

Ant colony algorithm for driving variance reduction techniques in Monte Carlo simulations of radiation transport

A. M. Lallena

Dpto. de Física Atómica, Molecular y Nuclear
Univ. Granada

Outline

- Introduction

- Implementation of the ant colony algorithm: LINAC

- Some applications

- Conclusions

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large calculation CPU times!!

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variance reduction techniques

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procedures permitting the reduction of the statistical uncertainties without increasing the calculation time

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•Russian roulette

•splitting

•interaction forcing

•directional bremsstrahlung splitting

•orange rejection

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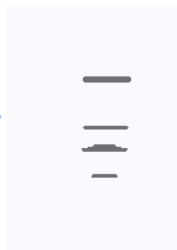
•VRT used properly may increase the efficiency of the simulation!!

how to do it?

Implementation of the ant colony algorithm: LINAC

LINAC geometry (Siemens Mevatron KDS)

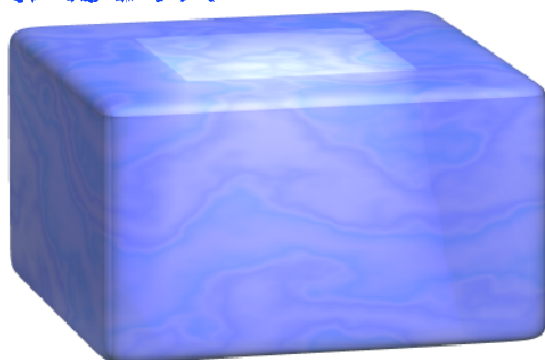
head



jaws

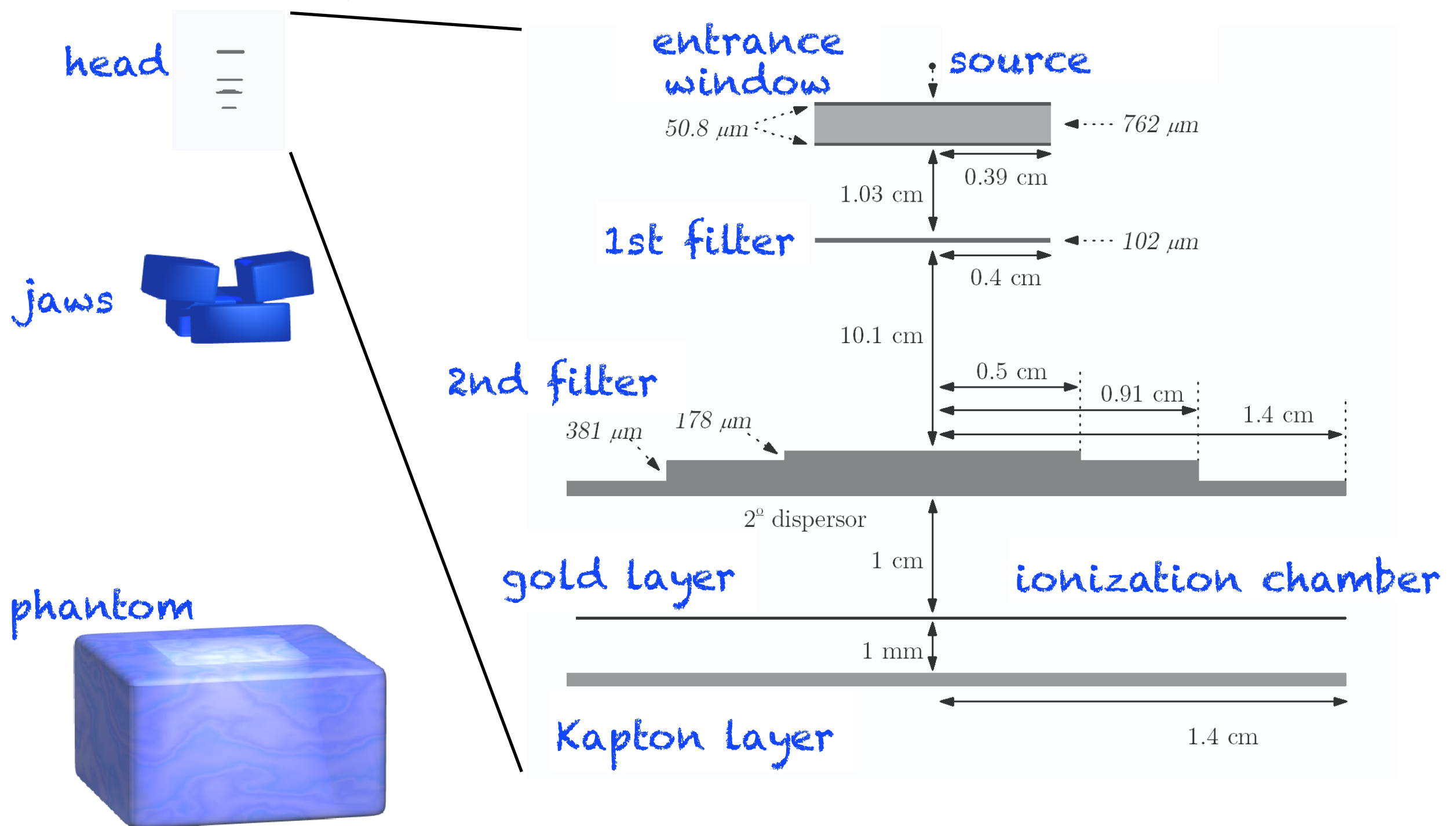


phantom



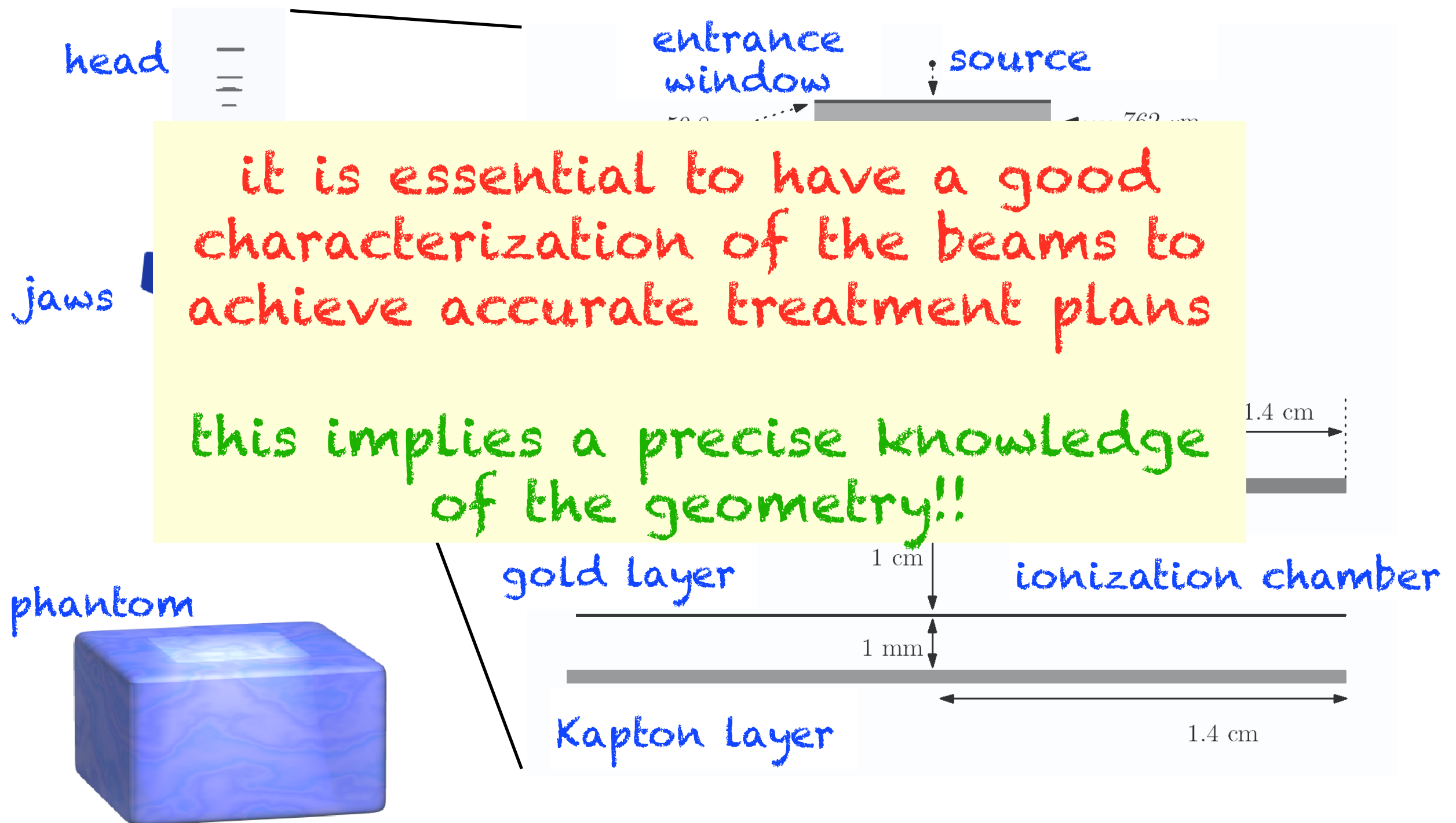
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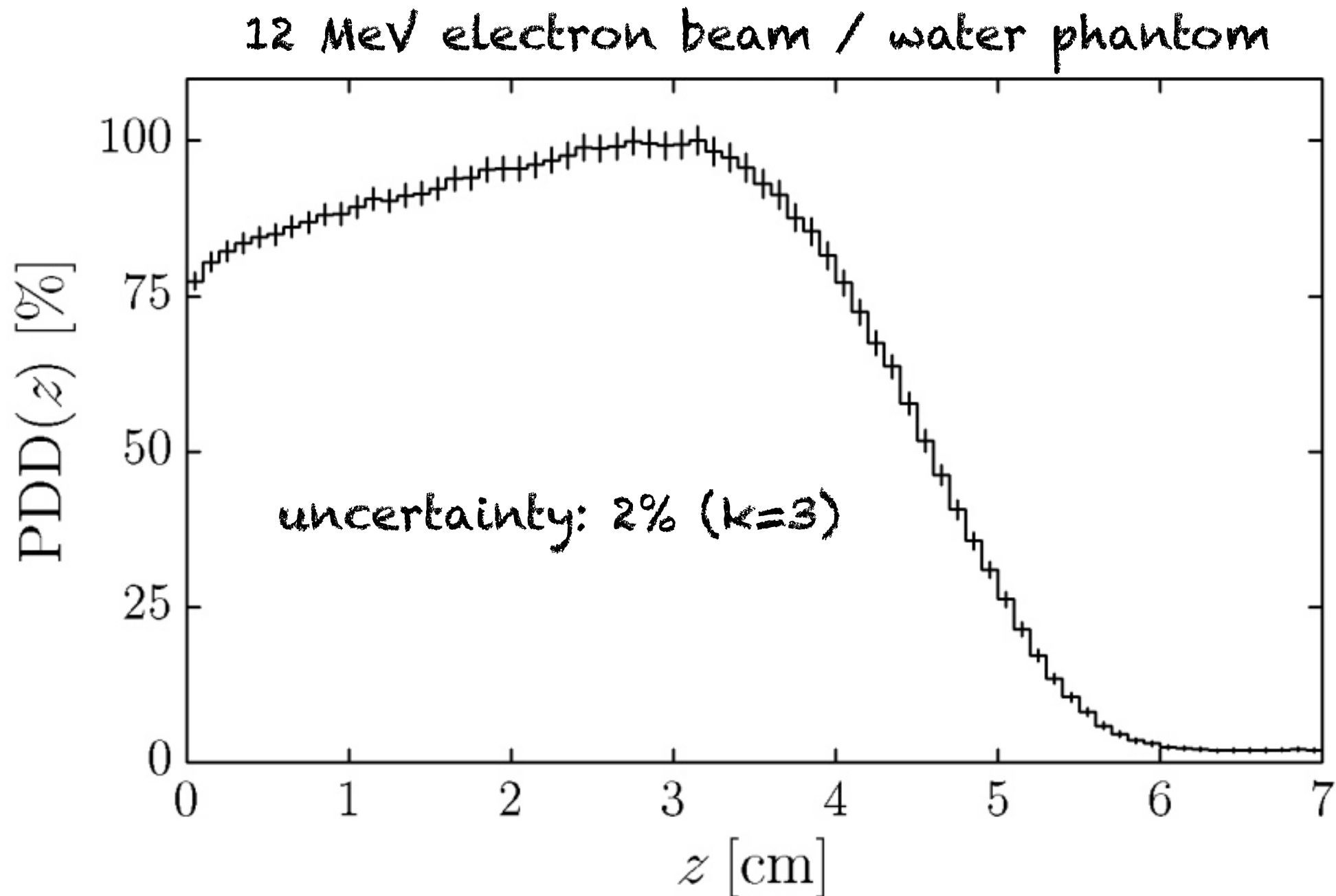


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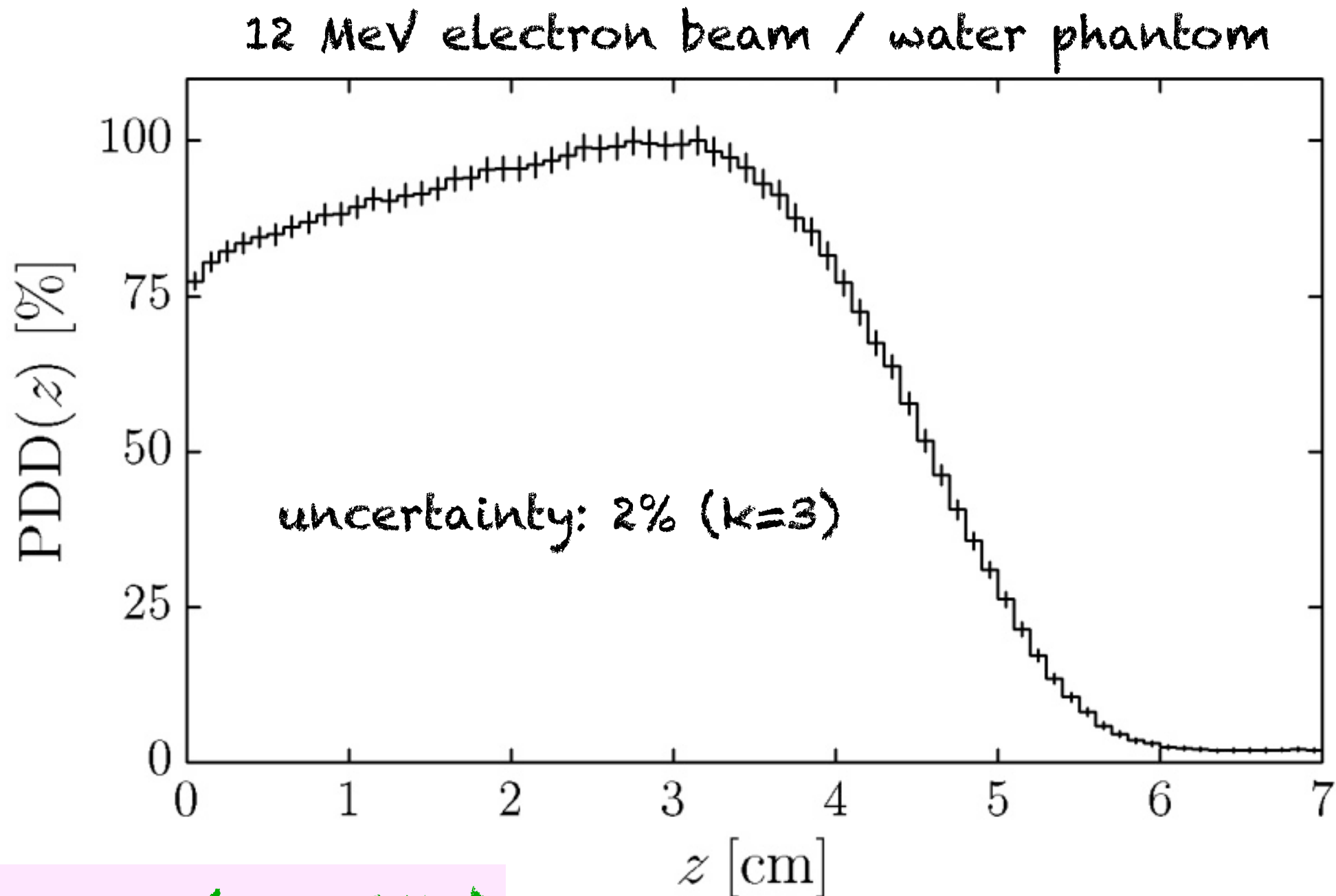
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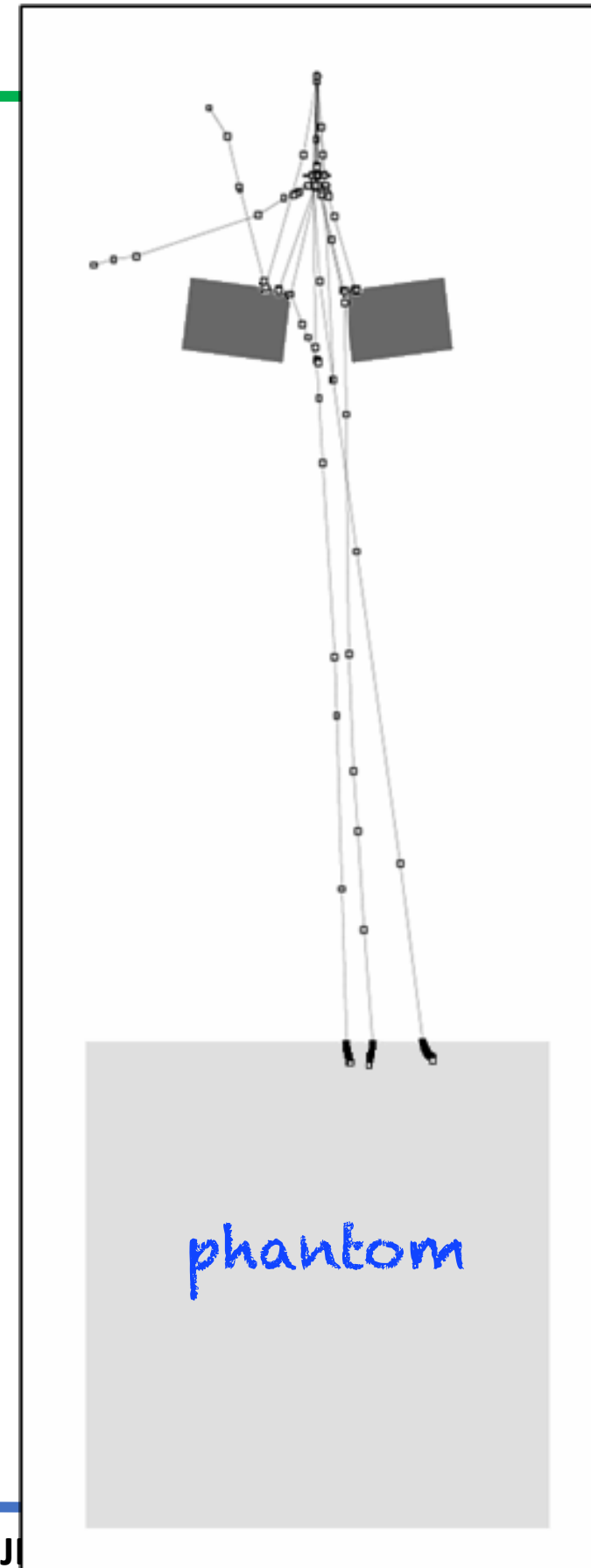


