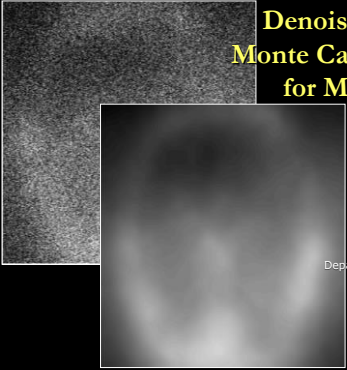



## Variance Reduction and Denoising Methods in Monte Carlo Simulations for Medical Imaging



W. Zbijewski  
Department of Biomedical Engineering  
Johns Hopkins University




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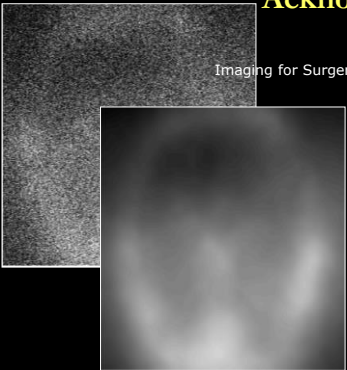
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## Acknowledgements



**The I-STAR Laboratory**  
Imaging for Surgery, Therapy, and Radiology  
<http://istar.jhu.edu/>

**Funding Support**  
Carestream Health  
NIH 2R01-CA-112163  
NIH R21-AR-062293




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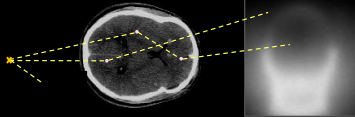
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## Overview

**MC-GPU**  
Head CBCT Scatter Projection



10<sup>10</sup> photons  
8.5 min / projection  
(on nVidia GTX 780 Ti)

**Analog Monte Carlo**  
Signal-to-noise ratio (SNR) proportional to  $\sqrt{\text{number of tracked particles}}$   
More particles = better SNR  
More particles = longer simulation time  
Achieving low noise MC estimates can be prohibitively long even on a GPU

**Algorithmic acceleration strategies**  
Variance Reduction (VR): modifies the tracking process (avoids bias)  
De-noising: typically post-processing (may introduce bias)  
Combination with analytical methods  
We will focus on MC scatter estimation in x-ray imaging  
Methods also applicable to dose scoring

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## Variance Reduction

Increase the number of events contributing to the signal

**General approach:**

- Modify the probability distribution
- Increase the fraction of histories leading to "detection"
- Include a weight to avoid biasing the signal

**Analog MC:**

- $X$ : space of photon histories
- $p(x)$ : probability density on space  $X$
- $S$ : mean signal

$$\bar{S} = \int_X S(x) p(x) dx$$

DR Hoyer, RL Harrison, Variance Reduction Techniques in Monte Carlo Calculations in Nuclear Medicine, 2nd edition, CRC Press 2013 with M Jurek, GE Medical, MA King

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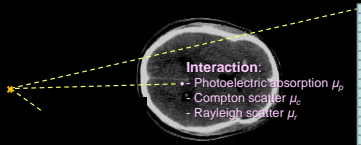
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## Variance Reduction – Scatter Forcing



**Analog MC probability distribution**

- $p(x)$ : [absorption, scatter] = [ $\mu_p / (\mu_p + \mu_c + \mu_r)$ ,  $(\mu_c + \mu_r) / (\mu_p + \mu_c + \mu_r)$ ]
- Photoelectric absorption does not contribute to the signal

**Let's force the photon to scatter**

- $q(x)$ : [absorption, scatter] = [0, 1]
- We need to weight the photons after forcing scatter:
- $w = p(x) / q(x) = (\mu_c + \mu_r) / (\mu_p + \mu_c + \mu_r)$

**Intuition about the weights**

Weight by the "analog" probability of the history

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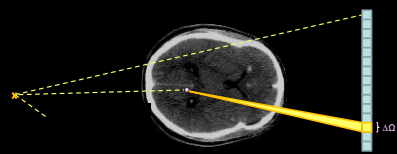
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## Forced Detection



