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Deep learning techniques in microdosimetry: using conditional generative adversarial networks to predict energy deposition on cellular length scales

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INTRODUCTION

- Studies of cellular radiation response traditionally use experimental and Monte Carlo (MC) methods, and both can present diverse challenges. There can be large variations in specific energy (energy imparted per unit mass) deposited in small targets and low doses[1].
- Focusing on computational aspects, we investigate the generation of realistic specific energy distributions on cellular length scales using a conditional generative adversarial network (CGAN)[2] trained using MC-generated datasets.

AIM

- This work investigates application of machine learning techniques to predict specific energy distributions in populations of irradiated voxelized targets on cellular length scales

METHOD

- A CGAN is trained using MC-generated distributions of specific energy (energy imparted per unit mass) scored in microscopic (1-11 micron) water voxels irradiated by photon sources (20-150 keV). Different dose levels (mean specific energies) are considered.
- The CGAN-generated distributions are assessed based on comparisons with MC data considering the generated mean, standard deviation, microdosimetric spread (quotient of standard deviation and mean) and number of voxels receiving no energy.

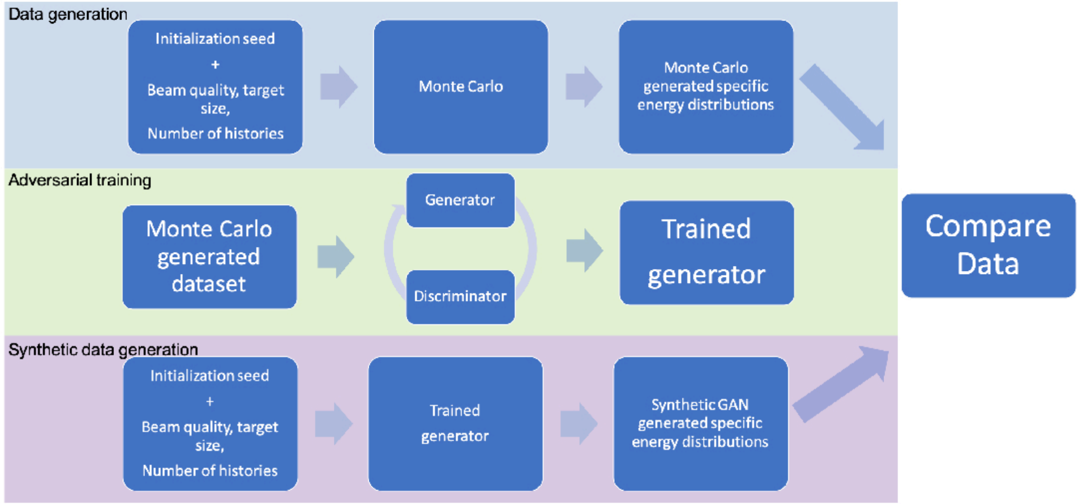

Figure 1: CGAN data generation workflow: (Top) Training data is generated using Monte Carlo simulations, generating specific energy distributions that are (Middle) then used in training Generative Adversarial Network. (Bottom) Once trained, the network is capable of producing any specific energy distribution that it was initially trained on in a small fraction of the time for MC simulations.

RESULTS

- The CGAN can produce any state within the training data domain, and relative errors in comparison with MC specific energy distributions depend on dose level.
- Considering the relatively low dose of 8 mGy (for which the microdosimetric spread is considerable at >100% for all targets, source energies), the mean relative errors over all target sizes and source energies are 9% (specific energy mean), 14% (standard deviation), and 20% (number of targets receiving no energy).
- The difference between MC generated and CGAN generated datasets decreases with increasing dose, e.g. with corresponding mean relative errors of 4%, 6%, and 14%, for specific energy, standard deviation, and number of targets receiving no energy, respectively at 20 mGy.
- Once trained, the CGAN can generate specific energy distributions much faster than MC: on average, 3.4 x 10^4 times faster the MC.