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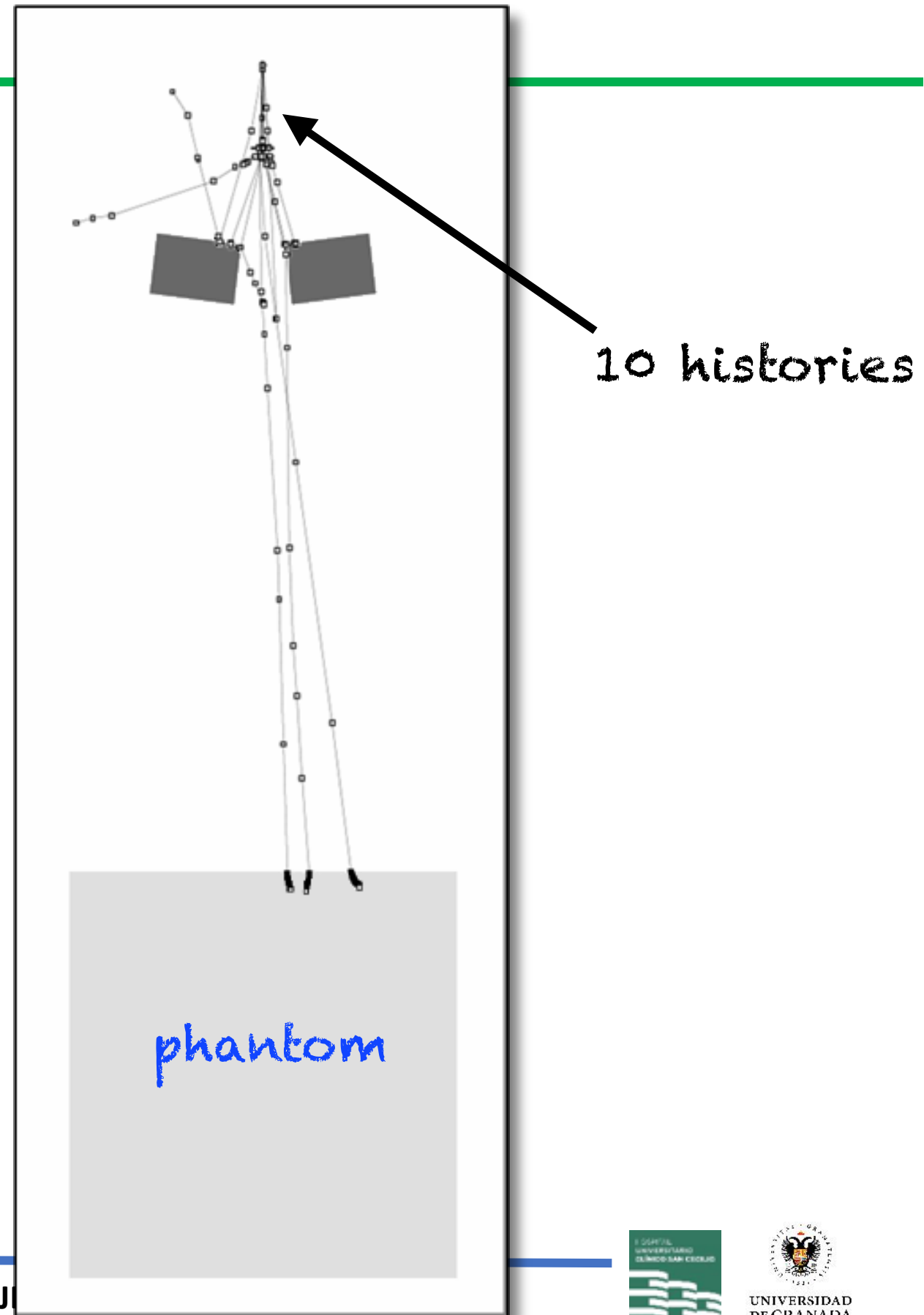


PC Pentium4 (1.6 GHz)
CPU time: 220 h

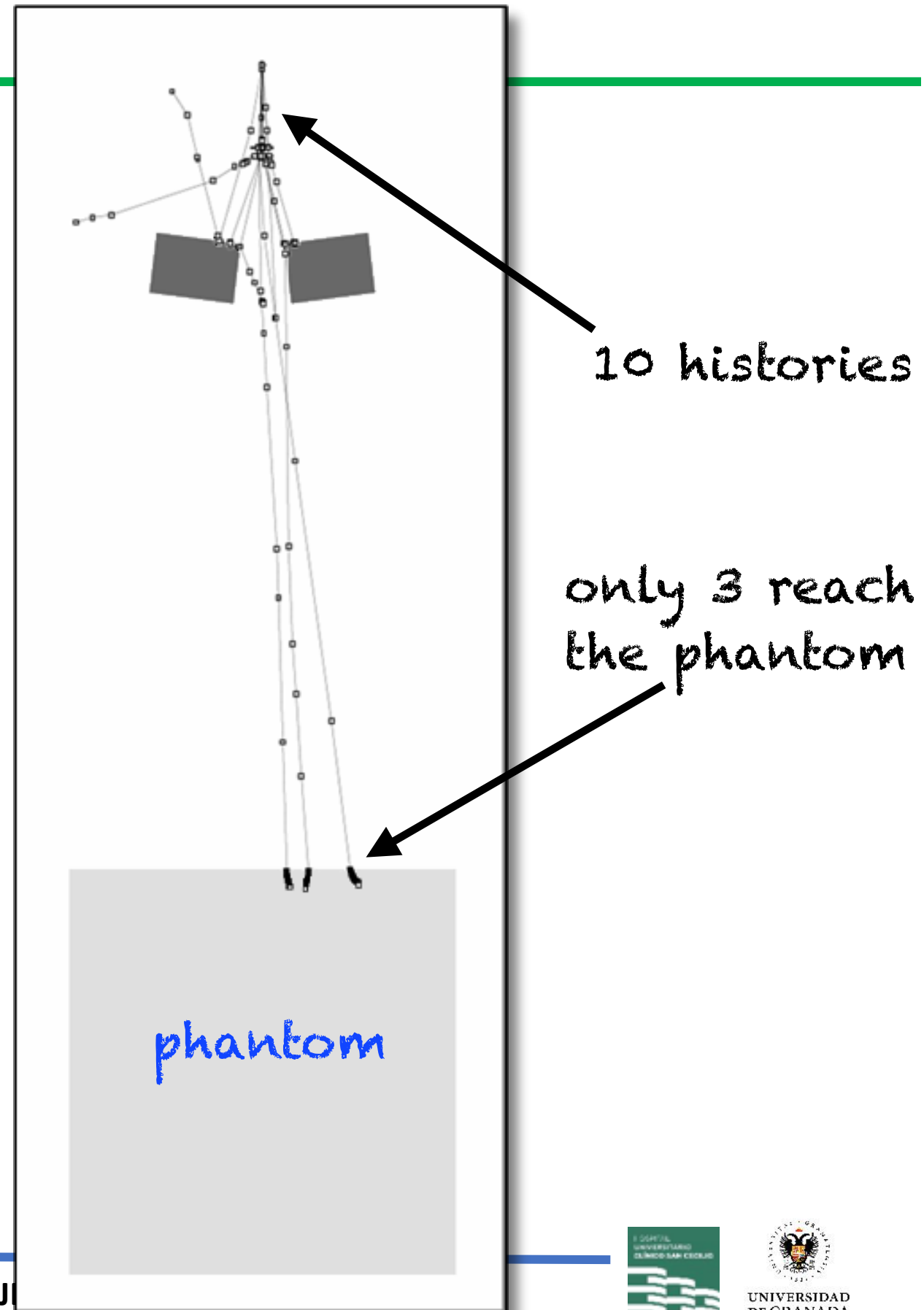
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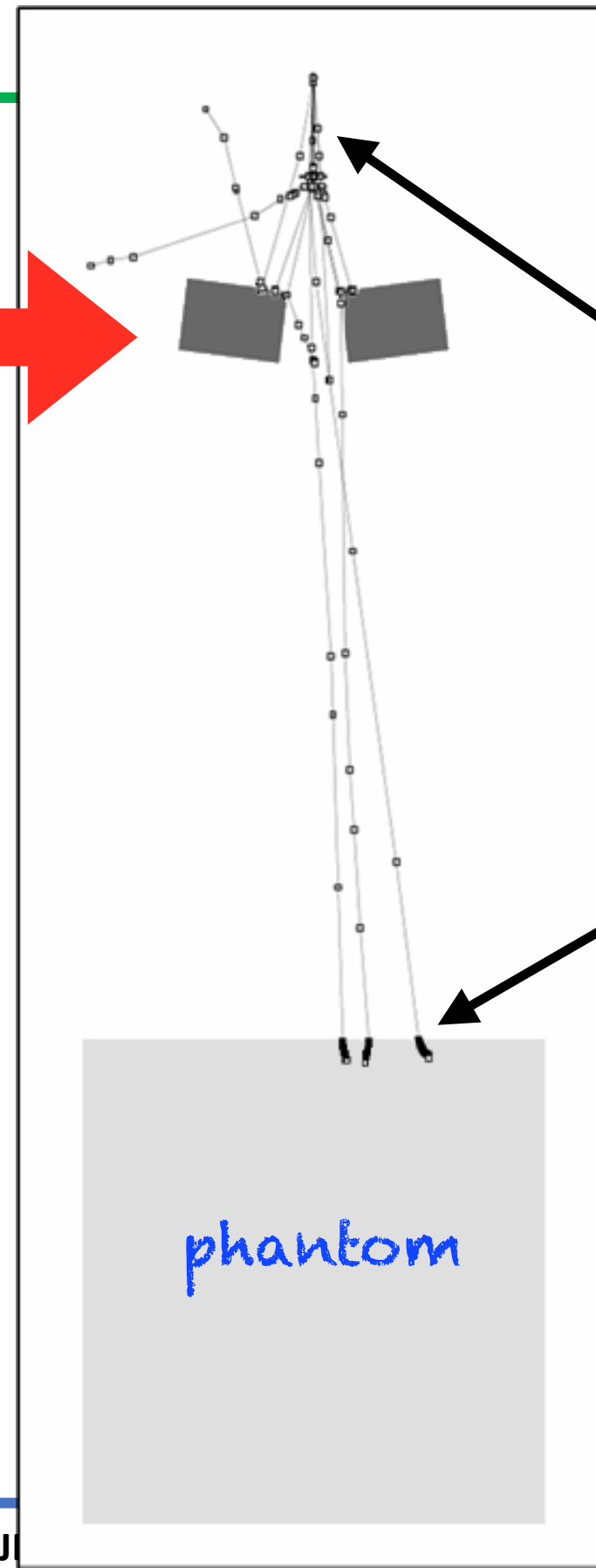


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most of the time
spent in simulating
particles absorbed or
backscattered in the
jaws



10 histories

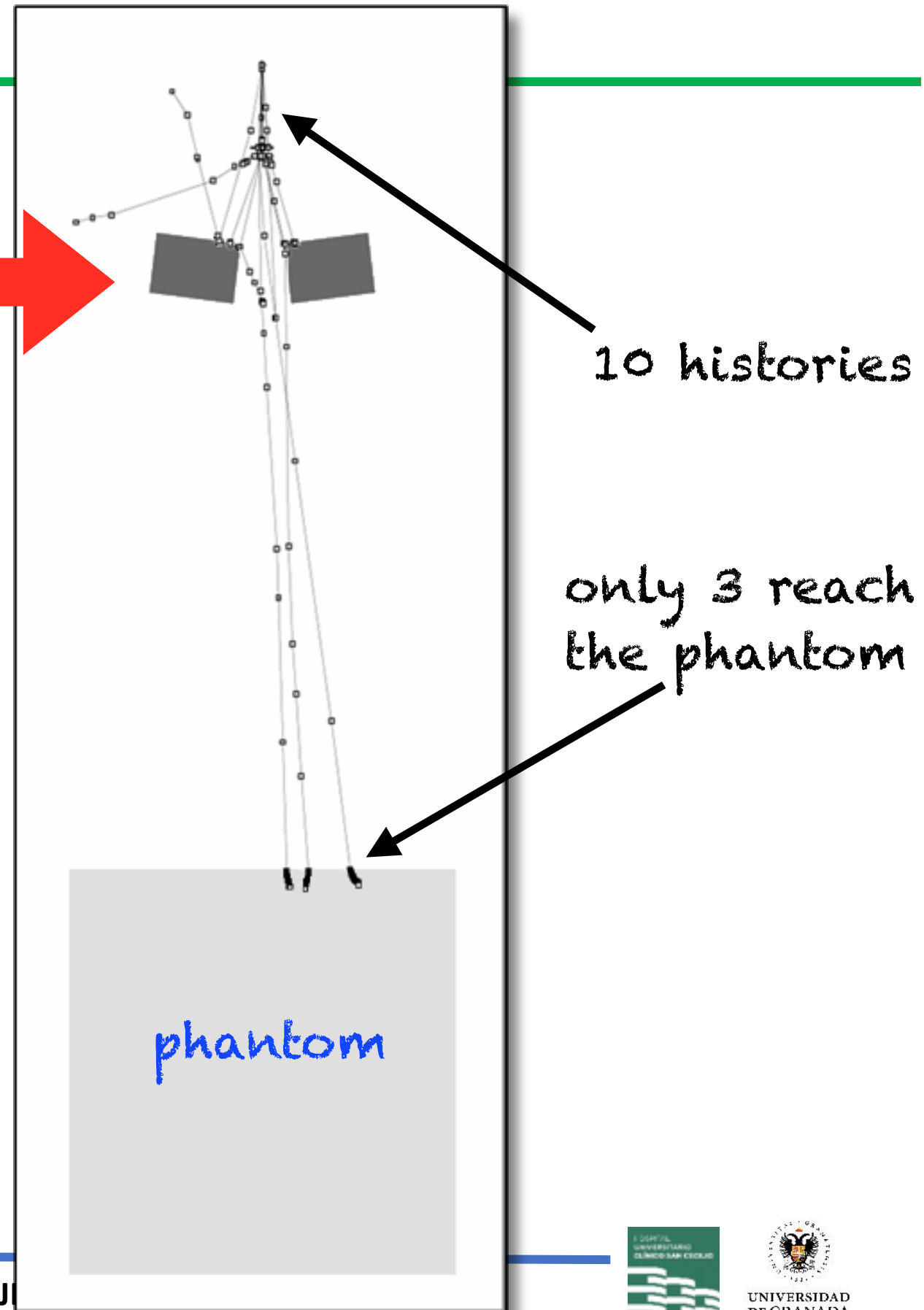
only 3 reach
the phantom

Implementation of the ant colony algorithm: LINAC

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VRT:

- Russian roulette: reduces simulation time but increases variance
- splitting: reduces variance but increases simulation time



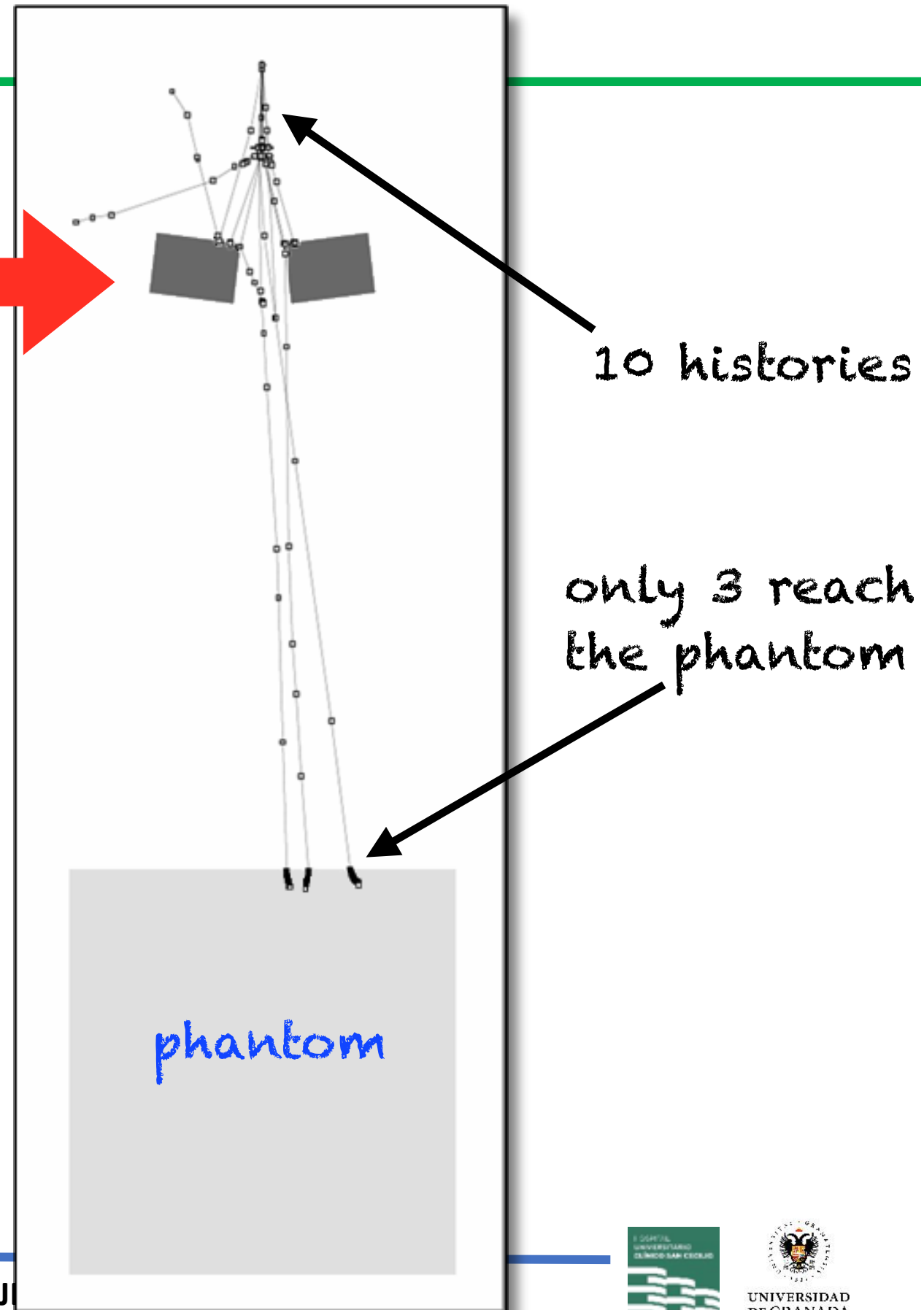
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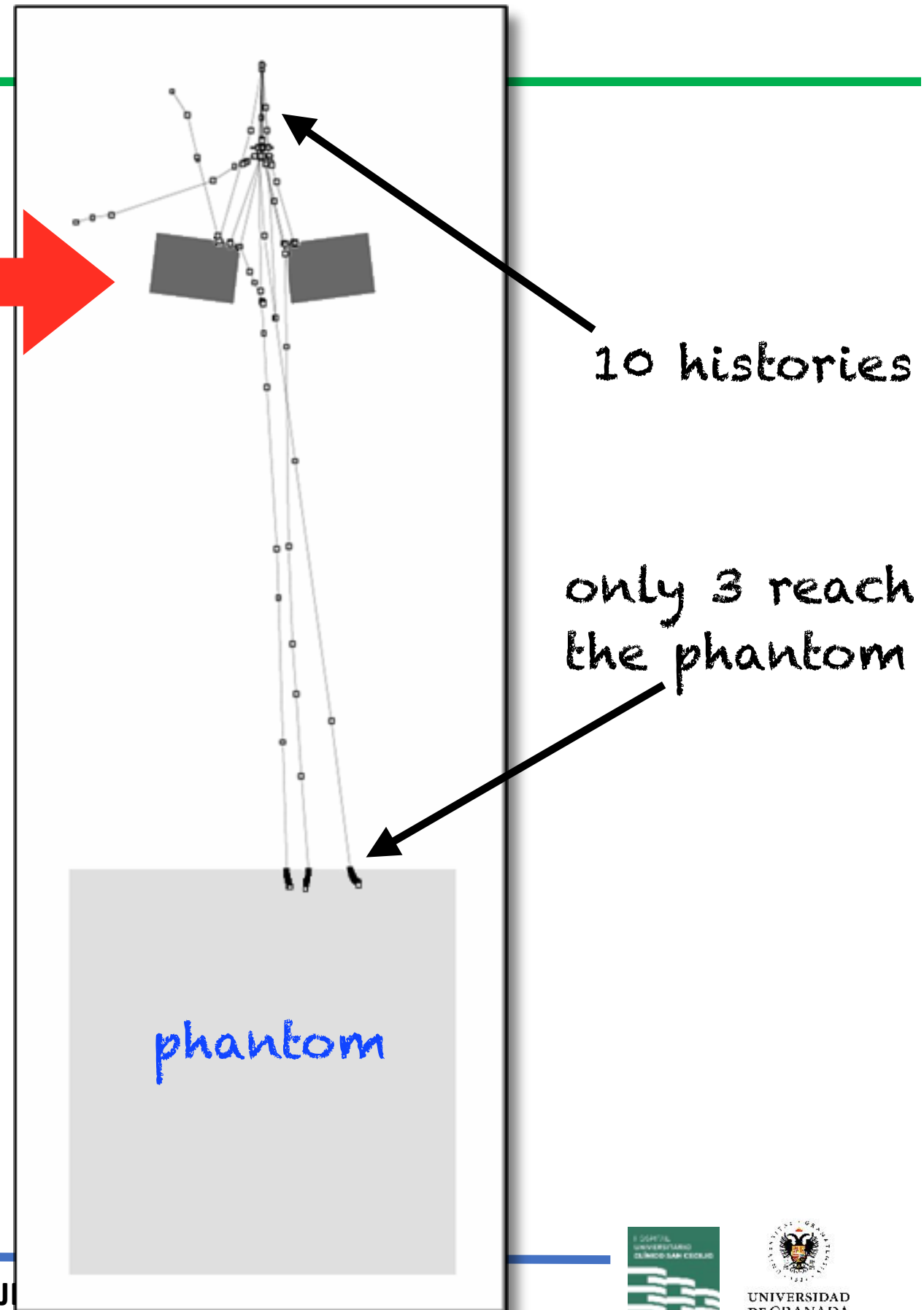
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where to apply
Rr / sp?

ant colony algorithm



Implementation of the ant colony algorithm: LINAC

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ant colony algorithm

- ants look for food following random walks
- if food is found, ants come back to the nest depositing pheromone
- ants tend to follow paths with a certain level of pheromone
- the level of pheromone increases in the optimal paths between nest and food

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particles
(electrons)

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- whole geometry is divided into virtual cells
- each cell is characterized by an importance value

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- once a particle enters a new cell, VRTs are applied according the particle weight (w) and the cell importance (I)

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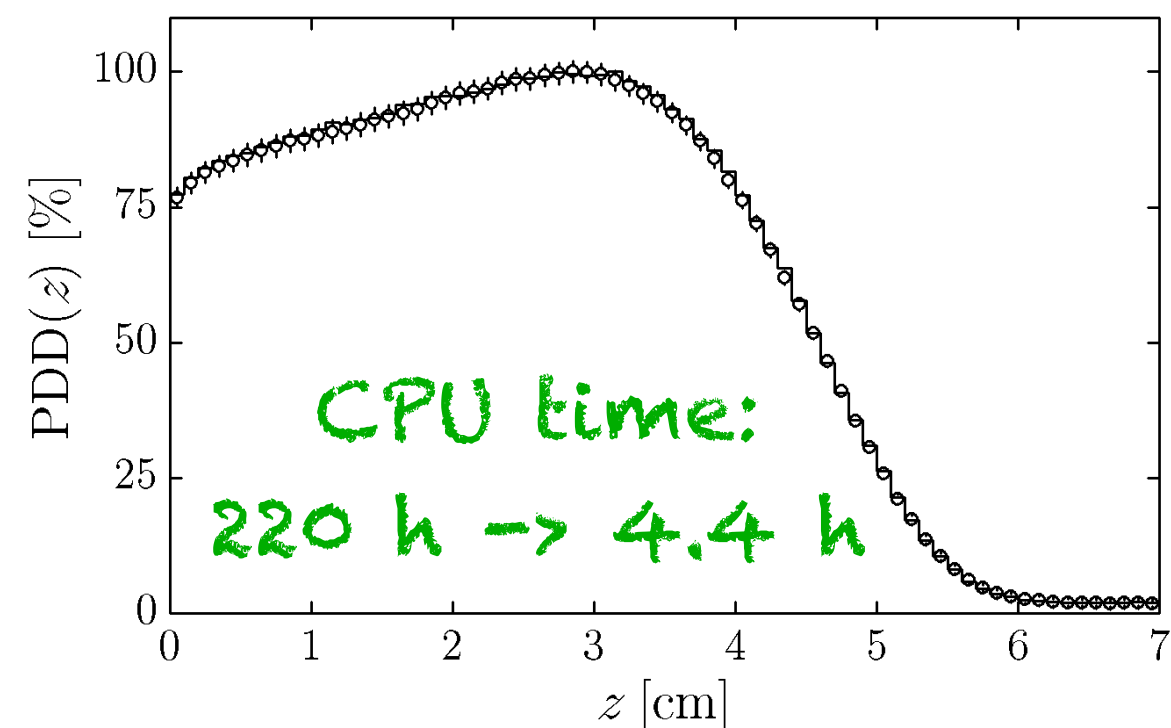
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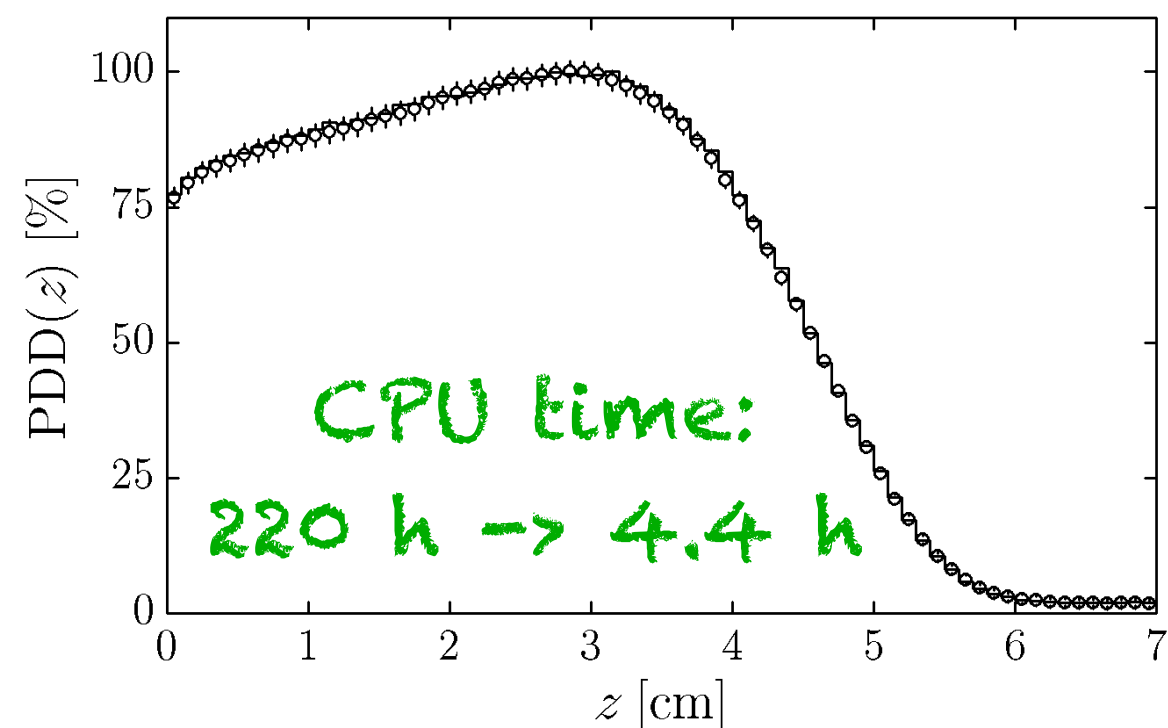
$$I = 2^k$$

$$k = \begin{cases} \left\lceil 5 \frac{P(i)}{P(0)} - 5 \right\rceil, & \text{if } P(i) \leq P(0), \\ \left\lceil 7 \frac{P(i) - P(0)}{1 - P(0)} \right\rceil, & \text{if } P(i) > P(0). \end{cases}$$

$$P(i) = \frac{N_f(i)}{N_0(i)}$$

$N_0(i)$: number of particles entering i -cell

$N_0(i)$: number of particles entering i -cell and reaching ROI

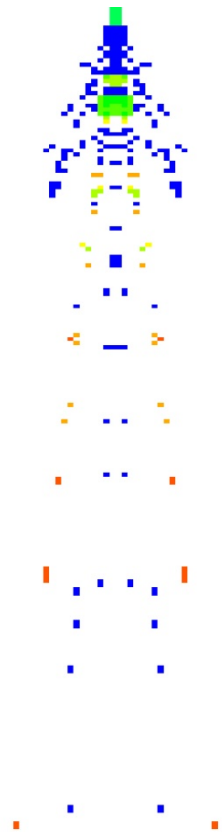


importance
maps

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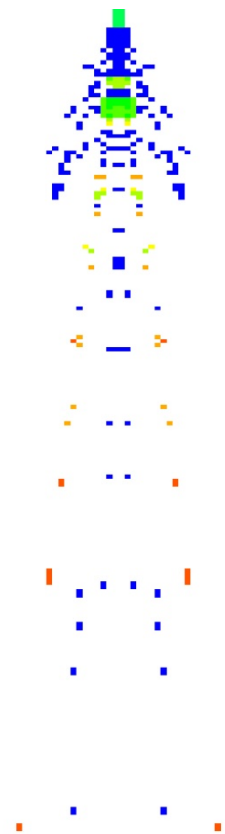
importance maps

$N=10^2$

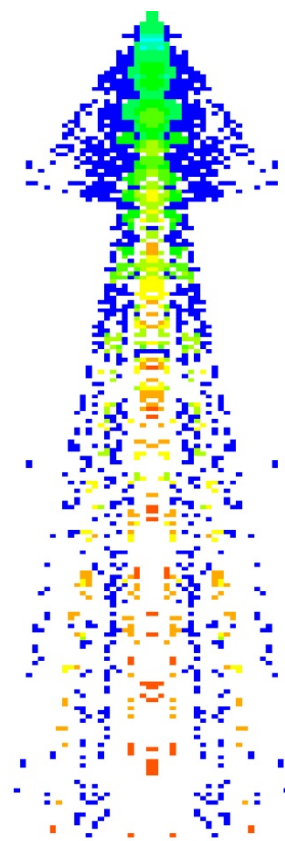


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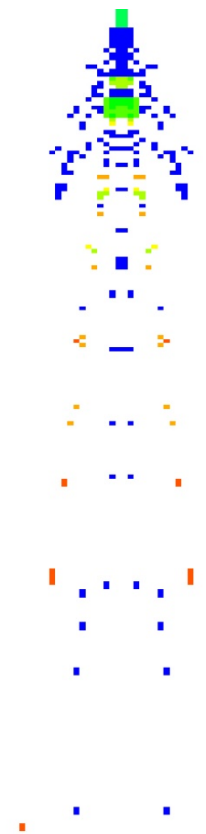


$N=10^3$

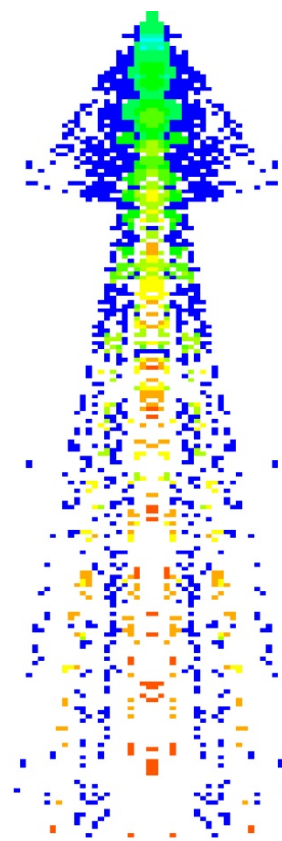


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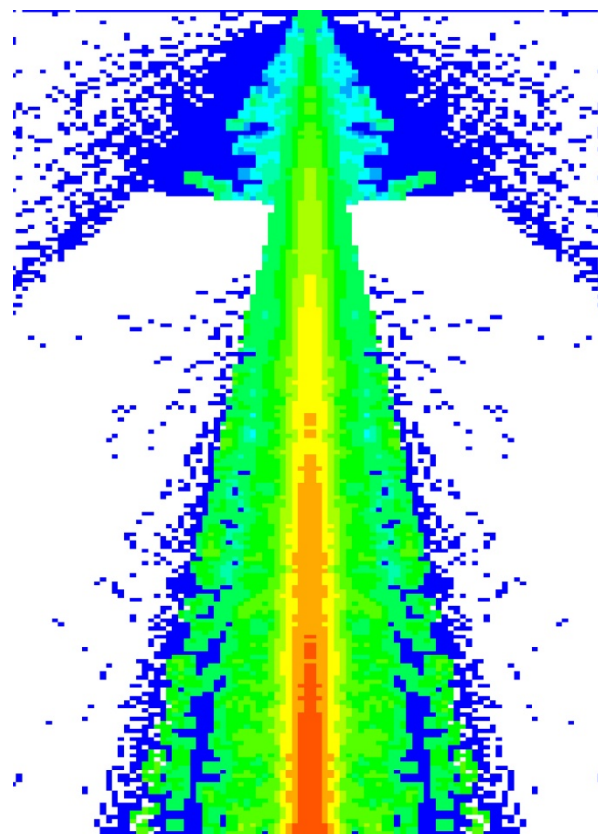
$N=10^2$



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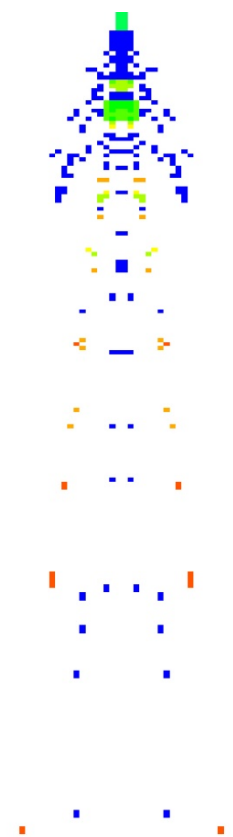


$N=10^4$

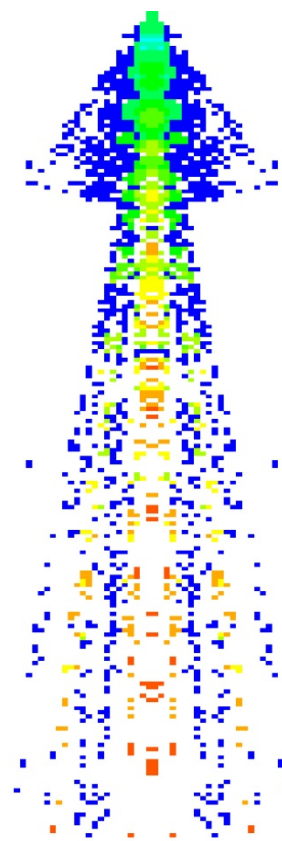


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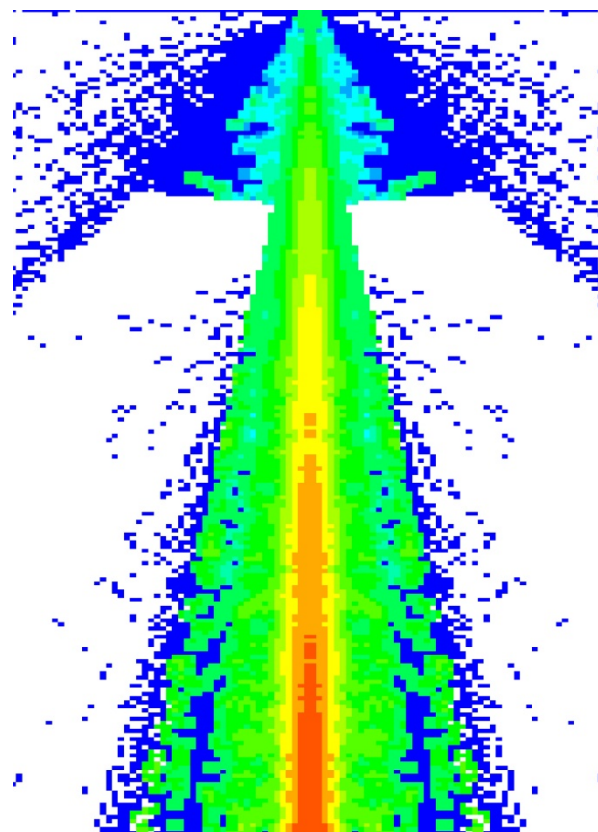
$N=10^2$



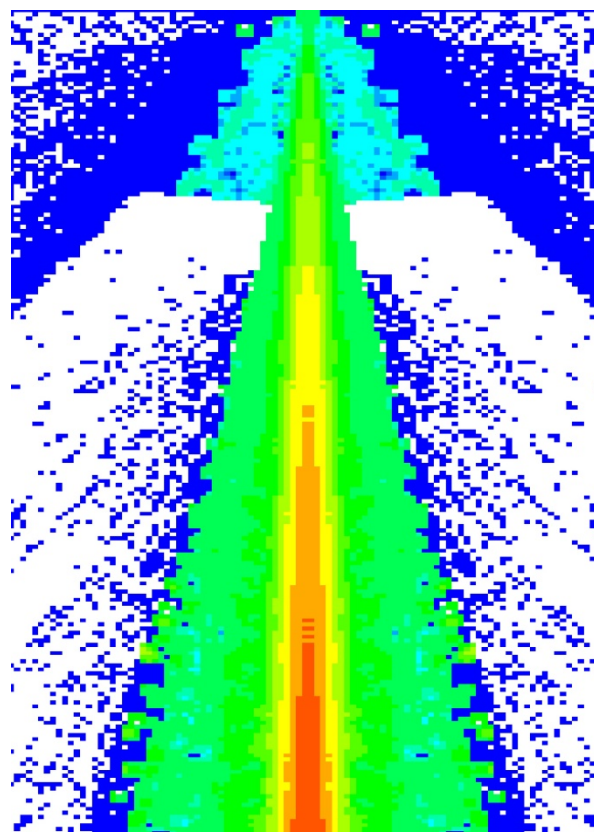
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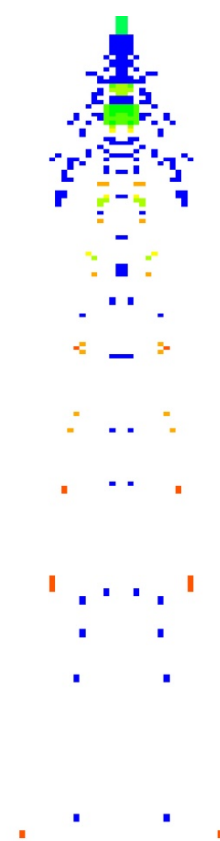


