



ACCURATE MONTE CARLO INPUTS FOR DOSE CALCULATION USING MULTI-ENERGY CT

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THE IMPORTANCE OF MC IN PROTON THERAPY

- For proton therapy applications, **Monte Carlo** (MC) techniques have many **advantages** over commercial algorithms:
 - Enhanced sensitivity to **complex geometries** and in-beam **density variations**,
 - Ability to report **dose** to **medium**,
 - Calculation of **LET distributions**,

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- Estimation of **neutron dose** levels,
- Prediction of post-radiation **PET activity** for *in-vivo* range verification.



Paganetti et al. 2008 Phys. Med. Biol.

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PATIENT GEOMETRY TO MC INPUTS

- material composition in each voxel.

generated by the simulation: « Rubbish in, Rubbish out ».



• One of the **key steps** in the preparation of a MC simulation is the creation of the patient **geometry**, including the assignation of

 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

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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	Elen	ion (% by mass)	Der					
	Н	С	N	0	Elements with $Z > 8$	kg		
Adipose tissue 1	11.2	51.7	1.3	35.5	eterence	97		
Adipose tissue 2	11.4	59.8	0.7	27.8	Na(0.1), S(0.1), Cl(0.1)	, 95		
Adipose tissue 3	11.6	68.1	0.2	19.8	Na(0.1), S(0.1), Cl(0.1)	93		
Adrenal gland	10.6	28.4	2.6	57.8	P(0.1), S(0.2), Cl(0.2), K(0.1)	103		
Aorta	9.9	14.7	4.2	69.8	$Na0.2$, $P(T4)$, $S0.0$, $K_0.3$, $Ca(0.4)$	105		
Blood-erythrocytes	9.5	19.0	5.9	64.6		109		
Blood-plasma	10.8	4.1	1.1	83.2	Na(0.3), S(0.1), Cl(0.4)	102		
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)	106		
Brain-cerebrospinal fluid	11.1			88.0	Na(0.5), Cl(0.4)	101		
Braingrey matter	10.7	9.5	1.8	76.7	Na(0.2), P(0.3), S(0.2), Cl(0.3), K(0.3)	104		
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)	104		
Connective tissue	9.4	20.7	6.2	62.2	Na(0.6), S(0.6), Cl(0.3)	112		
Eye lens	9.6	19.5	5.7	64.6	Na(0.1), P(0.1), S(0.3), Cl(0.1)	107		
Gallbladder-bile	10.8	6.1	0.1	82.2	Na(0.4), Cl(0.4)	103		
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)	103		
Gastrointenstinal tract-	10.4	13.9	2.9	72.1	Na(0.1), P(0.1), S(0.2), Cl(0.1), K(0.2)	105		
Heart 1	10.3	175	31	68 1	Na(0.1), P(0.2), S(0.2), Cl(0.2), K(0.3)	105		







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DUAL AND MULTI-ENERGY CT

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HU₁





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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CT DATA TO MONTE CARLO INPUTS

- We want to extract full atomic composition and mass density, but we have only limited information (# of energies) per voxel.
 - <u>Tissue characterization for Monte Carlo dose calculation from CT data is an</u> <u>underdetermined problem</u>





CT DATA TO MONTE CARLO INPUTS

- We want to extract full atomic composition and mass density, but we have only limited information (# of energies) per voxel.
 - <u>Tissue characterization for Monte Carlo dose calculation from CT data is an</u> <u>underdetermined problem</u>
- 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)





EIGENTISSUE REPRESENTATION OF HUMAN BODY

vector of partial electron densities:

Density of electrons

$$\mathbf{x} = \hat{\rho}_{e} [\lambda = [x_{1}]$$

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

 $\mathbf{x} = y_1 \cdot \mathbf{ET}_1 + y_2 \cdot$



All information relevant for dose calculation can be stocked in a

Fraction of electrons of element *M* in the tissue

- $\lambda_1 \ \lambda_2 \ \dots \ \lambda_M$
- $\begin{bmatrix} x_1 & x_2 & \dots & x_M \end{bmatrix}$

$$\mathbf{ET}_2 + \ldots + y_M \cdot \mathbf{ET}_M$$

Vector of the partial densities in the *M*th eigentissue





EIGENTISSUE REPRESENTATION OF HUMAN BODY

 The ET are orthogonal vectors directed in the direction where there is the highest variance within the dataset.

- They are sorted in a way that the variance of their respective y_i
 decreases rapidly as *i* increases.
 - A given tissue can be **accurately** characterized using only **few** y_i:
 - $\mathbf{x} \simeq y_1 \cdot \mathbf{ET}_1 + y_2 \cdot \mathbf{ET}_2 + \overline{y_3} \cdot \mathbf{ET}_3 \dots + \overline{y_M} \cdot \mathbf{ET}_M$





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.





SELF-CONSISTENCY OF THE METHOD

- accurate range prediction
 - Mono-energetic proton beam of 183 MeV/u
 - Dose to medium scored in 0.1 mm slices
 - 250 000 histories per run



We tested the method in the context of Monte Carlo simulations using TOPAS to determine **how many** ETs are necessary to allow





SELF-CONSISTENCY OF THE METHOD

 Monte Carlo simulations using TOPAS for four reference tissues







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SELF-CONSISTENCY OF THE METHOD

- Monte Carlo simulations using TOPAS for four reference tissues
- Only two ET are enough to get a submillimetric precision on **proton** range prediction.









ADAPTATION TO CT DATA

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







 $\hat{\mu}(E_i,\mathbf{ET}_1)$ $\hat{\mu}(E_i, \mathbf{ET}_2)$ $\rightarrow \mu(E_i, \mathbf{x}) \approx f\left(k_1^{(i)}, k_2^{(i)}, \ldots\right) \rightarrow$ $\hat{\mu}(E_i, \mathbf{ET}_M)$



ADAPTATION TO CT DATA

- virtual materials.
- If K information is available (i.e. K energies), **decomposition** is each voxel.





• Once their attenuation coefficient is estimated, the ETs are treated as

performed to extract the **fraction** of the K more meaningful ETs in

$$\hat{\mu}(E_K, \mathbf{ET}_1) \\ \vdots \\ \hat{\mu}(E_K, \mathbf{ET}_K) \end{pmatrix}^{-1} \begin{pmatrix} \mu(E_1) \\ \vdots \\ \mu(E_K) \end{pmatrix}$$

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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 (noise is neglected)







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.







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**:

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- Not limited to only two parameters (EAN and ED)
- Valid through the **whole range** of X-ray energies (e.g. kV and MV)
- RMS errors of 0.11% on SPR for 43 reference tissues
- **Future work**: test the method in realistic conditions including noise
- **Recent publication**: A. Lalonde and H. Bouchard, A general method to derive tissue parameters for Monte Carlo dose calculation with dual- and multi-energy CT, Phys. Med. Biol.

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