PCA) on reference dataset to extract a new basis of variables that can describe human tissues composition more efficiently by reducing the dimensionality of the problem.
  - We call these variables Eigentissues (ET)

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EIGENTISSUE REPRESENTATION OF HUMAN BODY

- All information relevant for dose calculation can be stocked in a vector of partial electron densities:

Density of electrons

Fraction of electrons of element *M* in the tissue

$$\mathrm{x} = \rho_e \, [\lambda_1 \ \lambda_2 \ \dots \ \lambda_M]$$

$$= [x_1 \ x_2 \ \dots \ x_M]$$

- The ET representation consists of a linear transformation of x:

$$\mathrm{x} = y_1 \cdot \mathrm{ET}_1 + y_2 \cdot \mathrm{ET}_2 + \dots + y_M \cdot \mathrm{ET}_M$$

Vector of the partial densities in the M^{th} eigentissue

THE GENERAL IDEA OF PCA

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THE GENERAL IDEA OF PCA

Original image

R | R+G | R+G+B

PC1 | PC1+PC2 | PC1+PC2+PC3

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THE GENERAL IDEA OF PCA

- For human tissues, the **colours** are the **elements**, and the **principal components** are the **eigentissues**.

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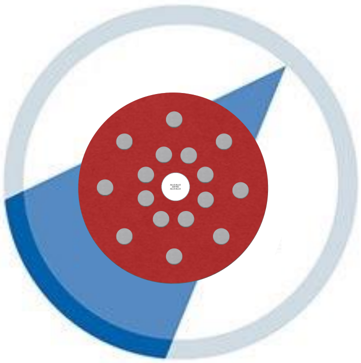
APPLYING PCA TO HUMAN TISSUES

- Human tissues are composed of a limited number of elements. Including trace elements, only 13 different chemical components are reported in the literature.
- Also, the weight fraction of these elements is often strongly correlated (ex: P & Ca) or anticorrelated (ex: C & O).
- The eigentissues allow to characterize human tissues with less than 13 variables without losing much accuracy.

ADAPTATION TO CT DATA

- Using a suitable stoichiometric calibration, the photon attenuation of each ET can be estimated for any spectrum or imaging protocol.



$$\rightarrow \mu(E_i, x) \approx f\left(k_1^{(i)}, k_2^{(i)}, \ldots\right) \rightarrow \begin{array}{c} \hat{\mu}(E_i, \mathrm{ET}_1) \\ \hat{\mu}(E_i, \mathrm{ET}_2) \\ \vdots \\ \hat{\mu}(E_i, \mathrm{ET}_M) \end{array}$$

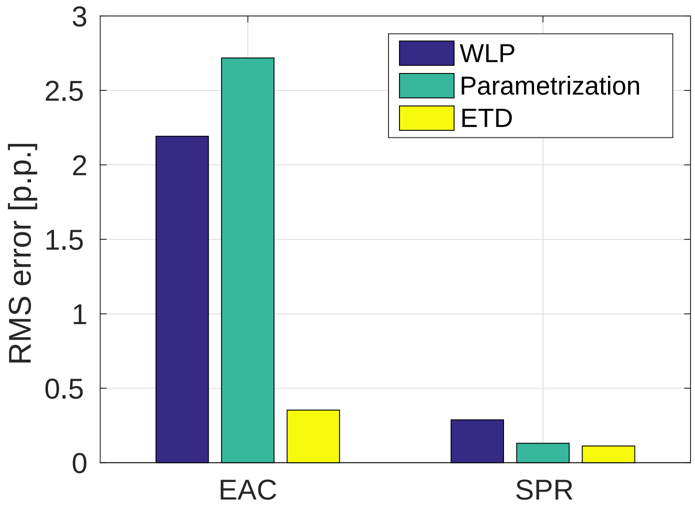
ADAPTATION TO CT DATA

- Once their attenuation coefficient is estimated, the ETs are treated as virtual materials.
- If K information is available (i.e. K energies), decomposition is performed to extract the fraction of the K more meaningful ETs in each voxel.

$$\begin{pmatrix} \hat{y}_1 \\ \vdots \\ \hat{y}_k \end{pmatrix} \equiv \begin{pmatrix} \hat{\mu}(E_1, \mathrm{ET}_1) & \dots & \hat{\mu}(E_K, \mathrm{ET}_1) \\ \vdots & \ddots & \vdots \\ \hat{\mu}(E_1, \mathrm{ET}_K) & \dots & \hat{\mu}(E_K, \mathrm{ET}_K) \end{pmatrix}^{-1} \begin{pmatrix} \mu(E_1) \\ \vdots \\ \mu(E_K) \end{pmatrix}$$

APPLICATION TO DECT: BENCHMARKING WITH OTHER METHODS

- Comparison with two recently published methods for the characterization of 43 reference soft tissues using DECT:
  - Water-Lipid-Protein (WLP) decomposition (Malusek *et al.* 2013)
  - Parameterization (Hünemohr *et al.* 2014)
- Simulated HU for 80 kVp and 140/Sn kVp spectra of the SOMATOM Definition Flash DSCT



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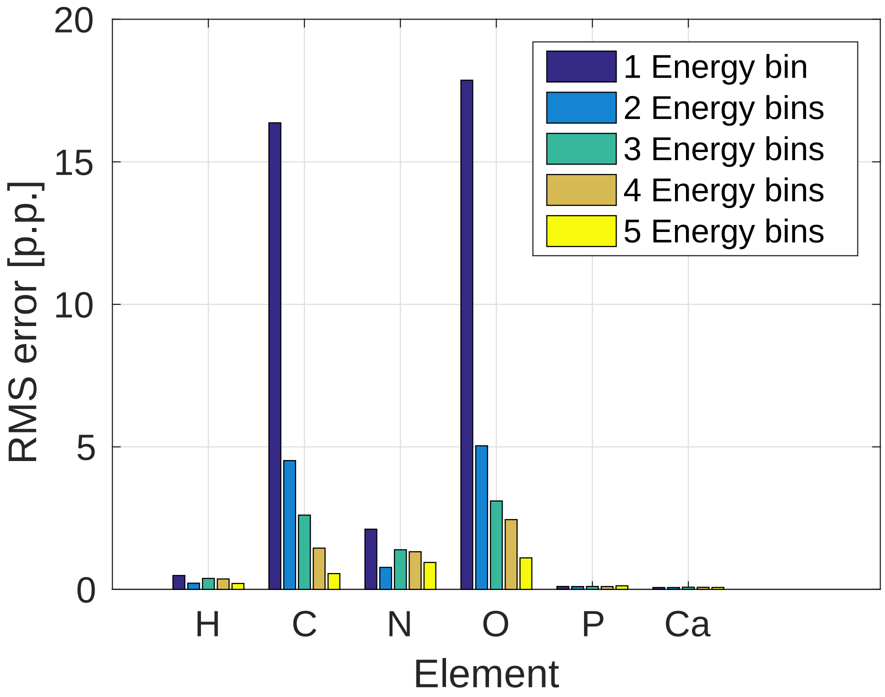
POTENTIAL EXTENSION TO MECT

- Separating a 140 kVp spectrum in five energy bins, the method shows improvement in extracting elemental weights with more than two information.



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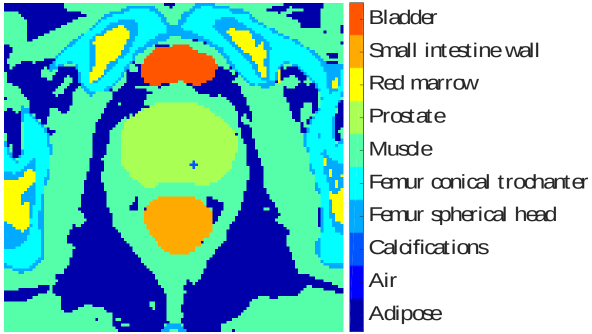
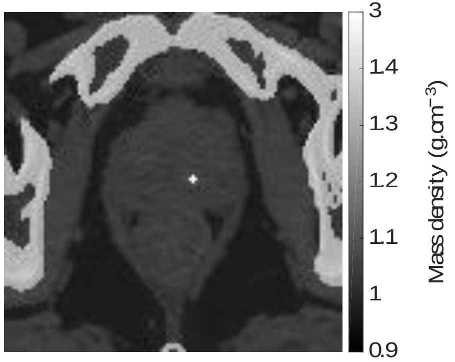
VALIDATION OF ETD ON PATIENT GEOMETRY