$N=5 \cdot 10^5$

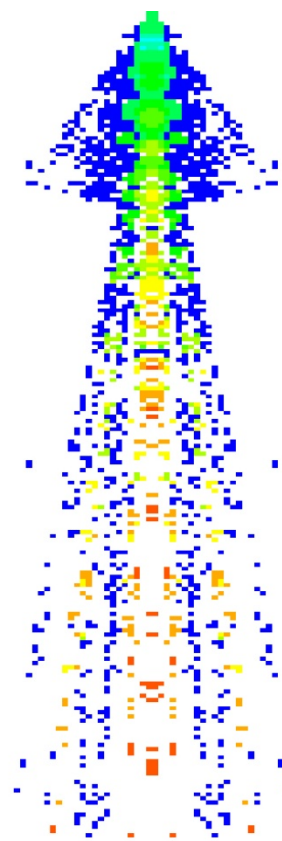


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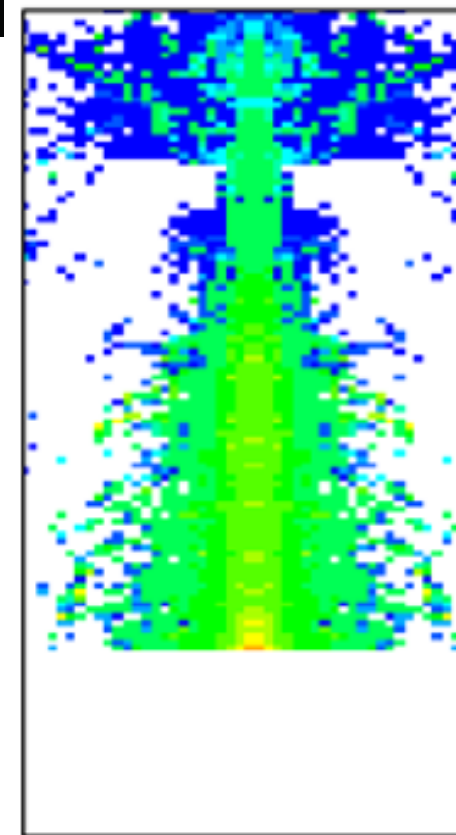
$N=10^2$



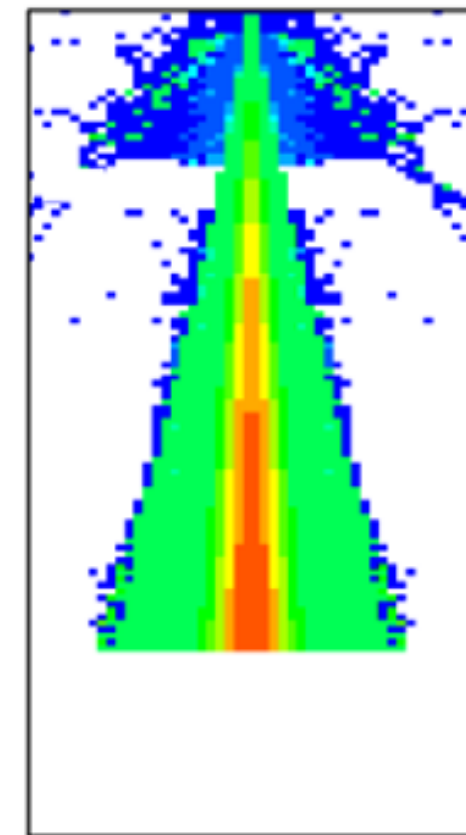
$N=10^3$



$E < 6 \text{ MeV}$

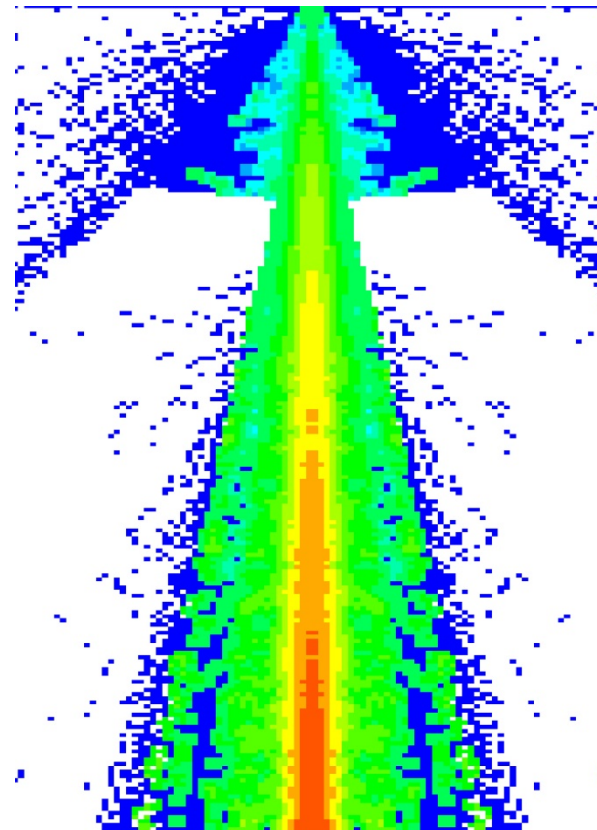


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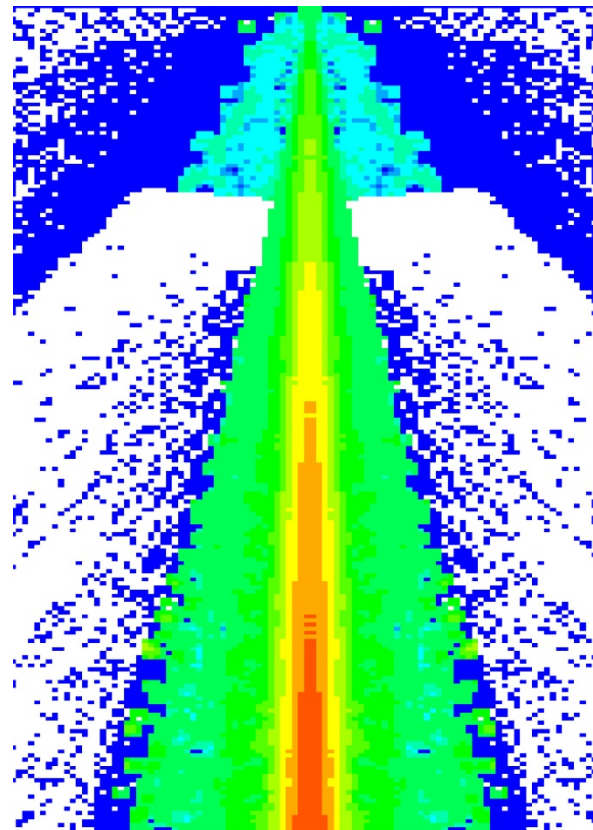


air

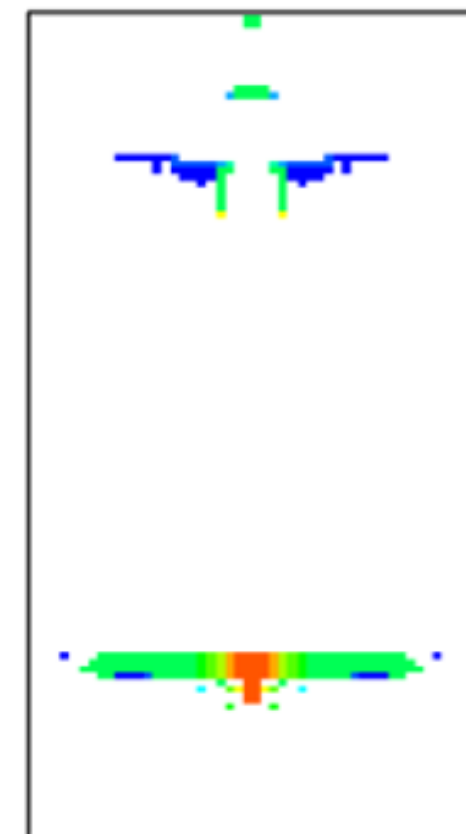
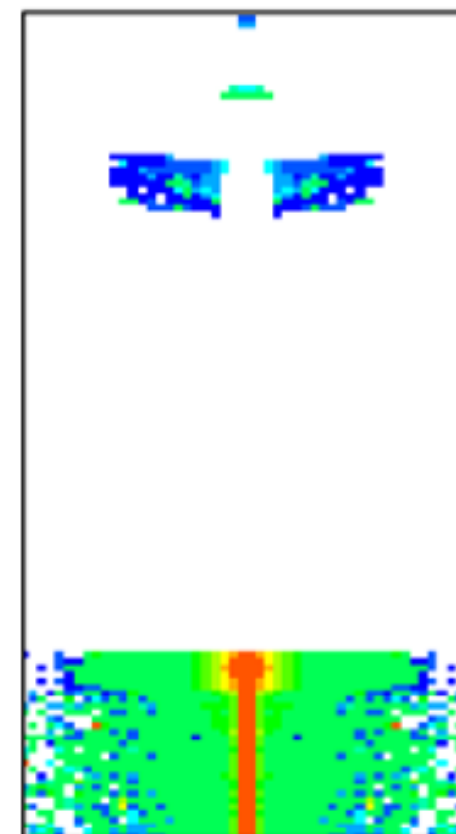
$N=10^4$



$N=5 \cdot 10^5$



dense
materials



Implementation of the ant colony algorithm: LINAC

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- algorithm allowing an efficient application of VRT:
handled automatically!!!

- based on the scoring of the importance map

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- algorithm allowing an efficient application of VRT:
handled automatically!!!

- based on the scoring of the importance map

- is it general enough?

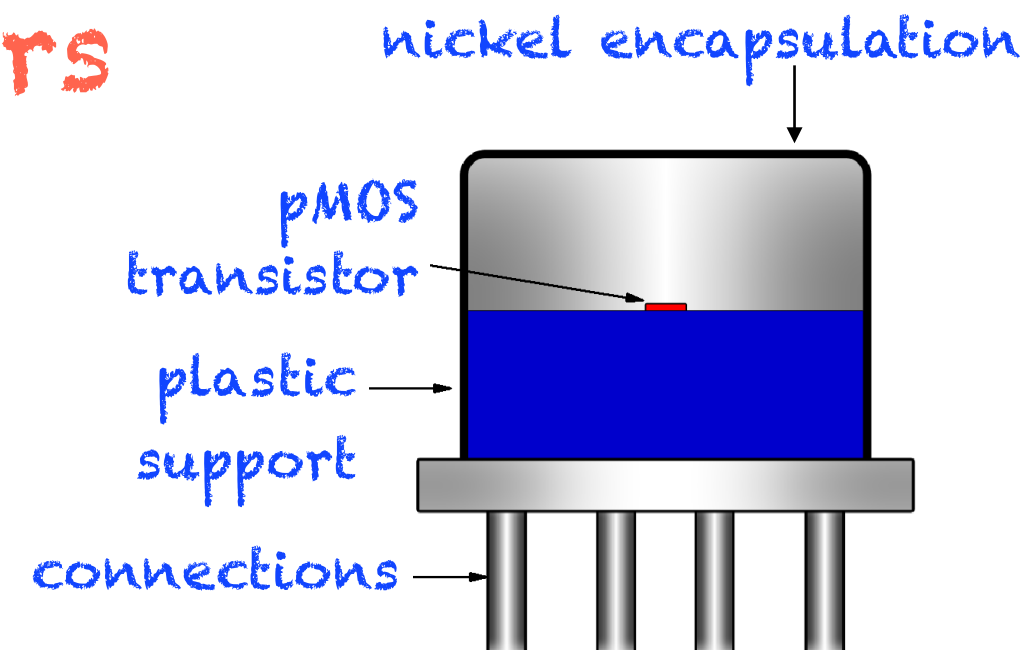
- which are the main characteristics to be care of?

Some applications

MOSFET used as dosimeters

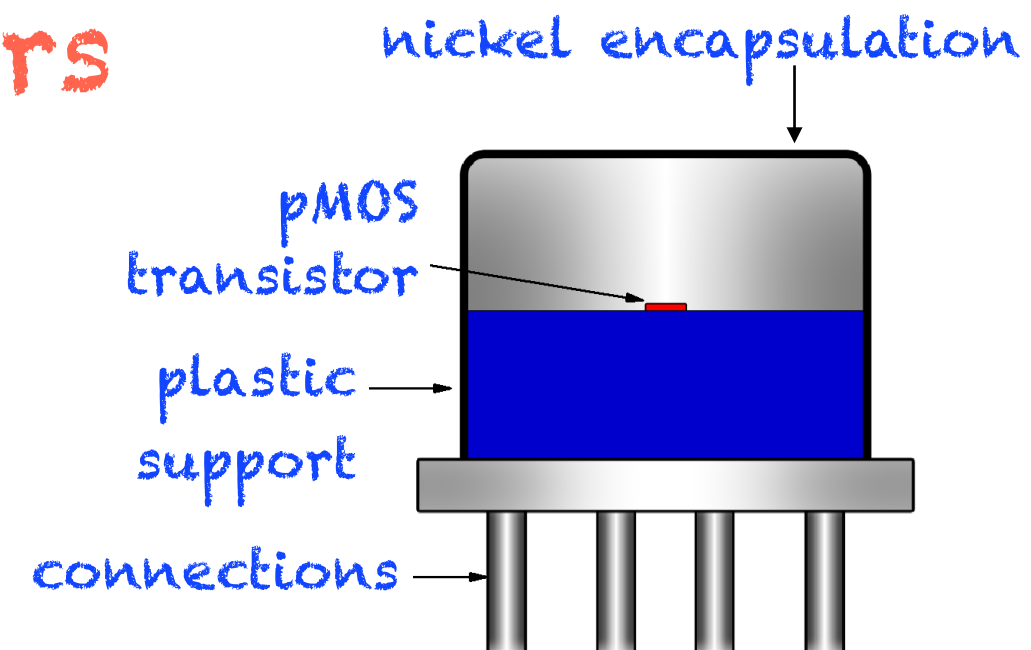
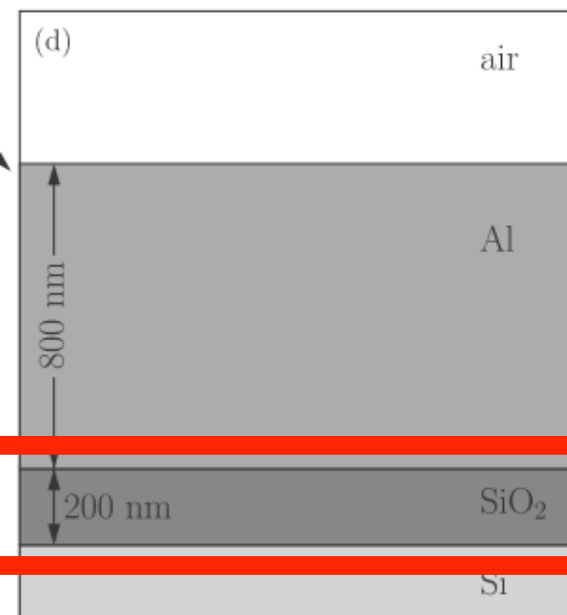
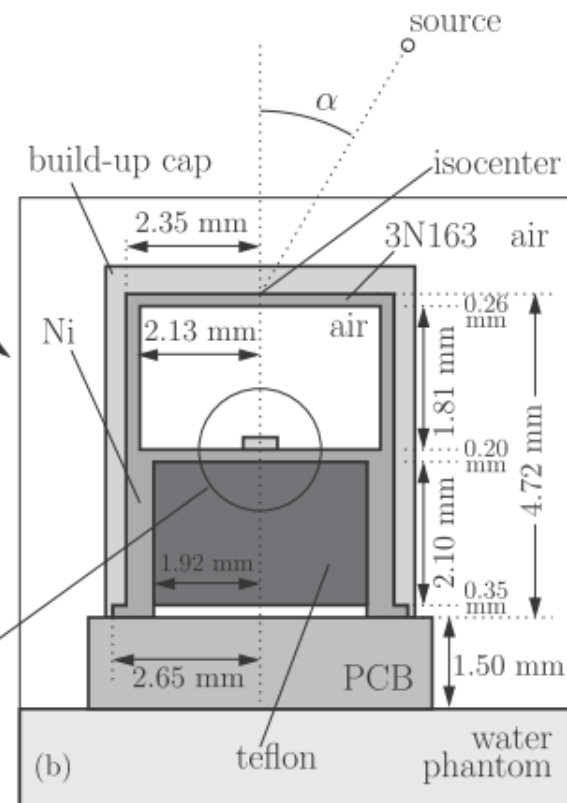
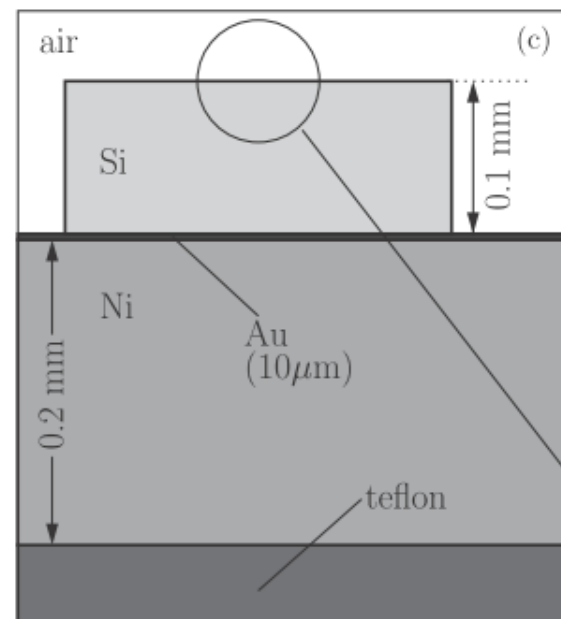
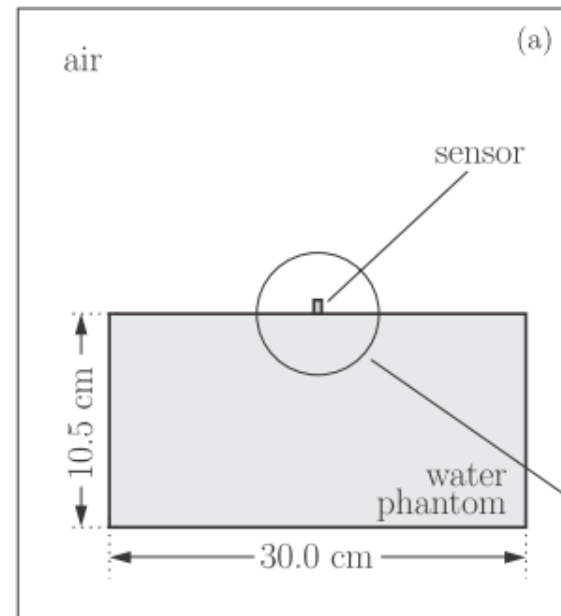
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MOSFET used as dosimeters