FIGURES

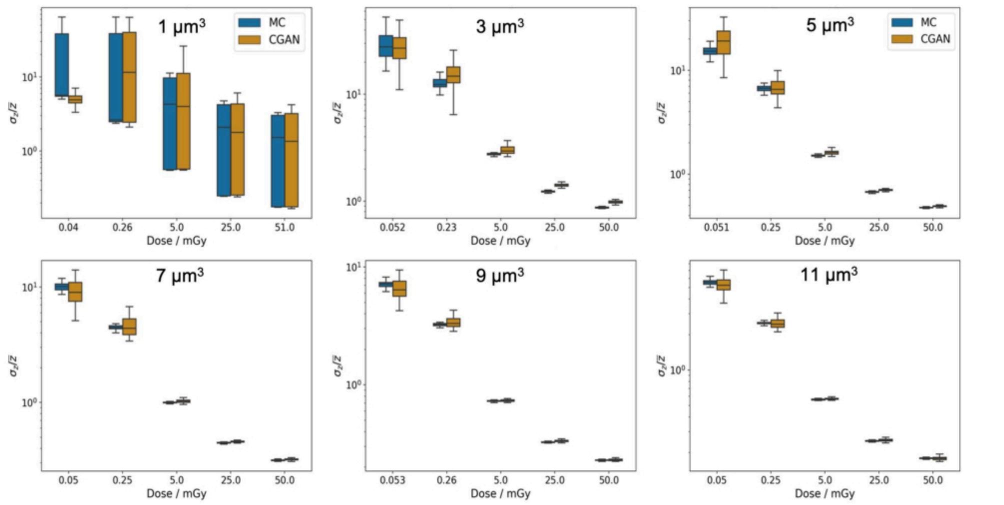

Figure 2: *Comparison of individual CGAN generated specific energy distributions to that of the MC generated using 100 keV monoenergetic photon source incident on voxel grid of varying side lengths (indicated in figure), at different dose levels based on the produced microdosimetric spread (quotient of standard deviation and mean of specific energy distribution). Each box and whisker are a summary of results over many realizations of specific energy distributions generated using CGAN and MC techniques.*

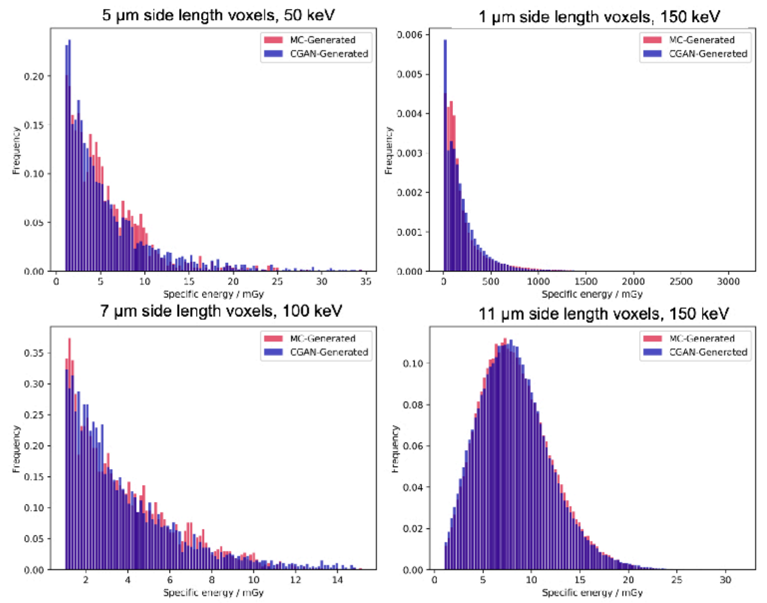

Figure 3: Comparison of averaged specific energy distribution considering 50 individual realizations of different permutations of source energy, target size and mean specific energy.

CONCLUSIONS AND FUTURE WORK

- The CGAN can generate realistic specific energy distributions over the range of doses considered, 0.05-100 mGy. The accuracy of the algorithm increases at higher dose levels, at 20 mGy mean absolute error averaged over all beam quality and target size variations of 4%, 6%, and 14% respectively.
- Ongoing work includes investigating CGAN ability to replicate higher order textural information beyond mean, standard deviation and number of zeroes as well as further optimization of network to improve data generation accuracy.
- Future work will involve using CGAN techniques in conjunction with radiobiological models to develop predictive models capable of considering biological effects.

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CONTACT INFORMATION

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[2] M. Mirza, and S. Osindero, Conditional Generative Adversarial Nets. arXiv:1411.1784, (2014).

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