- A virtual patient generated from real anatomical data is used as ground truth for MC dose calculation
  - A reference tissue with known composition is assign to each voxel, while the density is allowed to vary.
  - SECT and DECT images are simulated using Matlab
  - Dose calculation is performed using the EGSnrc user-code BrachyDose for Brachytherapy and TOPAS for proton therapy





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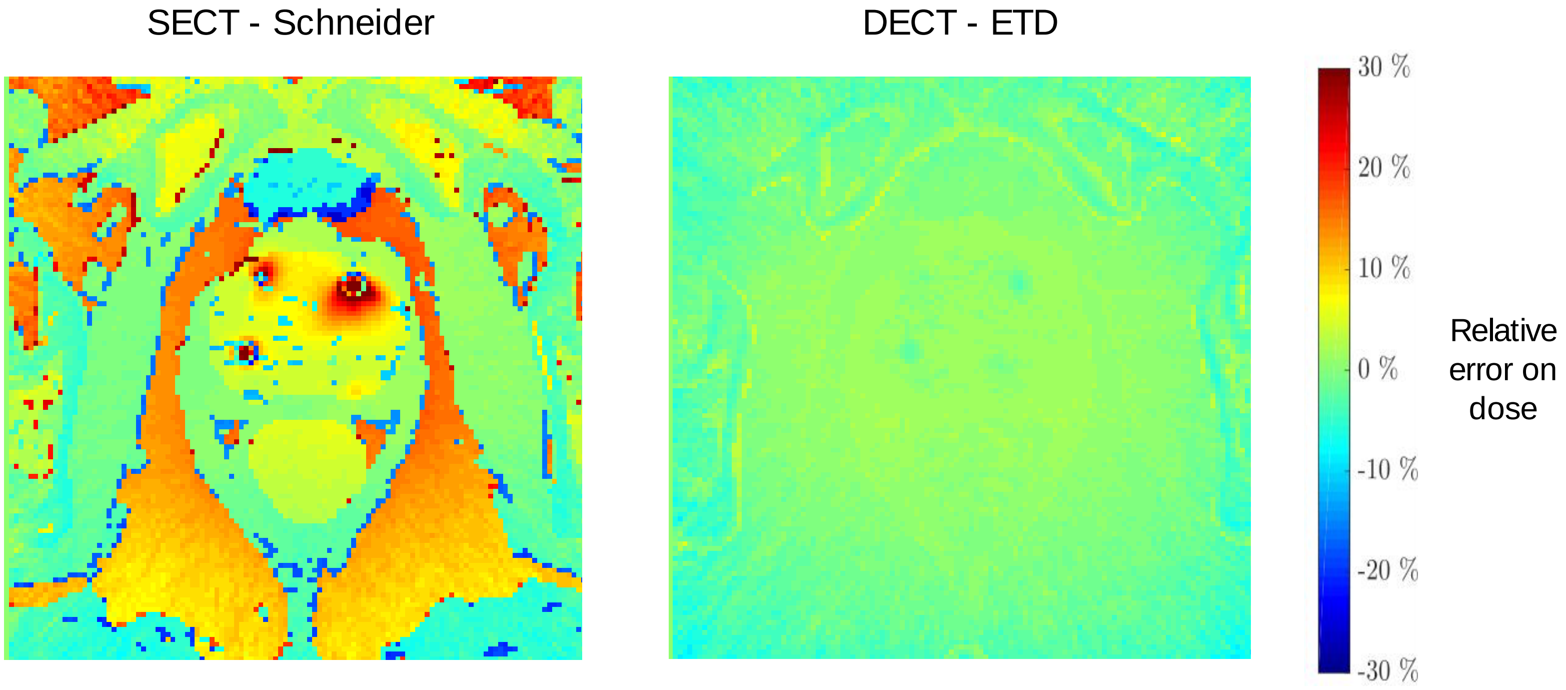
ETD FOR BRACHYTHERAPY: RESULTS



See Poster #144 - Remy *et al.*

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ETD FOR PROTON THERAPY: RESULTS