**Measure scatter at a particular detector cell**

- Only small fraction of events contributes to the signal
- Even worse if seeking distribution at a point (point detectors)
- Also applies to dose scoring

**Let's force towards the detector cell**

- Pick scatter angle within the solid angle of the cell ( $\Delta\Omega$ )
- Weight: Ratio of events scattered towards the detector vs. events scattered into  $4\pi$
- Scatter cross section over  $\Delta\Omega$  vs. total scatter cross section
- Followed by sending the particle directly to the detector (ray-tracing)

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Consider a VR technique where at each Compton interaction, a virtual scattered photon is created and forced towards a fixed detector cell. Let:

- $\sigma$  be the total cross section for Compton interaction.
- $\partial\sigma/\partial\Omega$  be the differential cross section for the direction towards the center of the detector cell (assumed constant across the cell).
- $\Delta\Omega$  be the solid angle covered by the detector cell as seen from the point of interaction.

What weight needs to be assigned to the virtual photon to avoid bias in the resulting scatter distribution:

19% A. No weight.

13% B.  $\partial\sigma/\partial\Omega \cdot \Delta\Omega$

6% C. Bias cannot be avoided by weighting

38% D.  $\sigma / \Delta\Omega$

25% E.  $\sigma^{-1} \cdot \partial\sigma/\partial\Omega \cdot \Delta\Omega$

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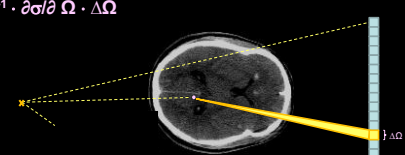
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**Answer:**  
 (e)  $\sigma^{-1} \cdot \partial\sigma/\partial\Omega \cdot \Delta\Omega$



**Forced detection\***  
 Probability that a photon would scatter into  $\Delta\Omega$  in analog simulation:

$$W_{FD} = \frac{\text{Scatter towards the detector cell}}{\partial\sigma/\partial\Omega} \cdot \frac{\text{Angular coverage of the detector cell}}{\Delta\Omega} / \frac{\text{Scatter into } \sigma}{\sigma}$$
(assumes differential cross section does not change much throughout the detector cell)

**Next step – send the photon directly to the detector**  
 Weight = attenuation along the path (ray tracing)  

$$W = W_{FD} \cdot e^{-\int \mu dx}$$

\*P. Williamson, Monte Carlo evaluation of kernels at a point for photon transport problems, MSc Thesis, TU Delft, 1987  
 C.J. Leinold, A fast Monte Carlo simulator for dosimetry in X-ray Computed Tomography, PhD Thesis, TU Delft, Netherlands, 1996.

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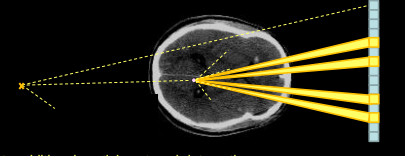
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**Interaction Splitting**



Create additional particles at each interaction

- Split into  $N_p$  photons
- Weight each by  $1/N_p$
- Track all new particles

\*P. Dally and F.J. Beukema, Accelerated simulation of cone beam X-ray scatter projections, IEEE TMI 23 (2004)

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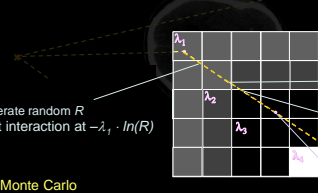
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## Woodcock Tracking

**Mean Free Path (MFP)  $\lambda \sim 1/\sigma$**



- generate random  $R$
- next interaction at  $-\lambda_i \cdot \ln(R)$
- new material ( $\lambda_2$ )
- sample again
- and again...
- interaction at  $-\lambda_4 \cdot \ln(R)$
- virtual interaction with no change in motion  $P=1-\lambda_4/\lambda_3$

