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A Monte Carlo volumetric-ray-casting estimator for global fluence tallies on GPUs ☆

Jeremy E. Sweezy

Los Alamos National Laboratory, P.O. Box 1663, MS A143, Los Alamos, NM 87545, United States of America

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A B S T R A C T

A Monte Carlo fluence estimator has been designed to take advantage of the computational power of graphical processing units (GPUs). This new estimator, termed the volumetric-ray-casting estimator, is an extension of the expectation estimator. It can be used as a replacement of the track-length estimator for the estimation of global fluence. Calculations for this estimator are performed on the GPU while the Monte Carlo random walk is performed on the central processing unit (CPU). This method lowers the implementation cost for GPU acceleration of existing Monte Carlo particle transport codes as there is little modification of the particle history logic flow. Three test problems have been evaluated to assess the performance of the volumetric-ray-casting estimator for neutron transport on GPU hardware in comparison to the standard track-length estimator on CPU hardware. Evaluation of neutron transport through air in a criticality accident scenario showed that the volumetric-ray-casting estimator achieved 23 times the performance of the track-length estimator using a single core CPU paired with a GPU and 15 times the performance of the track-length estimator using an eight core CPU paired with a GPU. Simulation of a pressurized water reactor fuel assembly showed that the performance improvement was 6 times within the fuel and 7 times within the control rods using an eight core CPU paired with a single GPU.

1. Introduction

Accelerators augmenting Central Processing Units (CPUs) is currently one of the possible paths towards exascale computing. Sixty one of the 500 fastest supercomputers in the world, including Oak Ridge National Laboratory's (ORNL) Titan (the 3rd fastest), use Graphical Processing Unit (GPU) accelerators [45]. Several research groups have demonstrated specially built Monte Carlo particle transport on GPUs [19,18,6,50] with significant increases in performance. However, a general Monte Carlo code, such as Los Alamos National Laboratory's (LANL) MCNP6® [15] code, represents hundreds of person-years of development and porting the entire code base to support specialized hardware is not feasible.

Traditionally, Monte Carlo methods have been used to calculate a few local fluence values. Today, the challenge for Monte Carlo codes is to calculate global particle fluence [29]. Global fluence rates are needed to calculate local power densities

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E-mail address: jsweezy@lanl.gov.

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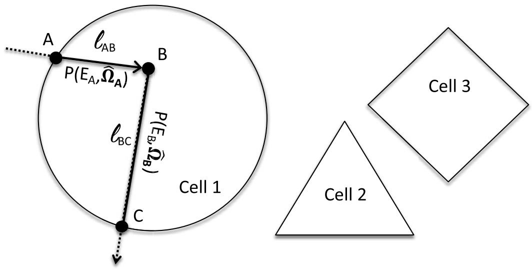

Fig. 1. Track-length estimator. A random walk particle enters Cell 1 at point A, has a collision at point B, and exits Cell 1 at Point C. $P(E_A, \hat{\boldsymbol{\Omega}}_{\boldsymbol{A}})$ denotes the particle state starting at point A, with energy, E_A, and along direction $\hat{\boldsymbol{\Omega}}_{\boldsymbol{A}}$. $P(E_B, \hat{\boldsymbol{\Omega}}_{\boldsymbol{B}})$ is similarly defined. The TL estimator makes two contributions along the random walk, one at energy E_A with length l_{AB} and one at energy E_B with length l_{BC}.

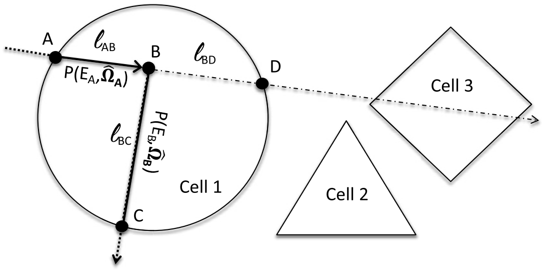

Fig. 2. Expected-value estimator. A random walk particle enters Cell 1 at point A, has a collision at point B, and exits Cell 1 at Point C. $P(E_A, \hat{\boldsymbol{\Omega}}_{\boldsymbol{A}})$ denotes the particle state starting at point A, with energy, E_A, and along direction $\hat{\boldsymbol{\Omega}}_{\boldsymbol{A}}$. $P(E_B, \hat{\boldsymbol{\Omega}}_{\boldsymbol{B}})$ is similarly defined. The EX estimator makes two contributions to cell 1 using Eq. (1), one contribution at energy E_A with length $l_{AD} = l_{AB} + l_{BD}$ and another contribution at energy E_B and with length l_{BC}.

for nuclear reactor core design, dose rates in facilities, neutron activation of reactor components, treatment planning for radiotherapy, and many other applications. The track-length (TL) estimator has been used as the standard estimator for calculating global fluence rates since the mid-1960's [14]. During the random walk, the particle's path length in each cell contributes to the track-length estimate of fluence (Fig. 1). The TL estimator has the advantage that no additional values must be calculated: the contribution to the track length fluence is the distance the particle traveled in the cell.

Spanier [41] points out that TL estimator is an unbiased estimator of the expected path length of a particle's flight through a cell. The single-particle expected path length can be calculated directly:

$$F(i, E, \hat{\boldsymbol{\Omega}}) = \frac{W}{\Sigma_{t,i}(E)} \left[1 - \exp\left(-\Sigma_{t,i}(E) l_i(\hat{\boldsymbol{\Omega}})\right)\right], \tag{1}$$

where i is the tally cell, E is the energy of the particle after collision or source event, $\hat{\boldsymbol{\Omega}}$ is the direction of the particle, W is the statistical weight of the particle, $\Sigma_{t,i}(E)$ is the total cross-section of cell i at energy E, and $l_i(\hat{\boldsymbol{\Omega}})$ is the ray length (distance from entrance, source, or collision location to possible exit) through cell i along direction $\hat{\boldsymbol{\Omega}}$. Eq. (1) is termed the expectation estimator (EX) by MacMillan [28] (Fig. 2). It is estimator XI in [14]. Macmillian found that the EX estimator generally provided a lower variance than the TL estimator, but considered it too expensive due to the cost of calculating the exponential function. Macmillian wrote:

> *The estimator, in spite of its excellent performance where scattering is small, is not attractive for general use, because, where scattering is large, it combines mediocre performance with relatively large computing time.*

The state of computing has changed since Macmillian's paper in 1966. New computing hardware provides opportunities to reconsider computational techniques that were once considered too expensive.

2. Volumetric-ray-casting estimator

The EX estimator can be extended to contribute to cells in which the random walk does not pass through. This is evident in Fig. 2: the ray along A–B also intersects Cell 3. The contribution to Cell 3 can also be calculated from Eq. (1), but the statistical weight must be modified to account for attenuation of the ray prior to entering the cell. The statistical weight entering cell i, $W_i(E)$, is calculated from the optical thickness between the collision or source point and the point the ray enters the cell: