Real-Time Patient-Specific CT Dose Estimation using a Deep Convolutional Neural Network

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Purpose

Common dosimetric quantities in CT such as the volume CT dose index (CTDIvol) or the dose-length product (DLP) do not appropriately represent the actual patient dose distribution. More sophisticated methods are not real-time capable. Therefore, we propose the deep dose estimation (DDE), a deep learning-based approach to estimate patient dose distributions in real-time.

Material and Methods

The gold standard to calculate patient-specific dose distributions is to perform a Monte Carlo (MC) simulation that models the physics of CT dose deposition. Being computationally expensive, MC cannot be applied in real-time. To overcome this drawback without losing accuracy we developed the DDE which uses a U-net architecture to reproduce MC dose distributions given a CT volume and a first order dose estimate volume as two-channel input.

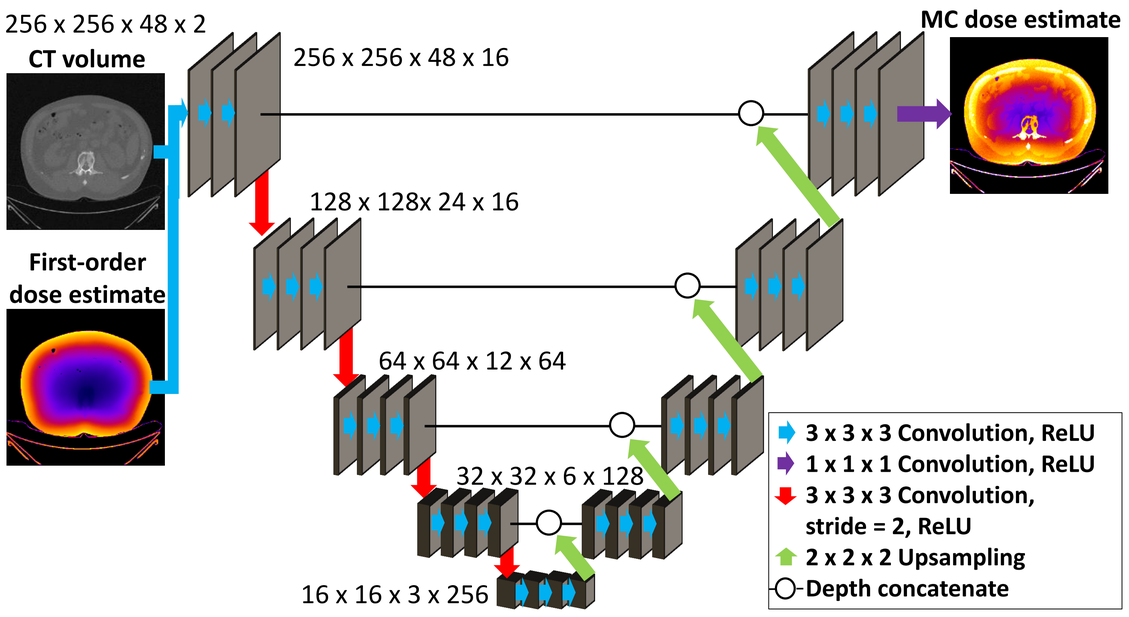


Figure 1: Basic principle of DDE. A 2-channel volume consisting of a CT reconstruction and a first-order dose estimate is given as input to a 3D U-net which is trained to reproduce the corresponding MC dose estimate.

A. First-order dose deposition

Given the emission characteristic of the x-ray source in terms of the differential photon fluence $\frac{d^2N}{d\Omega dE}$, the first-order dose deposition D_{1st} within a volume element dV at position $\boldsymbol{r}$ can be calculated as:

$$D_{1^{\mathrm{st}}}(\boldsymbol{r}) = \frac{dV}{\rho(\boldsymbol{r})dV} \int \frac{d^2N}{d\Omega dE} \left(\sum_{i \in \{\mathrm{PE\ /\ CS}\}} P_i(\boldsymbol{r}, E) \cdot E_i(E) \right) d\Omega\, dE,$$

where ρ describes the mass density distribution, $P_{\mathrm{PE\ /\ CS}}$ the probability density for an interaction via photoelectric effect (PE) or Compton scattering (CS), and $E_{\mathrm{PE\ /\ CS}}$ the corresponding energy transfer to electrons. Here, the interaction probability density is given as:

$$P_i(\boldsymbol{r}, E) = \mu_i(\boldsymbol{r}, E) \cdot e^{-\int_0^r \mu(\boldsymbol{s}+r' \cdot \boldsymbol{t}, E) dr'},$$

with μ_{PE} and μ_{CS} being the attenuation due to the photoelectric effect and Compton scattering. In case of a photoelectric interaction the energy is transferred completely to an electron (E_{PE} = E), while the energy transfer of Compton scattering is given as:

$$E_{\mathrm{CS}}(E) = \int \frac{d\sigma}{d\Omega}(E) \left(E - \frac{E}{1 + \frac{E}{m_e c^2}(1 - \cos(\theta))} \right) d\Omega.$$