**Analog Monte Carlo**  
Resampling of the path length at each material boundary  
Inefficient in voxelized geometries

**Woodcock Tracking ( $\delta$  scattering)\***  
Treat whole volume as made of the most attenuating material - shorter "steps"  
No boundary checking  
Virtual interaction accounts for difference between true MFP and the maximal MFP  
Implemented in MC-GPU  
Challenging when highly attenuating materials (implants) are present

\*E Woodcock et al. Techniques used in the GEM-Code for Monte Carlo neutron calculations in reactors and other systems of complex geometry. Argonne Nat. Lab., Report T-500, T-501 and T-502, 1962. E. Woodcock et al. GEM-Code: A fast accurate Monte Carlo code optimized for photon and electron optoelectronic treatment (presenting slide: conference, PSAB-45 (2000))

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## Other VR Techniques

**Mean Free Path Transformations\***  
Increase number of interactions in a region  
Change the probability distribution function of number of MFP till next interaction  
Stretch the paths – more interactions deeper  
Change path length depending on travel direction (exponential transforms)\*\*  
Force interaction to happen within a volume\*\*  
Weight the photon

**Russian Roulette\***  
To remove particles from tracking without bias  
Combined with splitting – remove photons not pointing towards the detector  
Randomly decide if a particle should be terminated or survive  
Probability of particle being terminated:  $P$   
Weight if particle survives:  $1/(1-P)$   
Weight for surviving particles  $> 1!$

\*E Marwan-Heg and M Kararwan. Variance reduction techniques for fast Monte Carlo MCCT under neutron moderation. Progress in Particle Physics Conference: 2010, pp. 1-10.  
\*\*C.M. Rogers and A.F. Sawada. Monte Carlo Techniques of Electron and Photon Transport for Radiation Dosimetry. The University of Guelph Radiation Academic Press 1990 (eds M.R. Kalin, BE Bingham PH ASU)

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## MC Simulation Efficiency

**Computational cost of VR**  
Additional arithmetic (weights)  
Potentially breaks parallelism (Interaction Splitting)  
Many events with low contribution to signal (Scatter Forcing)  
Widely fluctuating weights (introduces noise)

**Simulation time vs. Signal-to-Noise Ratio (SNR)**  
Efficiency:

$$\epsilon = 1 / (\sigma^2 \cdot T)$$

$\sigma^2$ : variance  
 $T$ : simulation time

Inverse variance per unit time  
Higher value – better efficiency  
To improve efficiency:  
 $\sigma^2 \downarrow$  or  $T \downarrow$ , but it's the product that counts  
Other definitions (involving SNR) exist - similar meaning

Journal Physics Letters: 2008, 139, 030105, 1-5.pdf  
C.M. Rogers and A.F. Sawada. Monte Carlo Techniques of Electron and Photon Transport for Radiation Dosimetry. The University of Guelph Radiation Academic Press 1990 (eds M.R. Kalin, BE Bingham PH ASU)

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Consider:  
 -Analog MC (aMC) simulation with a runtime of 300 sec.  
 -VR technique A that reduces the variance (for the same signal level) by a factor of 2 with a runtime of 600 sec  
 -VR technique B that reduces the variance by a factor of 3 with a runtime of 1000 sec.

Which of the statements is true:

28% A. Technique A improves efficiency compared to aMC  
 24% B. Technique B improves efficiency compared to aMC  
 14% C. Neither of the VR techniques improves efficiency over aMC  
 7% D. Efficiency of technique A is 2/3 of efficiency of technique B  
 17% E. Technique B has higher efficiency than technique A

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**Answer:**  
**(c) Neither of the techniques improves efficiency over analog MC**

Using  $\epsilon = 1 / (\sigma^2 \cdot T)$  defined previously:

**Analog simulation:**  
 Variance  $\sigma_0^2$   
 $T_0 = 300$  s  
 $\epsilon_0 = 1 / (\sigma_0^2 \cdot 300$  s)

**Variance reduction A:**  
 $\sigma_A = \sigma_0^2 / 2$   
 $T_A = 600$  s  
 $\epsilon_A = 1 / ((\sigma_0^2 / 2) \cdot 600$  s) =  $1 / (\sigma_0^2 \cdot 300$  s)