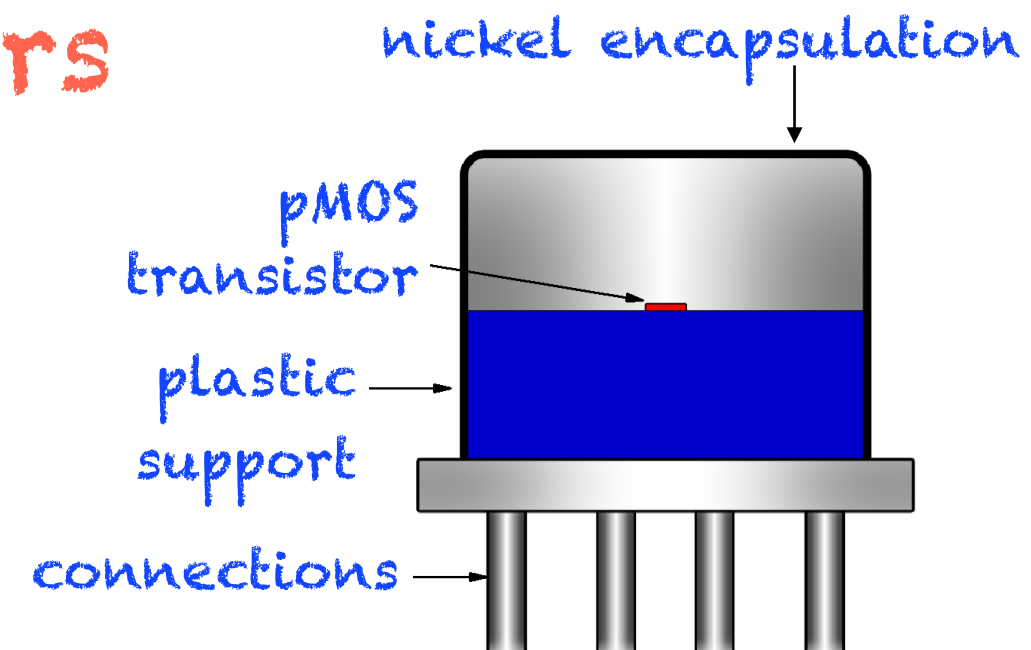
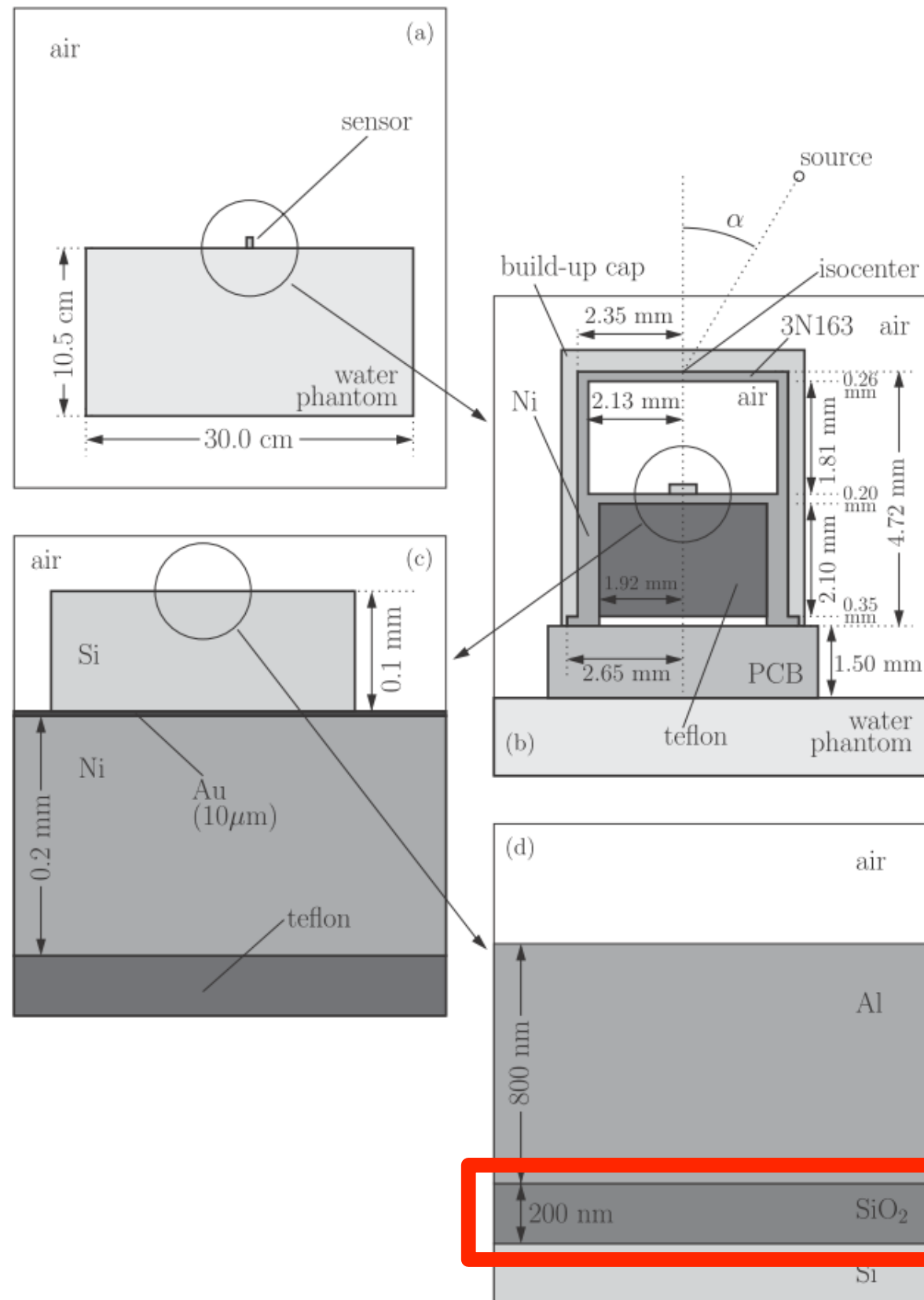
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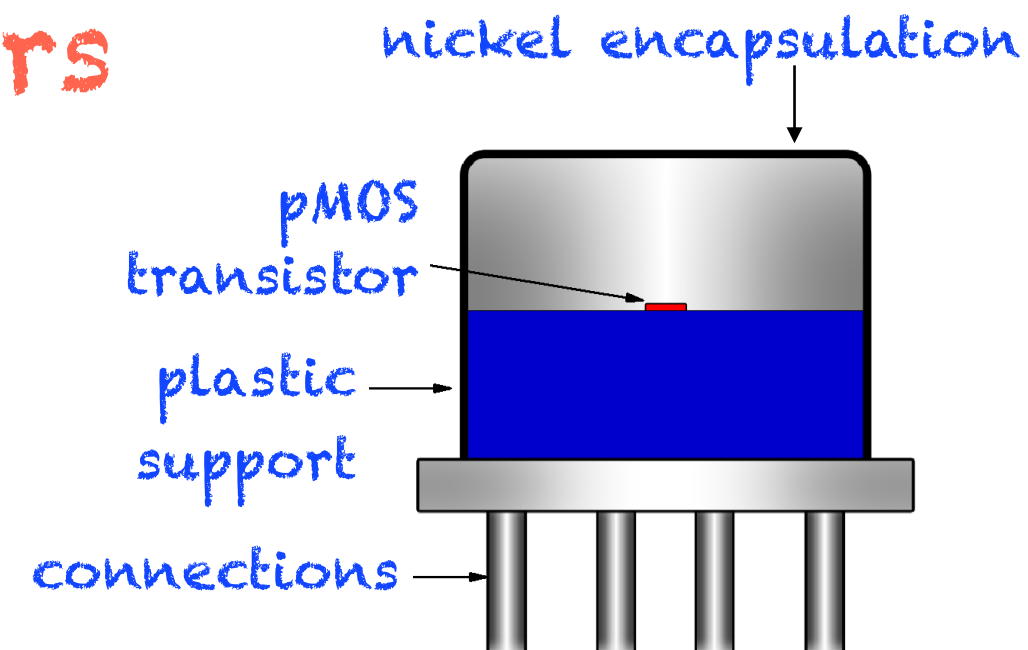
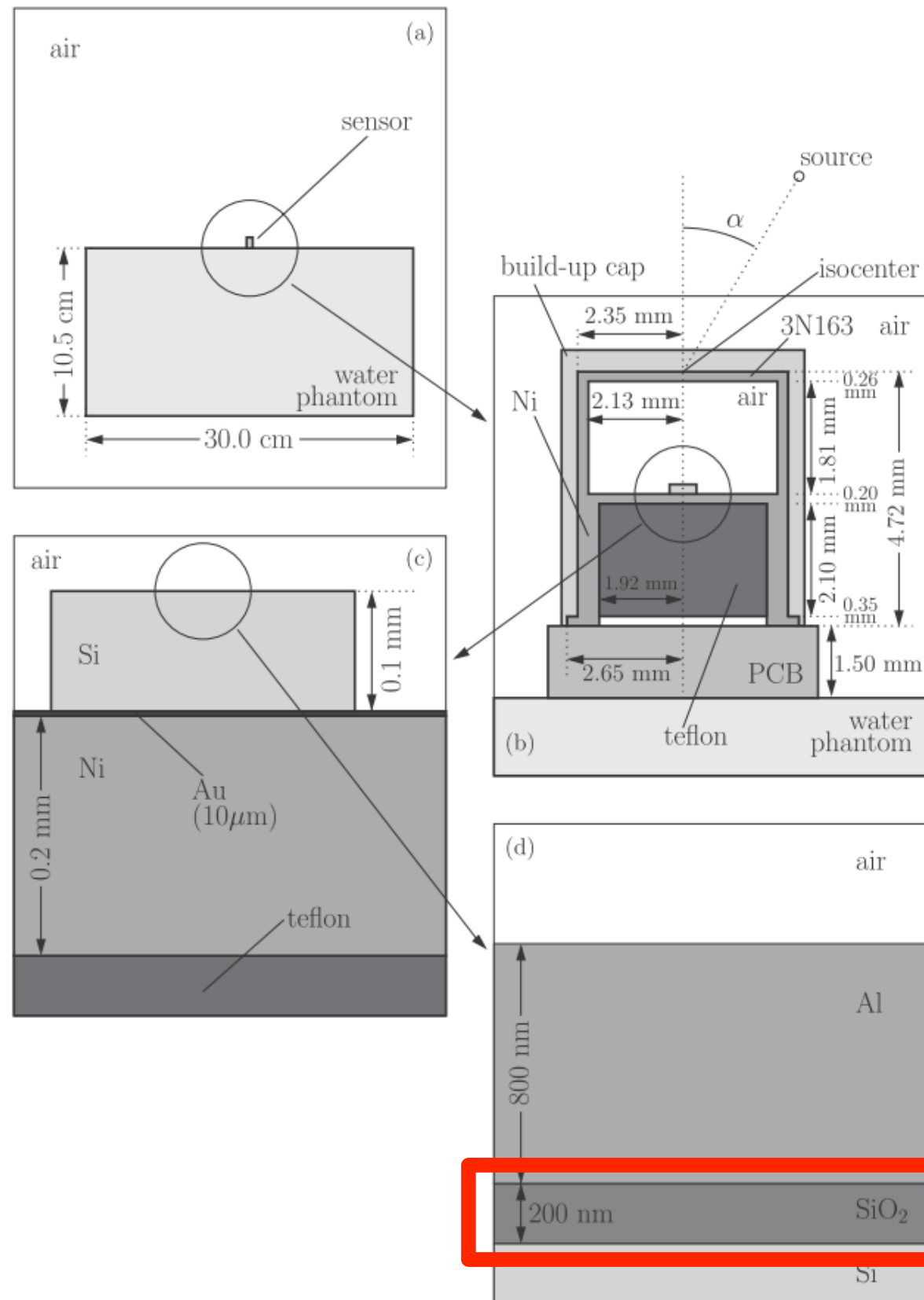
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- MOSFET response: energy deposited in the SiO₂ die
- detailed simulation within MOSFET
- very low statistic: 30 days for an uncertainty of 10% ($k=3$)

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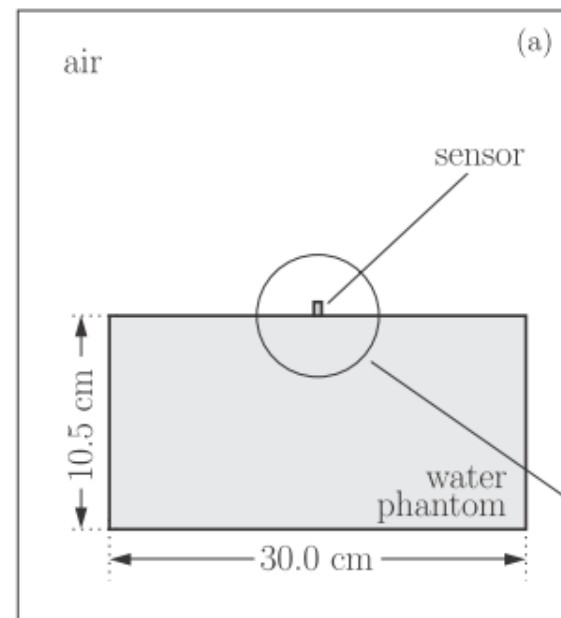


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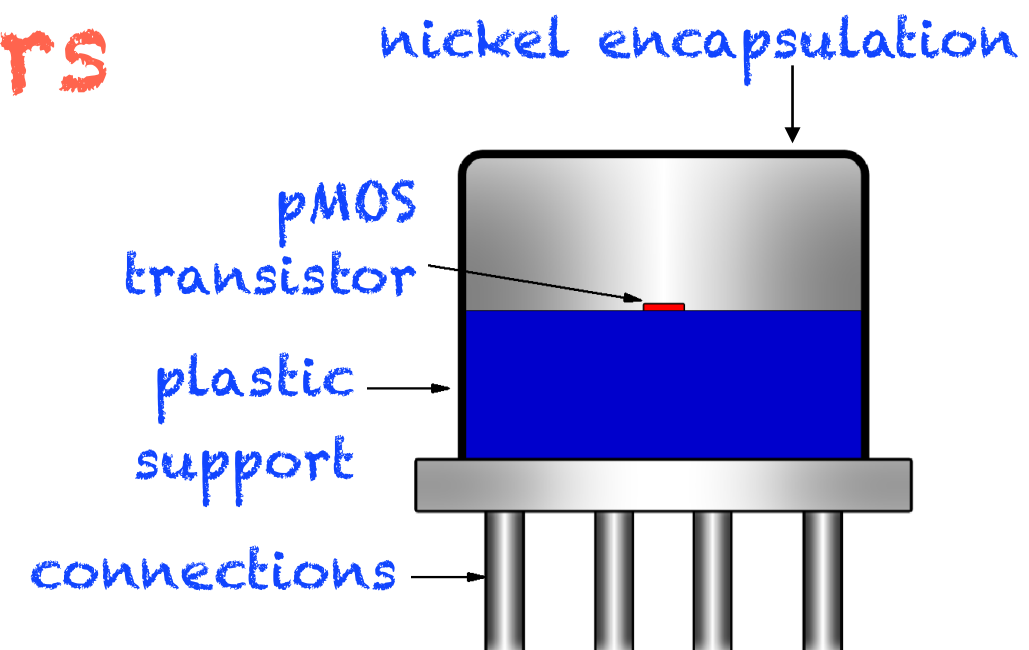
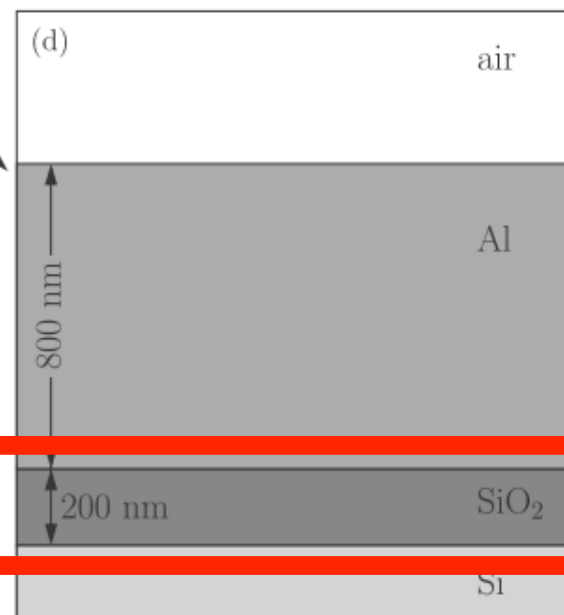
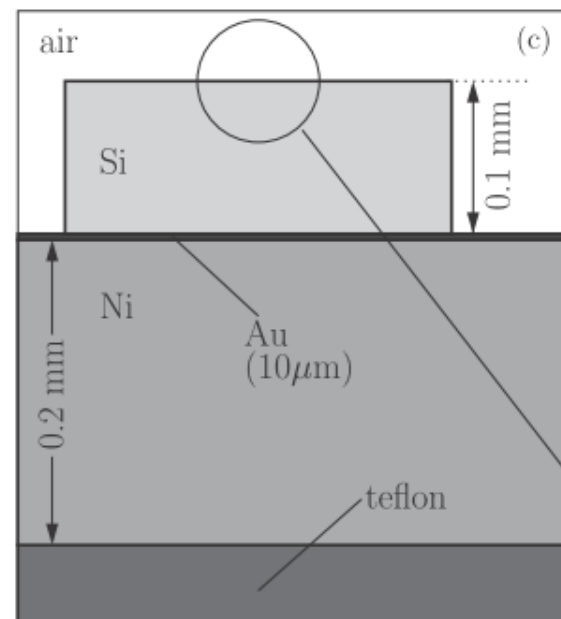
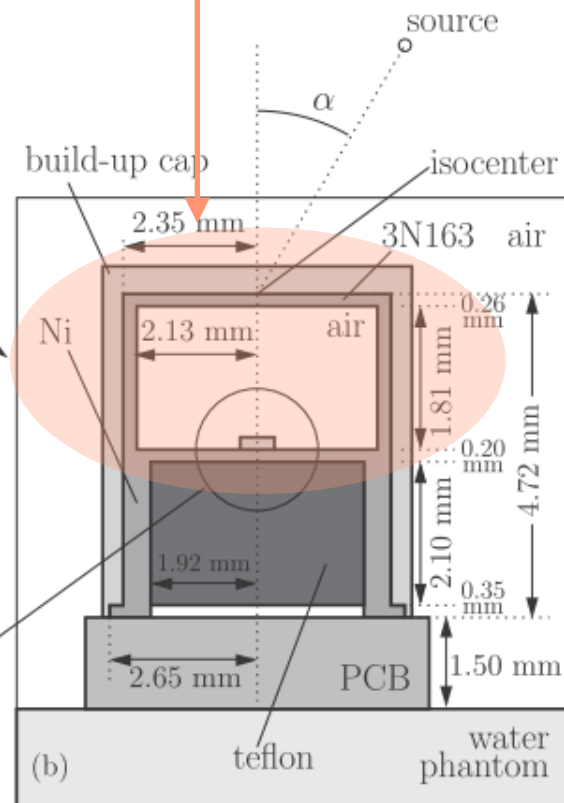
- no VRT for photons
- ROI is crucial:
 - SiO₂ as ROI does not work!

Some applications

MOSFET used as dosimeters



adequate ROI



- MOSFET response: energy deposited in the SiO₂ die
- detailed simulation within MOSFET
- very low statistic: 30 days for an uncertainty of 10% ($k=3$)

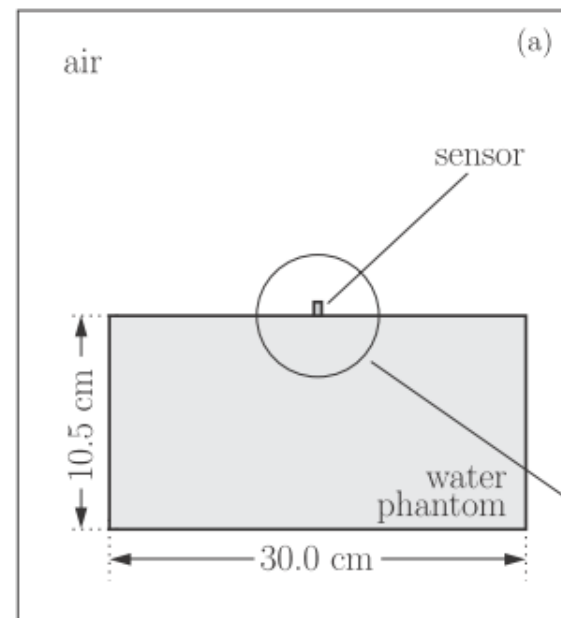
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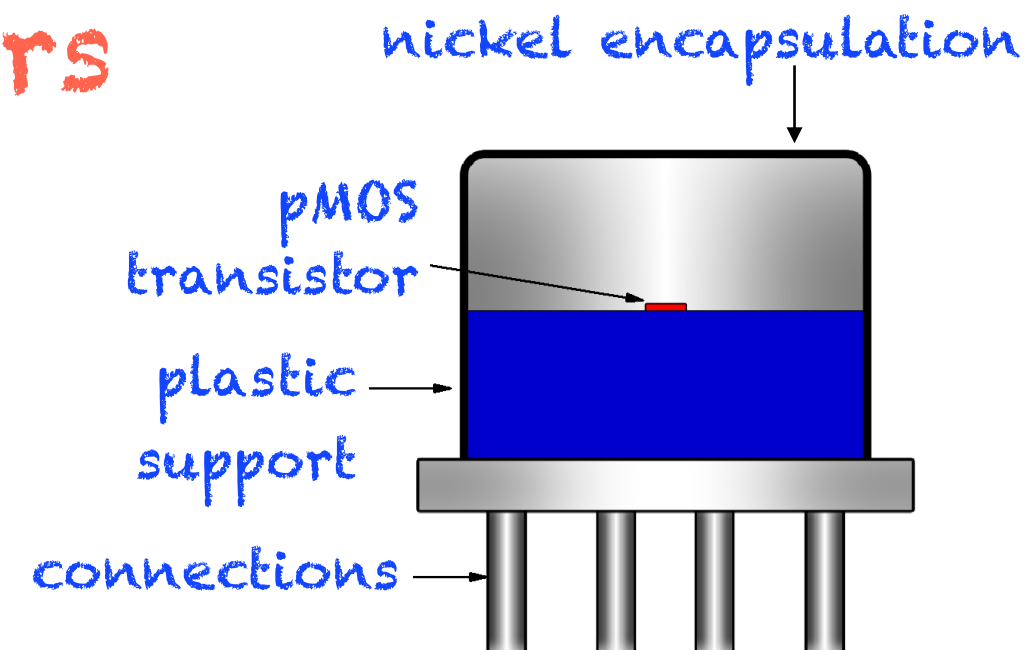
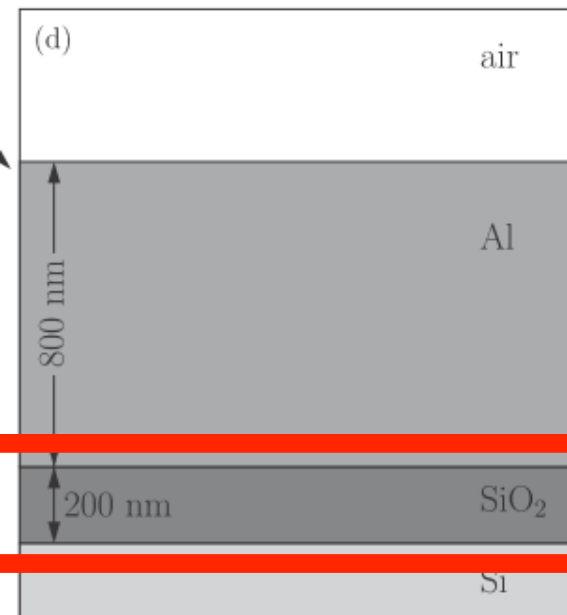
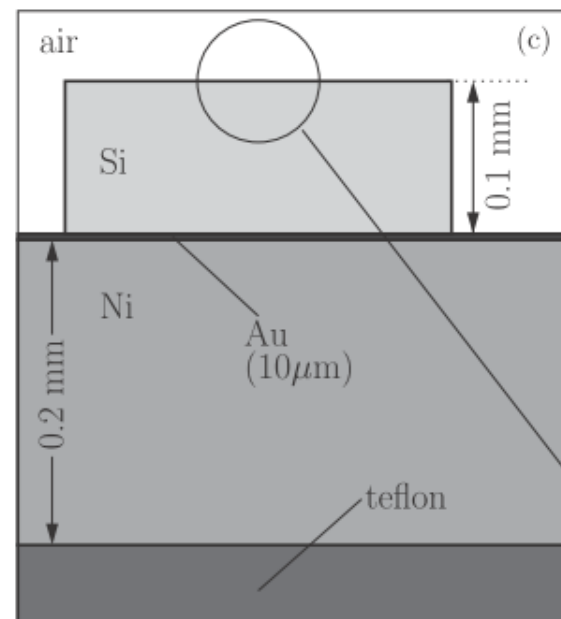
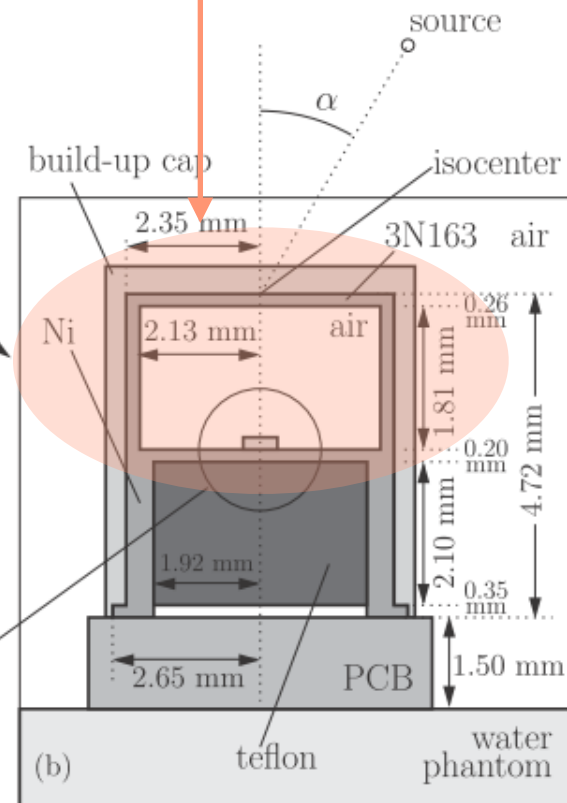
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•factor 20 reduction in CPU

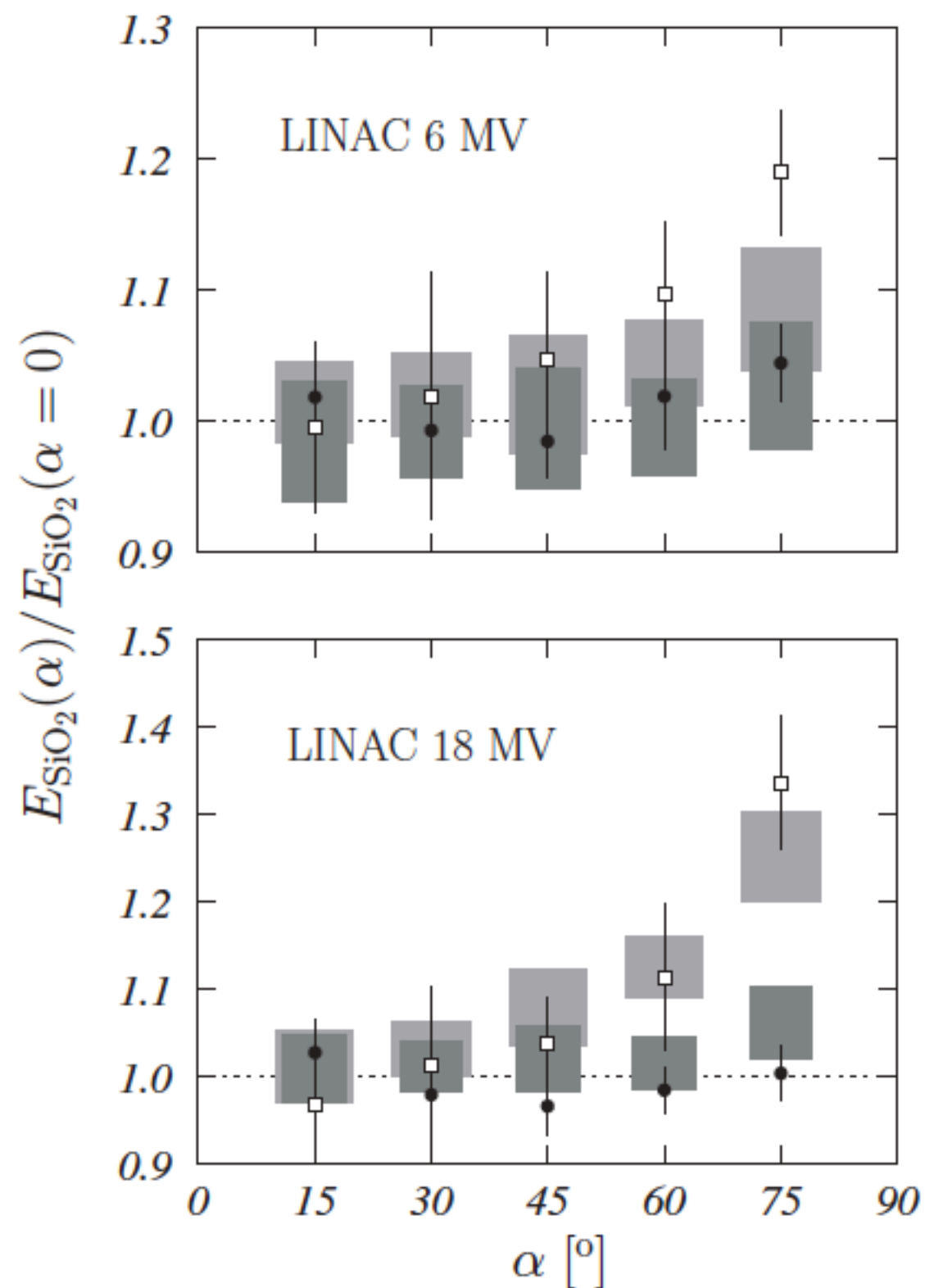


Figure 4. Effect of the additional brass encapsulation of the MOSFET. The experimental results (black dots) and the results of the corresponding simulations (darker gray bands) are compared to the results in the absence of the brass encapsulation shown in figure 3. In the case of the 6 (18) MV beam, the thickness of the brass casing is 0.3 (0.5) mm. Uncertainties correspond to 3σ .

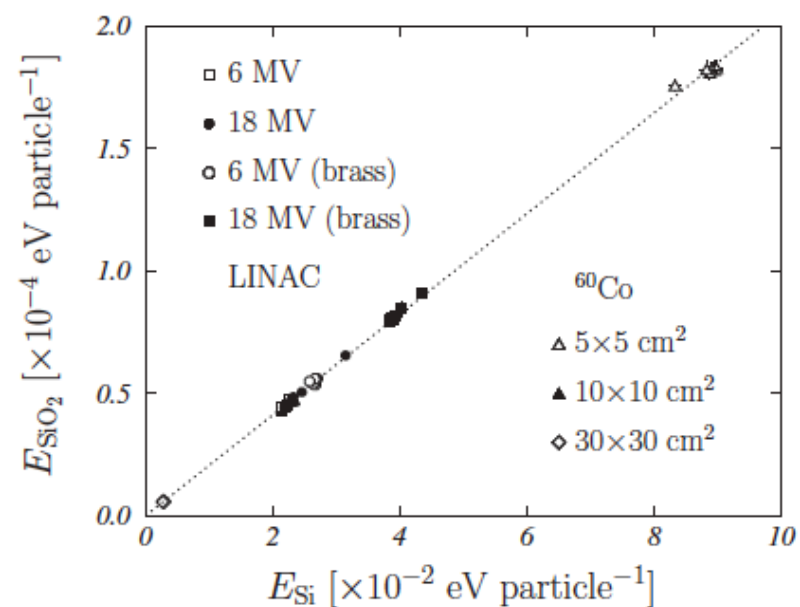


Figure 5. Energy deposited in the SiO_2 versus that deposited in the Si bulk. The corresponding values obtained in all our simulations are included. The straight line gives the linear regression of the data with a slope of 2.06×10^{-3} . Uncertainties in the data correspond to 1σ .

Some applications

Photon beams for radio surgery

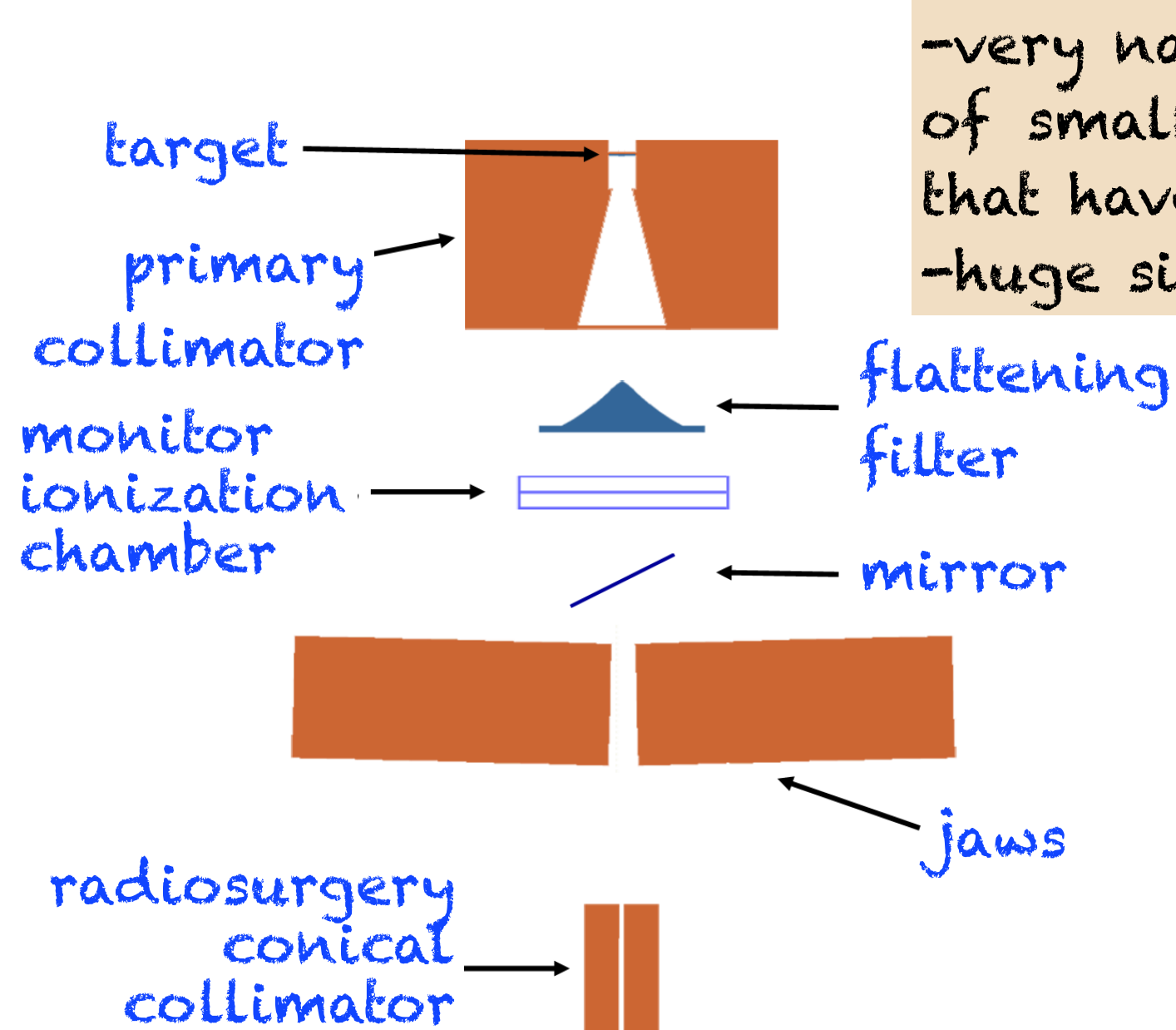
Some applications

Photon beams for radio surgery

- very narrow beams used for treatment of small lesions nearby healthy tissues that have to be preserved
- huge simulation CPU times!!