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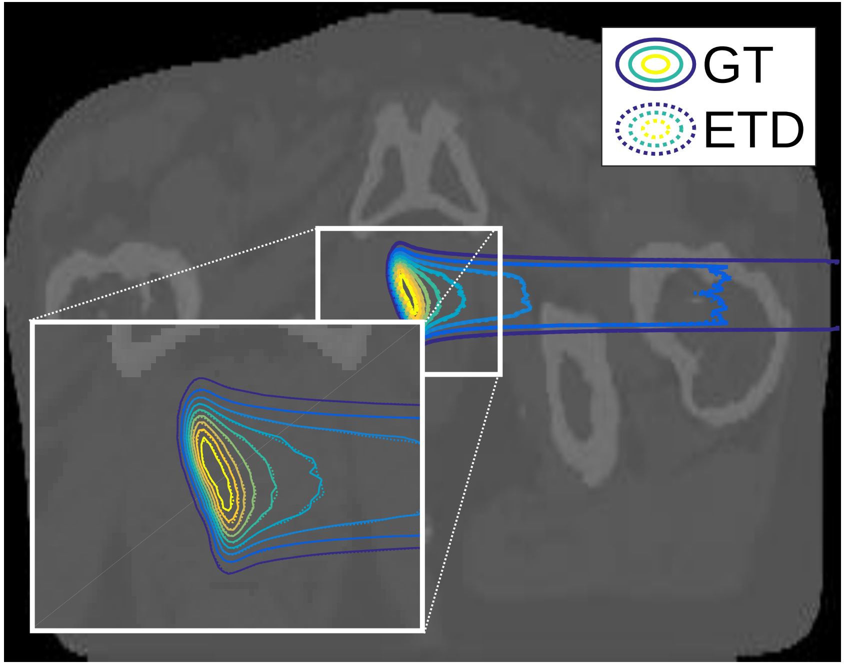

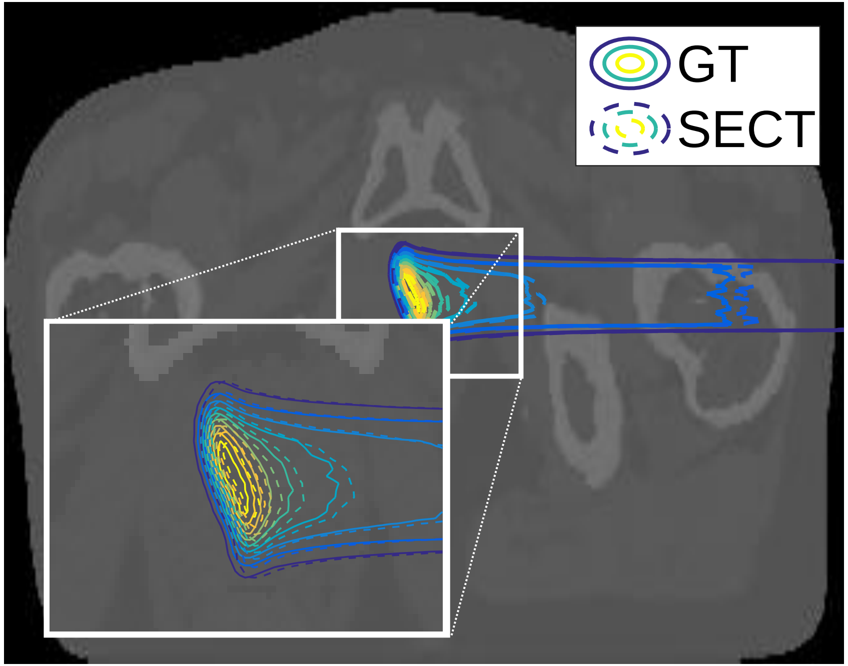

Range error up to 1.5 mm using SECT

CONCLUSION

- Eigentissues representation of human body composition minimizes the number of parameters needed for accurate characterization
- Adapting this representation to material decomposition of CT data allows extracting high quality Monte Carlo inputs from only few measurements
- The method is accurate and versatile:
  - Not limited to only two parameters (EAN and ED)
  - Valid through the whole range of X-ray energies (e.g. kV and MV)
  - More accurate dose calculation for both low-kV photons and protons than the gold-standard SECT approach
- Associated Publications:
  - A. Lalonde and H. Bouchard (2016), *A general method to derive tissue parameters for Monte Carlo dose calculation with dual- and multi-energy CT*, Phys. Med. Biol.
  - A. Lalonde, E. Bär and H. Bouchard (2017). *A Bayesian approach to solve proton stopping powers from noisy multi-energy CT data,* Med. Phys.

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- Mikaël Simard

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CHUM Centre hospitalier de l'Université de Montréal

Santé et Services sociaux Québec

NPL National Physical Laboratory