**Variance reduction B:**  
 $\sigma_B = \sigma_0^2 / 3$   
 $T_B = 1000$  s  
 $\epsilon_B = 1 / ((\sigma_0^2 / 3) \cdot 1000$  s) =  $1 / (\sigma_0^2 \cdot 333.3$  s)

$\epsilon_A = \epsilon_0$   
 $\epsilon_B < \epsilon_0$   
 $\epsilon_A > \epsilon_B$

Image: physics.carleton.ca/~jrogers/papers/egpvrRBM.pdf  
 DTM: Rogers and Al-Sayid, Monte Carlo Techniques of Electron and Photon Transport for Radiation Dosimetry in The Dosimetry of Ionizing Radiation, Academic Press 1990, vol. 40, Chap. 3B, Expanded 7th Edition.

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### Variance Reduction on GPUs

**Analog MC- GPU**

Track in parallel until detected/escape

**Efficient GPU implementation**  
 Simple parallelism  
 1 GPU thread per photon

**Variance Reduction in MC – GPU  
 Photon Splitting + Forced Detection**

Generate split photons

Start tracking  
 Stop tracking  
 Store status  
 Continue original

**Challenges for GPU implementation**  
 Tracking split into stages  
 Breaks parallelism  
 Cost in context switch  
 Complex memory management

A. Strohriegl et al., Ultra-Fast Monte Carlo Simulation for Cone Beam CT Imaging of Brain Trauma, AAPM 2014, TH-A-18C-9

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### Scatter Estimation with VR

Analog MC-GPU $10^{10}$ photons	MC-GPU + Variance Reduction $10^7$ photons – 512 split
Time = 510 s Noise = $4.8 \times 10^{-4}$ Efficiency = 0.9	Time = 80 s Noise = $3.5 \times 10^{-4}$ Efficiency = 9.7

**GPU-accelerated MC with VR\***

Optimized combination of photon splitting and variance reduction  
 ~10 fold improvement in efficiency over analog MC-GPU (depends on object/geometry)

**VR for MC executed on a CPU (Mainegra-Hing 2010)\*\***

Forced detection, Woodcock tracking, path length transformations  
 Splitting and Russian Roulette  
 Region dependent importance splitting  
 2-orders of magnitude improvement in efficiency  
 Relies heavily on splitting – may not be suited for GPU

\*A Saragioti et al. Monte Carlo study of the effects of system geometry and anticounter gradient on breast CT scatter distributions. Med Phys 40 (2013)  
 \*\*Mainegra-Hing and J. Kaspriske. Variance reduction techniques for fast Monte Carlo CBCT scatter estimation calculations. PWB for 2013

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### Beyond Variance Reduction

**Assumptions**

Distribution of interest (scatter, dose) is "smooth"  
 De-noising does not introduce significant bias

**Examples (scatter estimation)**

- Colijn et al (IEE TMI 2004)
- Richardson-Lucy fit
- Gaussian kernels
- Jarry et al (SPIE 2006)
- Polynomial fitting
- Bootsma et al (Med Phys 2013)
- Frequency domain filtering
- Butterworth filter
- Zbijewski et al (SPIE 2013)
- Kernel smoothing
- Gaussian kernels
- Thing and Mainegra-Hing (Med Phys 2014)
- Adaptive Savitzky-Golay filter
- egs\_cbat
- Xu et al (AAPM 2014)

**Challenges**

Noise reduction vs. bias

MC with low #photons } Fast  
Noisy

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Which of these acceleration methods are NOT considered MC Variance Reduction Techniques:

4%	A. Forced Detection
4%	B. Projection De-noising
13%	C. Interaction Splitting
13%	D. Scatter Forcing
13%	E. Woodcock Tracking

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**Answer:**  
**(b) Projection De-noising**

**Variance reduction**  
 Weights are applied to avoid bias  
 We discussed:  
 Forced Detection, Interaction Splitting, Scatter Forcing and Woodcock Tracking