Some applications

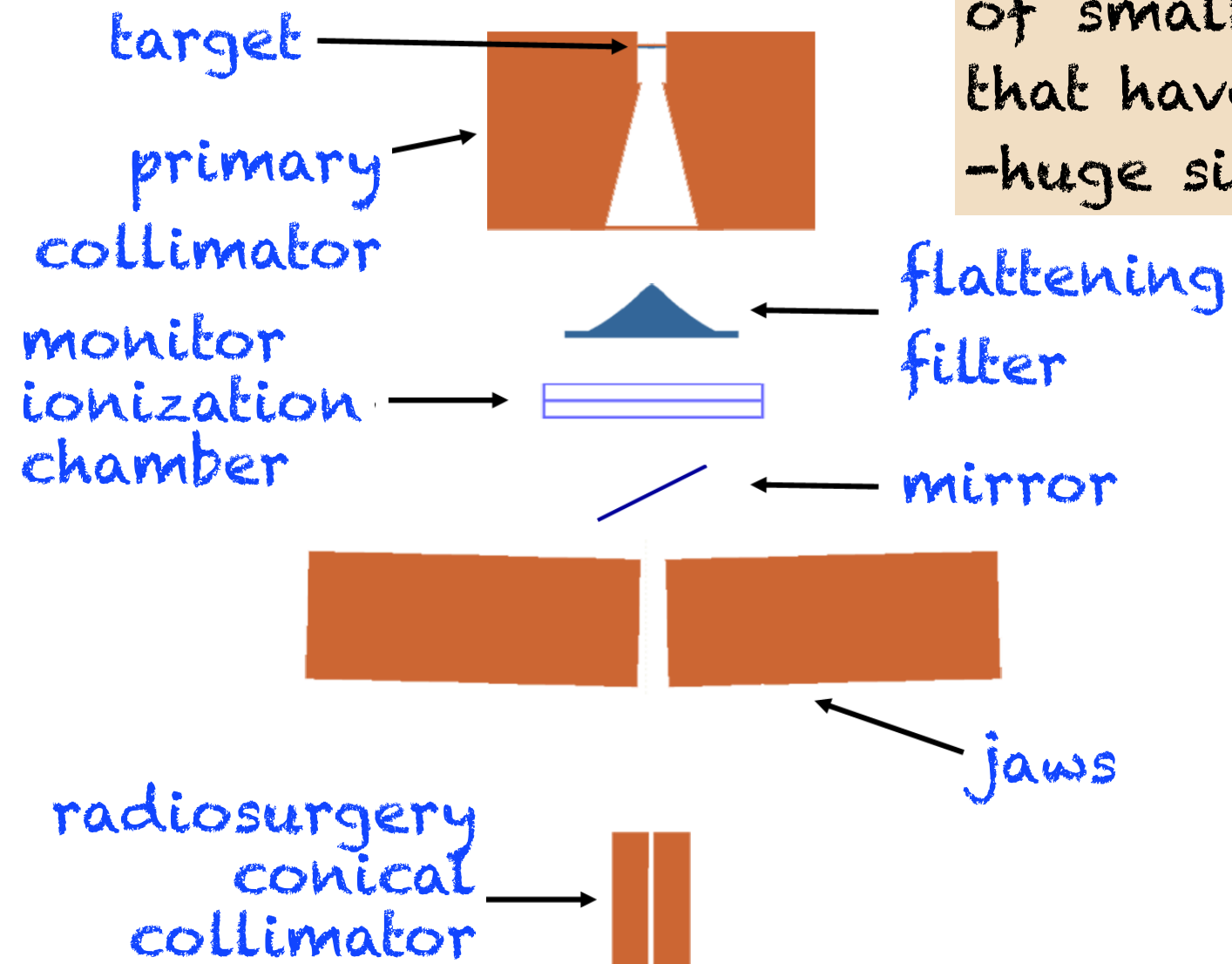
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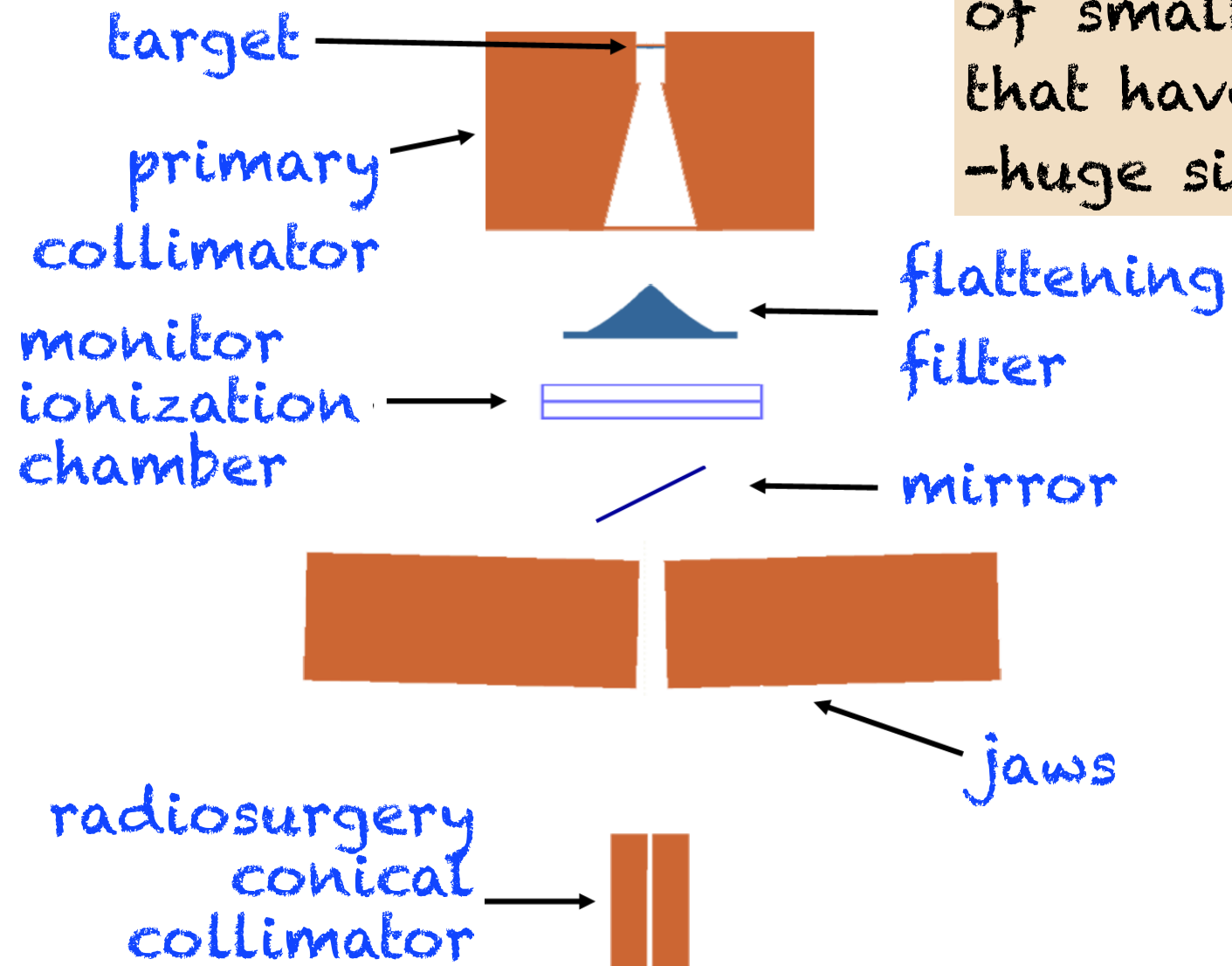
-VRT applied to both electrons and photons

$$I_1 = I(x, y, z, E, M) \text{ for electrons.}$$

$$I_2 = I(x, y, z, E, M, \theta, \phi) \text{ for photons.}$$

Some applications

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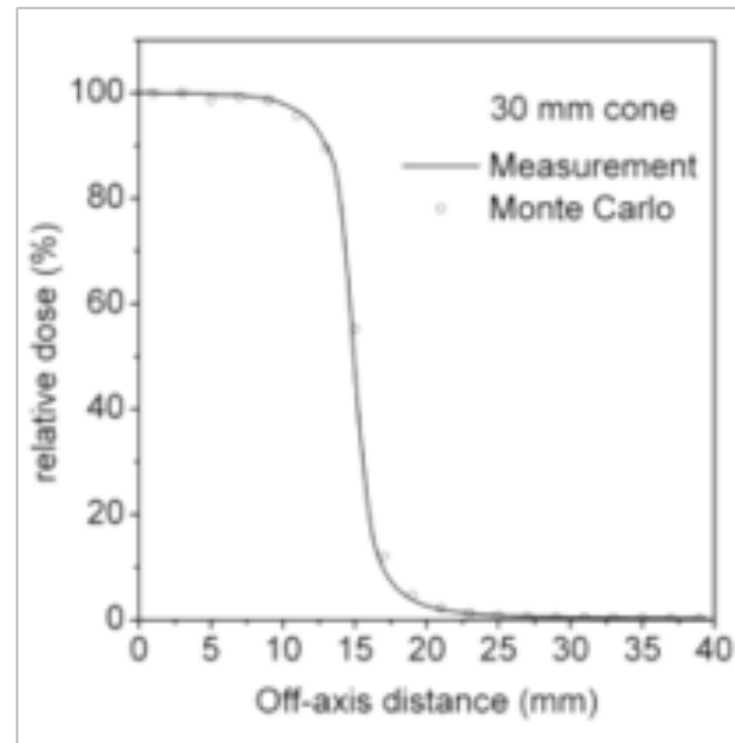
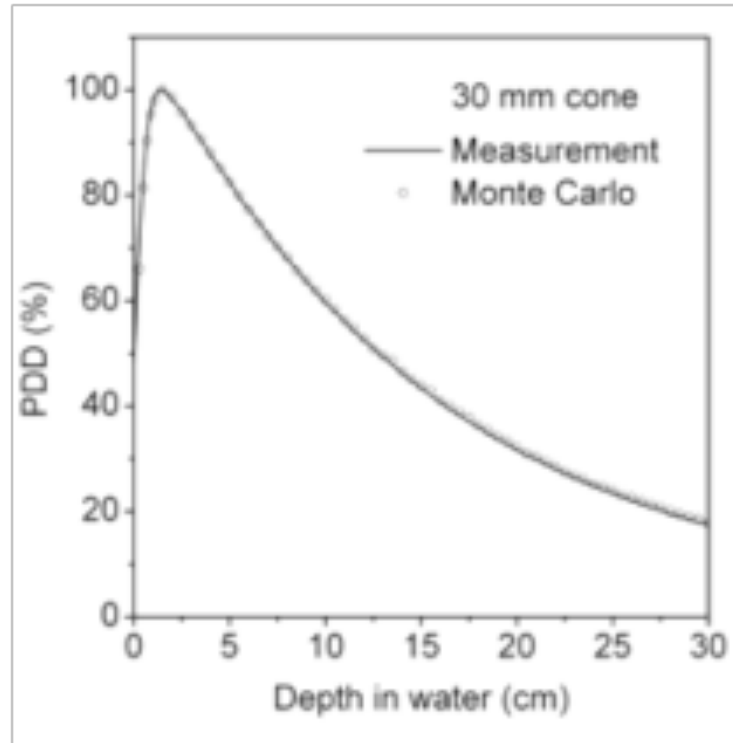
•directional Bremsstrahlung splitting is needed
-applied throughout the whole geometry

Some applications

Photon beams for radio surgery

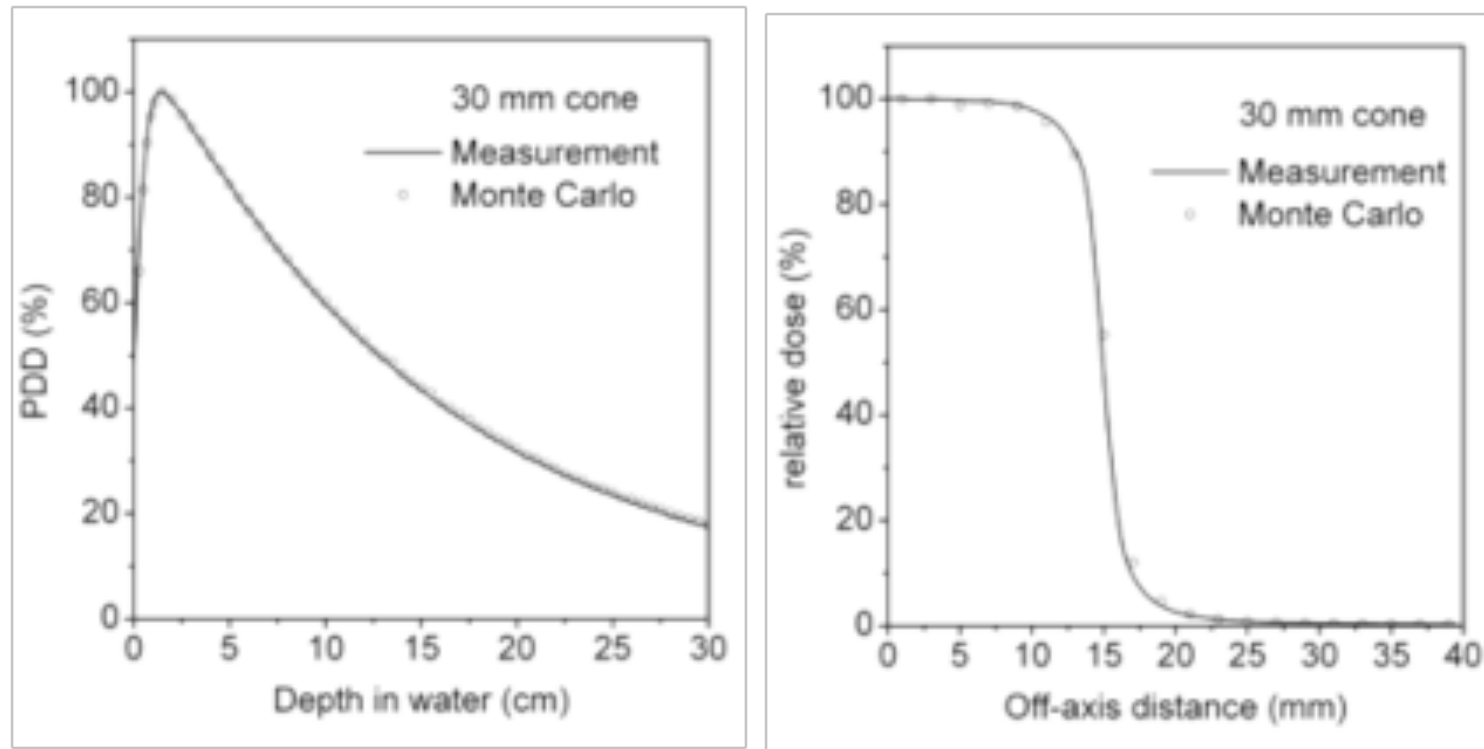
Some applications

Photon beams for radio surgery



Some applications

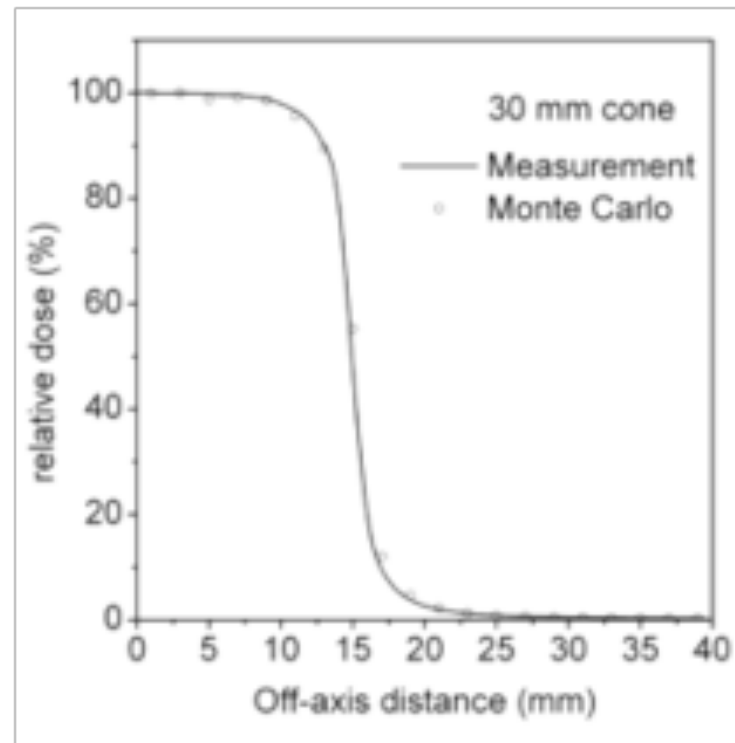
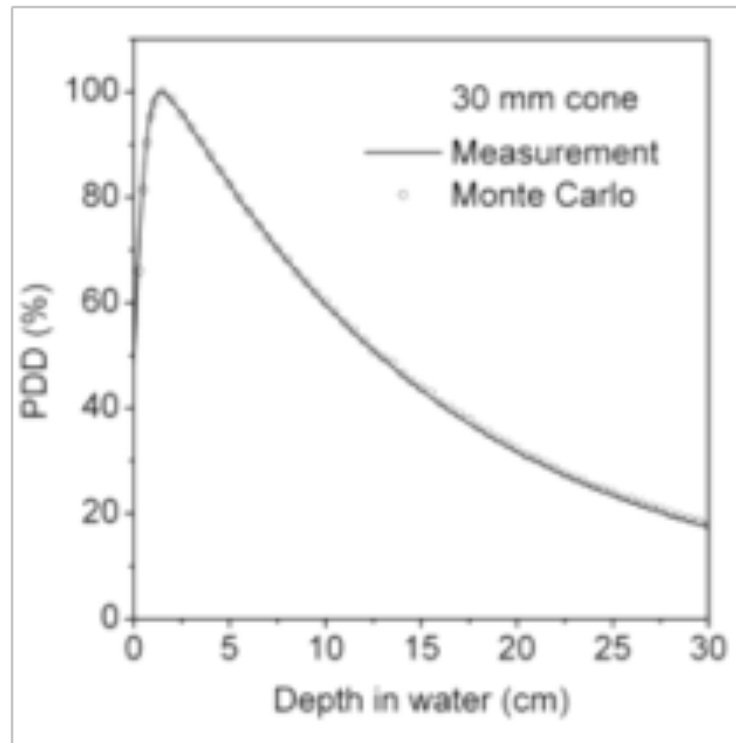
Photon beams for radio surgery



CPU times:
9 h (10 mm) to 0.9 h (30 mm)

Some applications

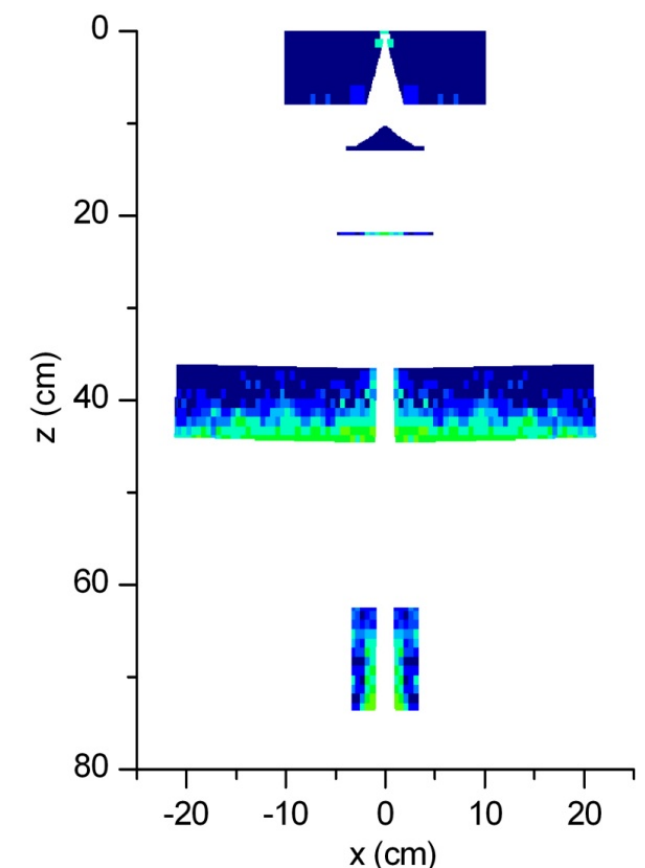
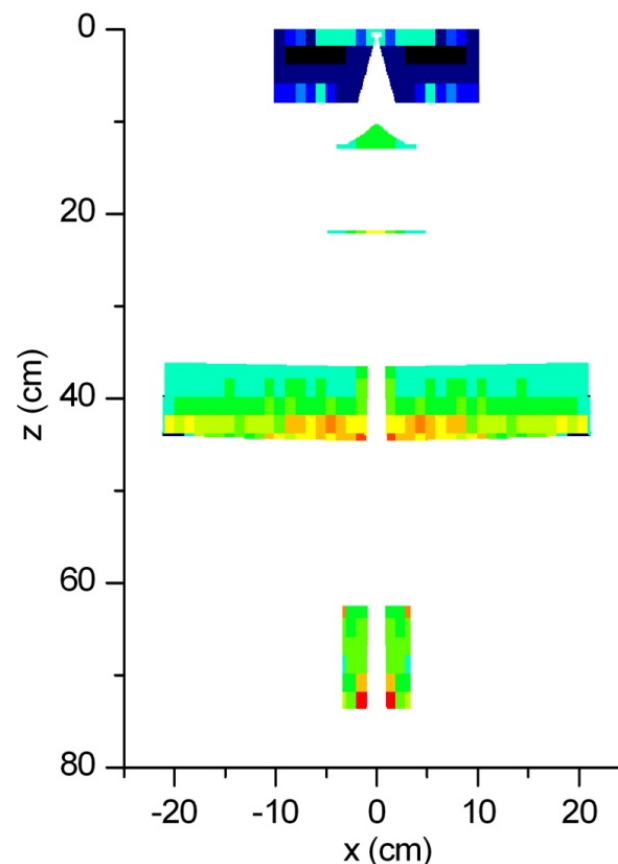
Photon beams for radio surgery



high
energy
photons

high
energy
electrons

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Some applications

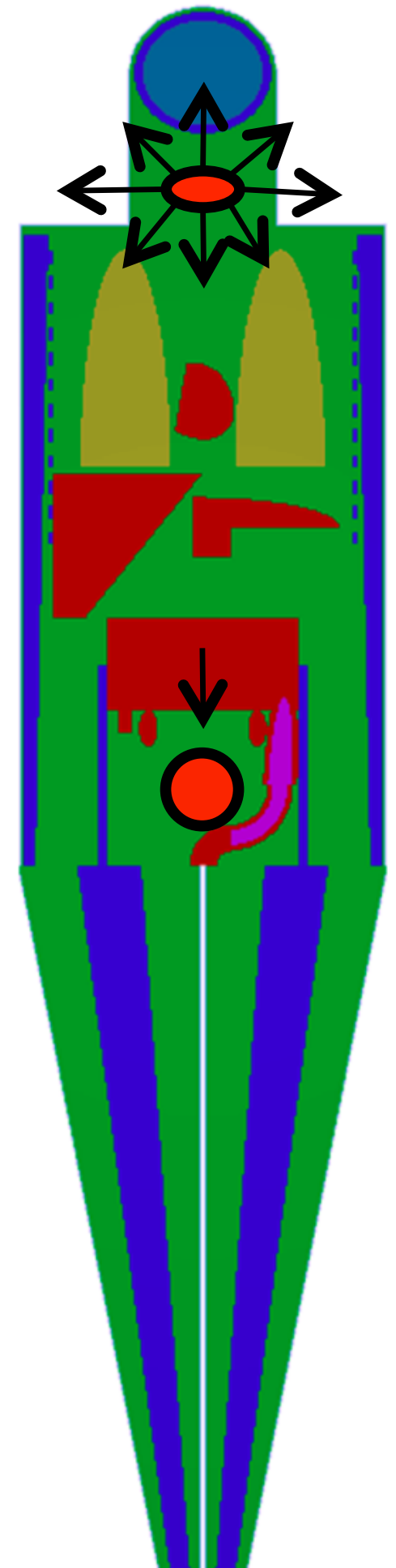
Some applications

Specific absorbed fractions

Some applications

Specific absorbed fractions

- inform about organ/tissue irradiation due to diagnostic or therapy of other organ
- interest in Nuclear Medicine