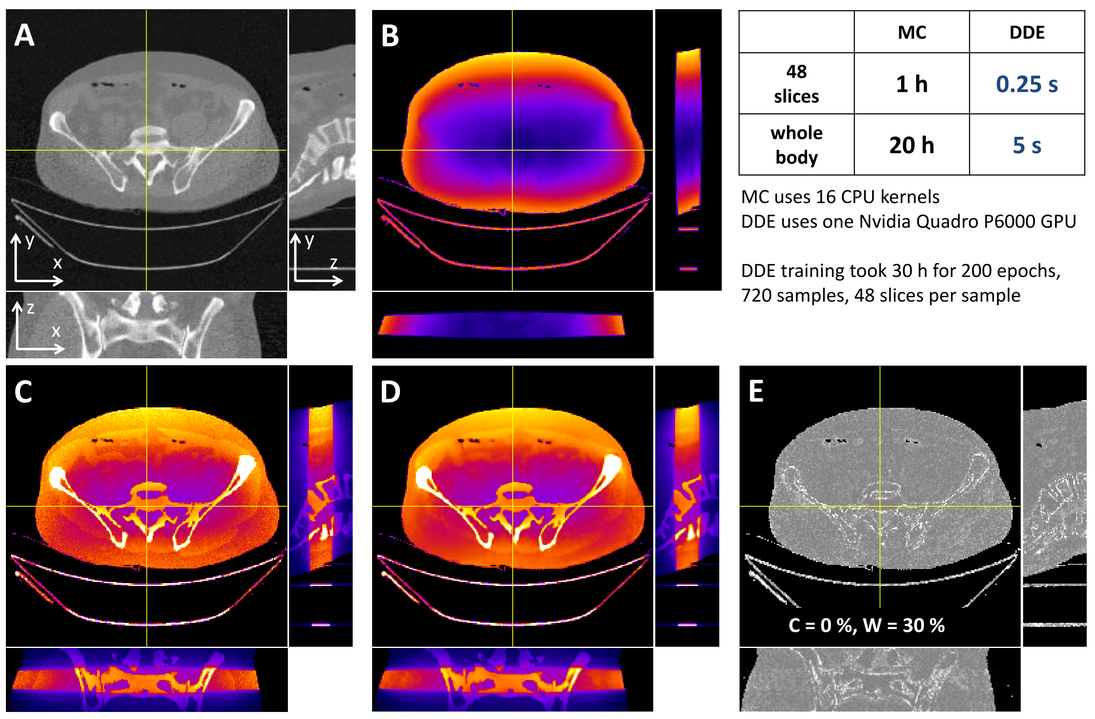
B. Deep dose estimation (DDE)

1) Data generation: CT images of whole-body CT scans of 15 patients were used to generate artificial data. Based on these prior data, circular CT acquisitions (720 projections / 360°) with a tube voltage of 120 kV were simulated for different anatomical regions (pelvis, abdomen, thorax). Additionally, shaped filters and tube current modulation was included in the simulation. CT images were reconstructed on a 256×256×48 voxel grid.

2) Model and training: The DDE network was implemented using the Keras framework. The training was performed on an Nvidia Quadro P6000 for 200 epochs using an Adam optimizer, a batch size of 2, and the mean relative error between the output and the MC prediction as loss function. As bone is underrepresented in all data sets, bone voxels received a twenty-fold weight compared to non-bone voxels when evaluating the loss function.

Results

DDE dose predictions for the validation data set were compared against ground truth MC dose estimates. As shown in figure 2, DDE yields almost the same accuracy as MC calculations, even in regions outside the field of measurement where the first-order dose estimate is zero. Since the DDE is slightly more blurred than the MC dose estimate, higher deviations arise at the boundaries of high density structures such as bone. A quantitative evaluation of all validation data sets yields a mean relative error of 3.0 % with respect to the ground truth. Furthermore, it can be observed that DDE can handle shaped filters and tube current modulation without a major loss of accuracy.



	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P6000 GPU

DDE training took 30 h for 200 epochs, 720 samples, 48 slices per sample

Figure 2: Input and prediction of DDE. A: CT reconstruction. B: First-order dose estimate. Note that bone is not visible as we approximate the patient to be water equivalent. C: MC dose estimate (ground truth). D: Prediction of DDE. E: Relative error of DDE with respect to the ground truth.

Conclusion

This study demonstrates the potential of DDE to calculate dose estimates with similar accuracy as MC simulations. Once the DDE is trained (≈ 30 h / 200 epochs and 720 training samples) a 256×256×48 voxel volume can be processed in 0.25 s. Thus, a patient-specific dose estimate for a whole-body CT would require less than 5 s.

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