**De-noising**  
 Generally cannot guarantee that no bias will be introduced\*  
 Acceptable bias may depend on application  
 Brute force optimization (parameter sweep)  
 Theoretical considerations\*

TS Theng and E. Manjra-Hej, Optimizing consistent CT scatter estimation in 3D, Proc for a clinical and virtual chest phantom, MedPhys 41 (2014)  
 \*Kaniadakis On the de-noising of Monte Carlo-calculated dual-Distributions, PLoS 6(1) (2011)

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**Other Acceleration Strategies**

**Sparse Detector Sampling / Fixed Forced Detection (Poludniowski 2009)**  
 Detector as a sparse, fixed grid of nodes (8x8 nodes)  
 Each interaction → forced detection into all nodes  
 Sparse sampling in projection angles  
 Interpolation in-plane and between views  
 Correction in ~2 min per scan for on-board CBCT

**Combination with analytical simulation (Kyriakou 2006)**  
 Analytical simulation (deterministic) for 1<sup>st</sup> order scatter  
 Monte Carlo (with Forced Detection and optional smoothing) for higher order scatter  
 Higher order scatter is smooth, only about 30% of total scatter intensity  
 Low #photons in MC for higher order scatter  
 ~0.5 min/projection for chest C-arm CBCT

© Poludniowski et al., An efficient Monte Carlo-based algorithm for scatter correction in flat-panel CT, PLoS 5(4) (2010)  
 \*\* Kyriakou et al., Combining deterministic and Monte Carlo calculations for fast estimation of scatter in breast CT, PLoS 5(1) (2010)

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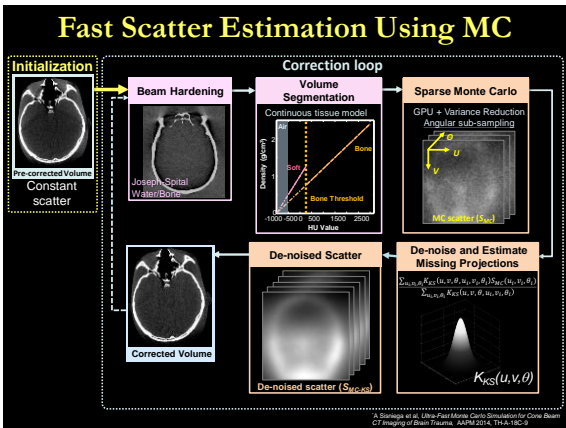
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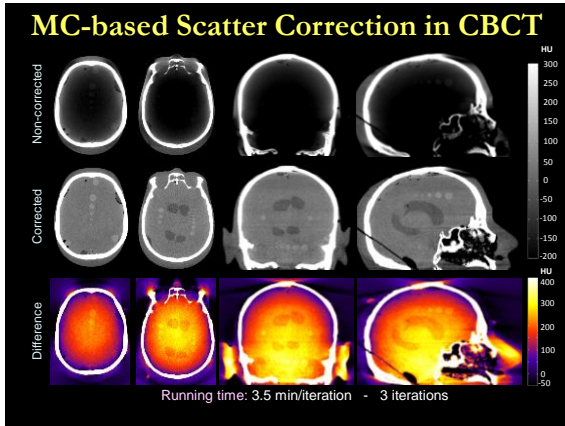
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### Summary and Conclusions

- Algorithmic acceleration techniques for MC**
  - Improve SNR per unit time
  - Essential for "real-time" MC applications
  - Scatter estimation and correction
- Variance Reduction**
  - Alter the tracking to generate more events of interest
  - Weighting to avoid bias
  - Well-established methodology
  - Implemented in some MC packages
  - 1-2 orders of magnitude acceleration (gain in efficiency)
- De-noising**
  - May introduce bias
  - More efficient when quantity of interest is smooth
  - Another ~1 order of magnitude acceleration
- Applications**
  - Correction of scatter in 1-10 min/scan
  - Real-time dose estimation

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