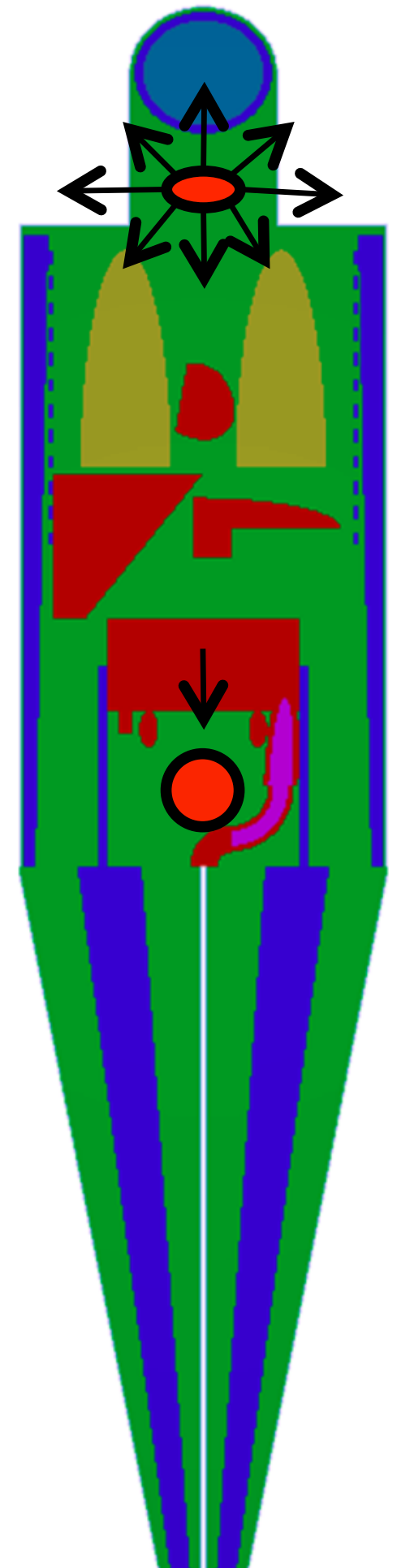


Some applications

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- problem: very low statistics because of organ volume and/or distance to source



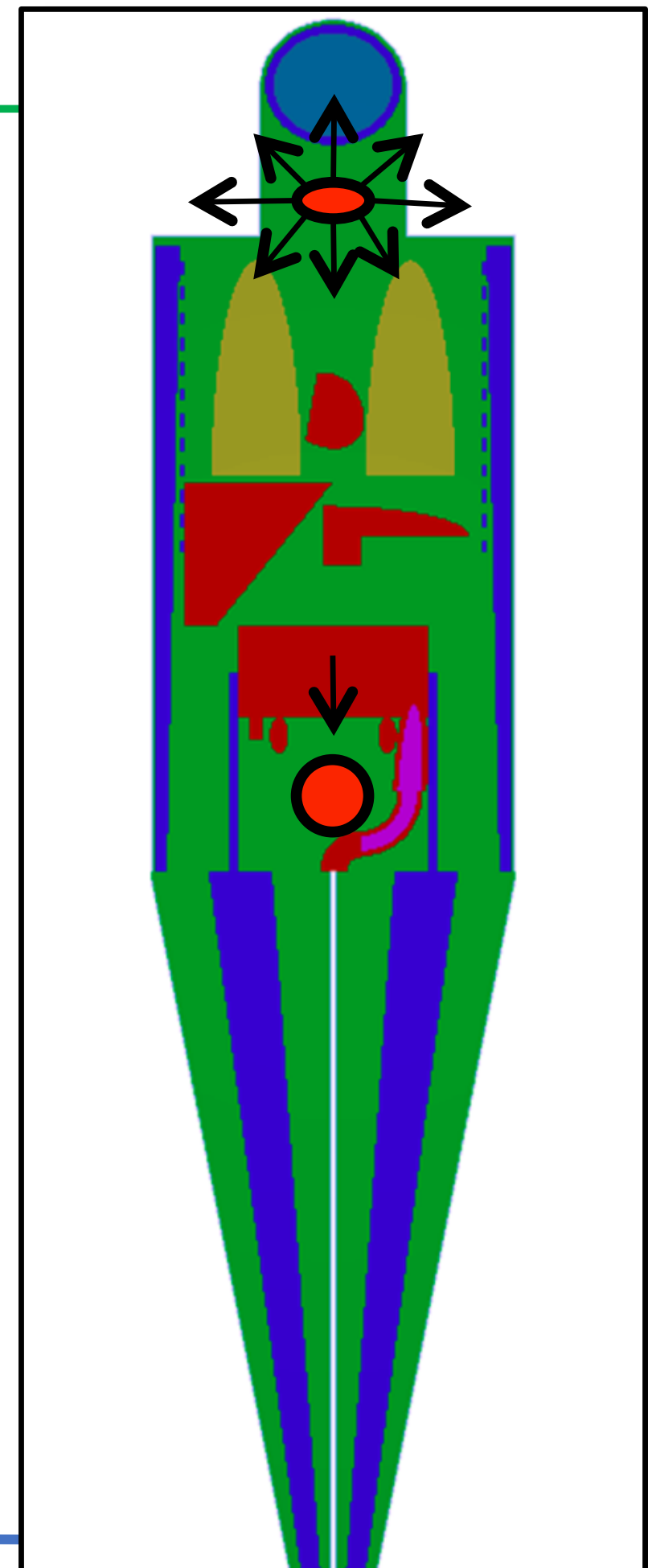
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Some applications

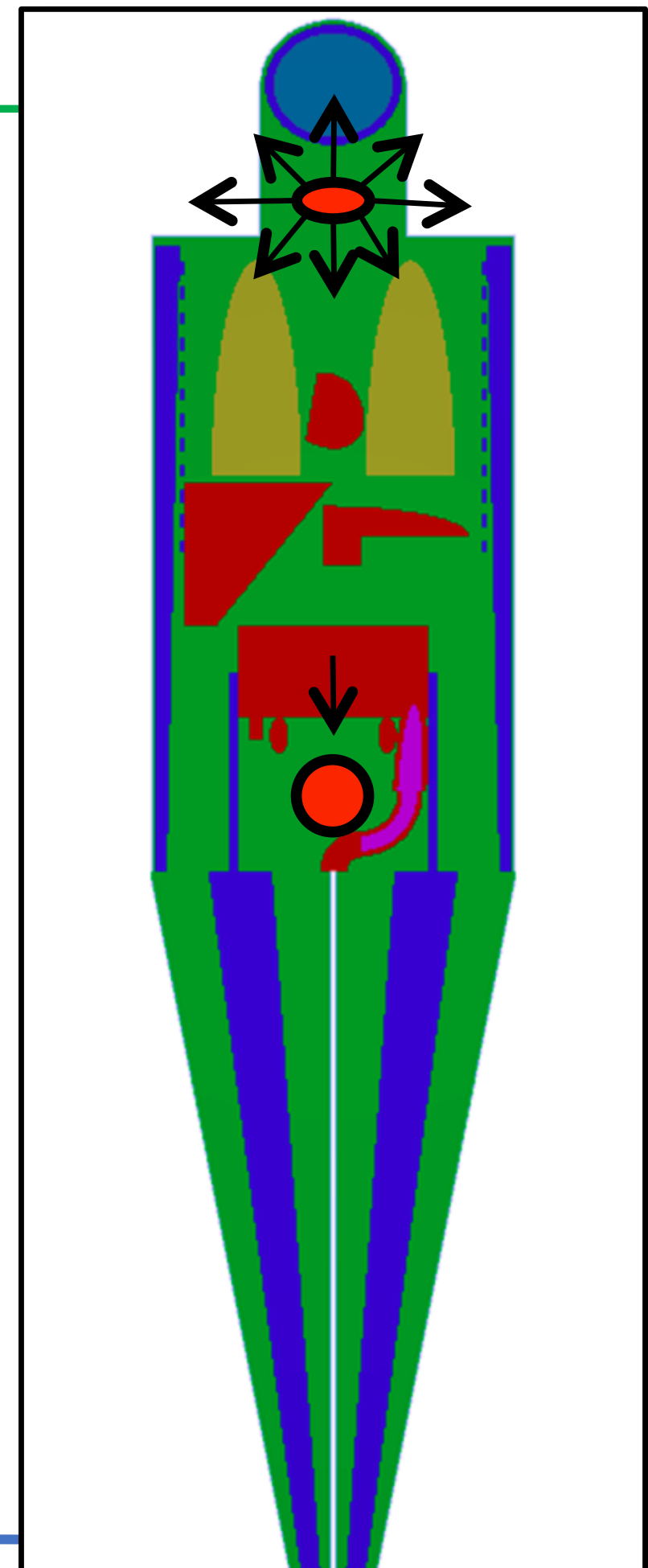
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Correction factors of micro-chambers



Some applications

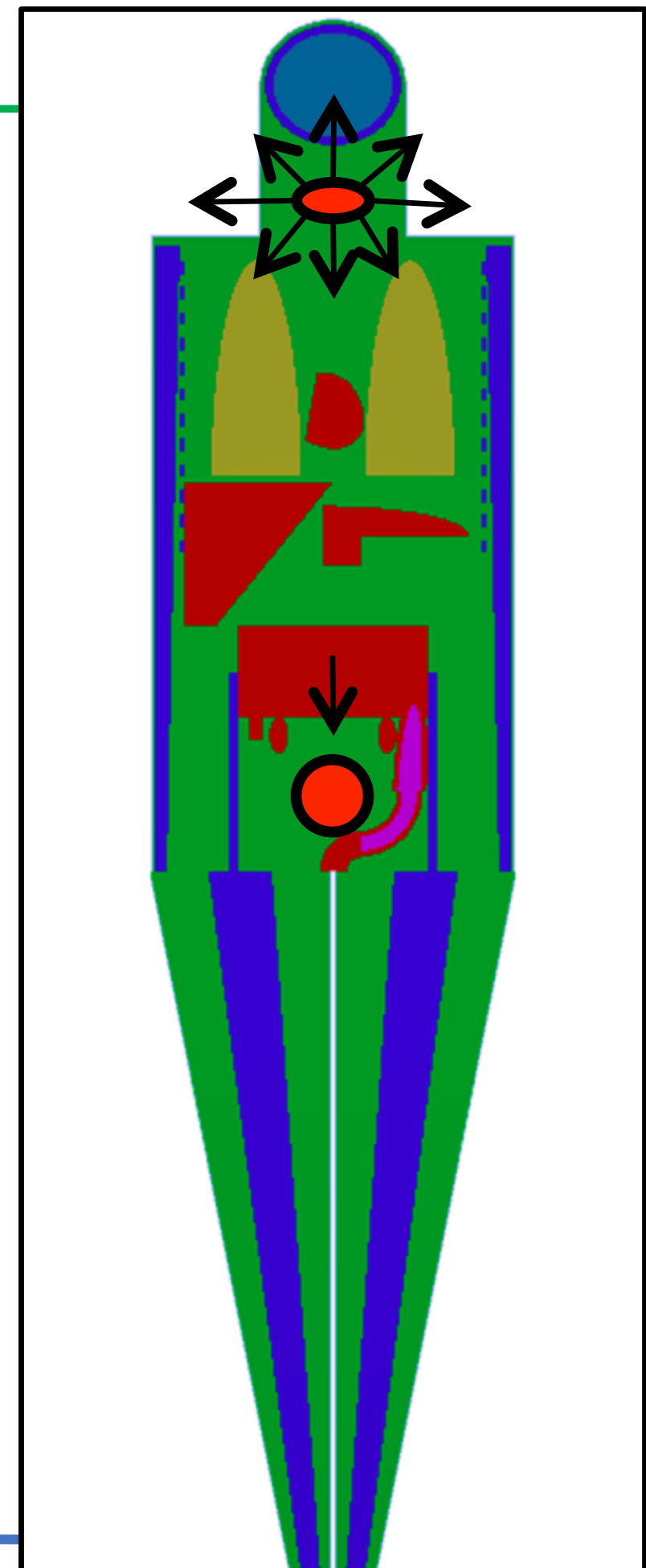
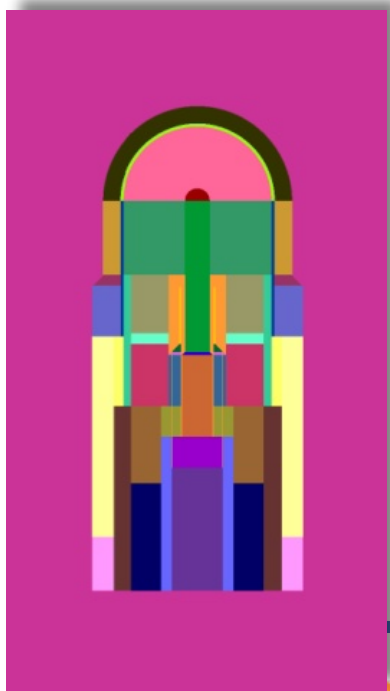
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Some applications

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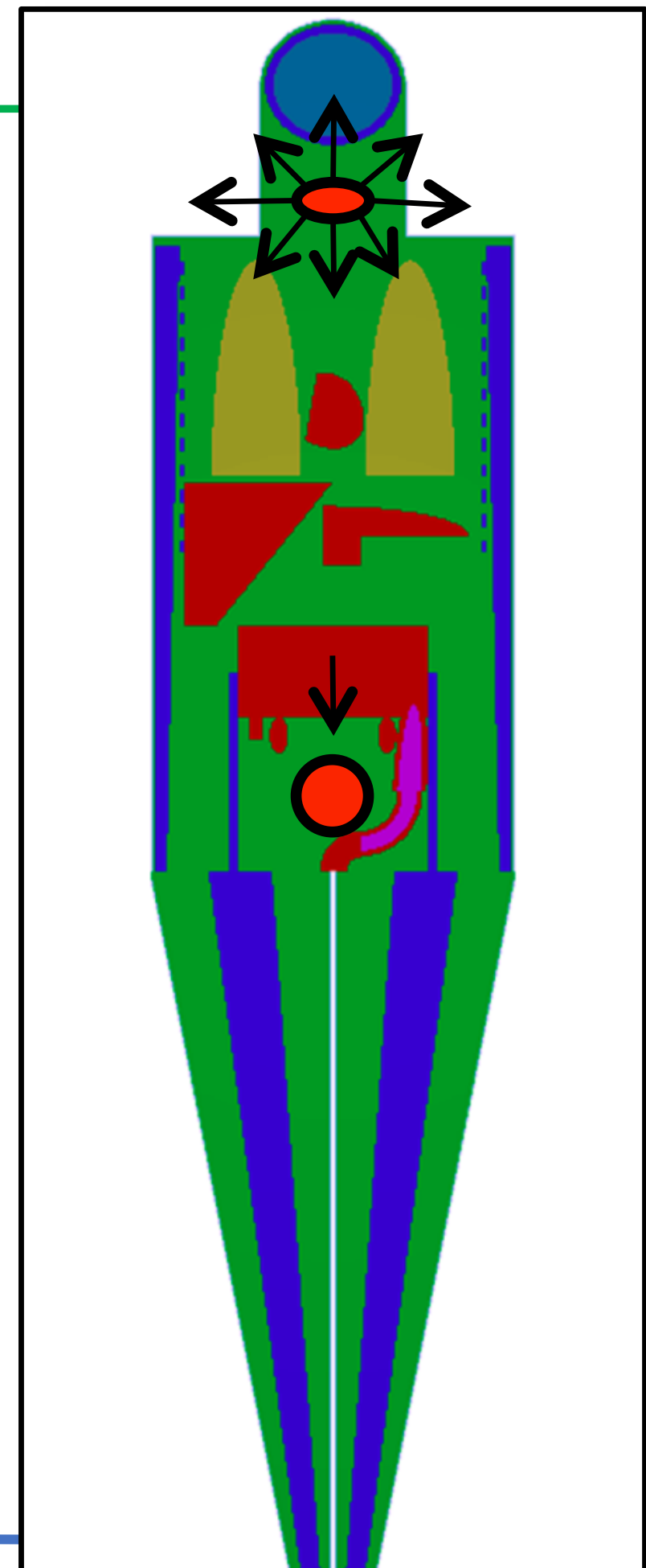
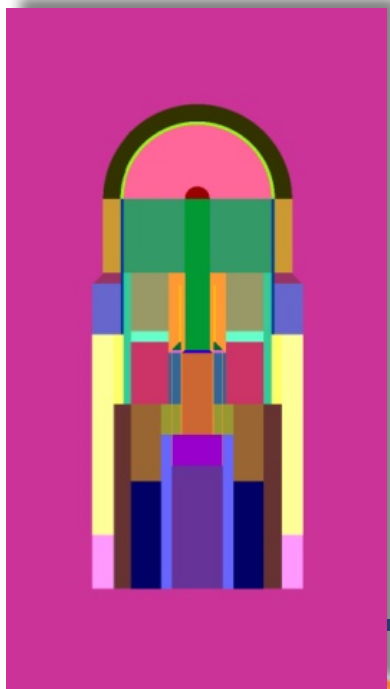
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Correction factors of micro-chambers

- efficiency increases by a factor 100!!



Conclusions

- An optimization algorithm based on 'ant colony behavior' has been developed
- It allows the efficient implementation of variance reduction techniques
- It uses the information scored on importance maps
- Minimum intervention by the user is required ... but details are relevant

S. García Pareja Hosp. Univ. Málaga (Spain)
M. Anguiano Univ. Granada (Spain)
G. Díaz Londoño Inst. Tech. Metropolitan Medellín (Colombia)
F. Salvat Univ. Barcelona (Spain)
L. Brualla Universitätsklinikum Essen (Germany)
A. Palma, M.Á. Carvajal Univ. Granada (Spain)
D. Guirado Hosp. Univ. Granada (Spain)
F. Erazo SOLCA Cuenca (Ecuador)
M. Vilches IMOMA Oviedo (Spain)
P. Galán Hosp. Univ. Málaga (Spain)

Ant colony algorithm for driving variance reduction techniques in Monte Carlo simulations of radiation transport

A. M. Lallena



Thanks for your attention

