CT BASED RADIOGRAPHY SIMULATIONS FOR BOTH INDUSTRIAL AND MEDICAL RADIOGRAPHY

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ABSTRACT. One of the important issues in the simulation work is proper representation of the simulated objects. The geometrical shapes of the simulated objects may range from very simple to very complicated geometries. In addition, a lot of objects come with heterogeneous material properties that need to be included into simulations. These two issues play important roles in both industrial and medical radiography simulations. CT (computed tomography) became widely available to the radiography community in the recent years. Since this technology provides two-dimensional images, CT images can be used to build models toward using in simulation work. In this work, we developed a CT image based algorithm to account for object shape complexities and heterogeneities. The resulting algorithm and absorbed energy doses in a human body part and ideal detector images obtained through the algorithm will be presented.

INTRODUCTION

In this article, we present an algorithm that utilizes CT data for industrial/medical radiography simulations. One of the challenging issues in the real world cases is representation of the test objects that can have very complex shapes and material that are quite heterogeneous. Although CAD drawings can handle complex geometries, the same cannot be said for continuously changing material properties. This is especially true for the human body that poses a real challenge to the CAD representation. In addition to its irregular geometrical shape, human body is as heterogeneous as it can get. Although some tissue types such as bone, muscle, cartilage are quite distinct, some other tissue types have properties that are very close to each other. The differences between those tissues are very subtle but real. Another problem with the human body is that transition from one type of tissue to another type is usually very smooth resulting in difficulties in determining the boundary. One escape from this bottleneck is utilization of CT images for modeling purposes. With the rapid proliferation of CT and MRI capabilities in medical world, it is very easy to obtain CT data for individuals. Although industrial CT is not as common as medical CT, it is not that unusual to come across in industrial applications either. The major difference between industrial materials and human body is that interfaces between two types of materials in industrial parts are likely to form a very distinct boundary in contrast with the human body. Therefore, CT images of heterogeneous industrial parts will be made up of multiple regions that are internally homogenous. One exception to this case shows up when the image pixels that coincide with the external and internal boundaries can not match the boundary exactly. Such pixels are likely to have gray scale values that are between the gray scale values of two bordering regions. In this paper, an algorithm to utilize CT data will be outlined and some examples will be provided.
TRANSPORT ALGORITHM

The simulation algorithm is based upon a deterministic approach where the governing equation is integral transport equation that is given below. Since the algorithm has been outlined in previous articles [1-3], we will not provide any details regarding the computational algorithm.

\[
I(r, E, \Omega) = \sum_{i} \int_{0}^{R_{p}} \left[ q(r, r', E, \Omega) dE \right] \left[ \Sigma_{e}(r' - R, E, \Omega) dr' \right] dR + I(r_{o}, E, \Omega) e^{-\Sigma_{e}(r, E, \Omega) dE} \]

In equation (1), \(I(r, E, \Omega)\) is angular photon flux (fluence rate), \(q(r, E, \Omega)\) is angular scattered photon source, \(\Sigma_{e}(r, E, \Omega)\) is space and energy dependent linear total attenuation coefficient obtained from XCOM, Berger et al. [4], \(r\) is spatial coordinates vector \((x, y, z)\), \(r_{o}\) is spatial coordinates vector for object boundary, \(E\) is photon energy, \(\Omega\) is direction vector, \(R\) is photon pathlength along direction vector, \(R_{p}\) is photon pathlength from object boundary. Since this article uses examples from the medical radiography world and absorbed dose distributions are computed, we introduced the kerma (kinetic energy deposited into the medium) approach into our algorithms. In kerma approach, an electronic balance is assumed and energy deposited in the unit mass of medium is computed through equation (2) given below.

\[
Absorbed \ Dose(r) = \int_{0}^{E_{max}} \frac{\Sigma_{e}(r, E, \Omega)}{\rho} I(r, E) dE \]  

(2)

where \(\Sigma_{e}/\rho\) is mass-energy absorption coefficient that were taken from Hubbell et al. [5]. The outcome of our computational algorithm is photon flux distribution, \(I(r, E)\), inside medium and it is converted into absorbed dose distribution through equation (2).

CT DATA MANIPULATION

Our computational algorithm uses voxels for geometric modeling of the problem domain. All independent and dependent quantities such as interaction coefficients, photon fluxes and photon sources are assumed to be constant throughout the voxels. Therefore, if material properties can be assigned to a specific voxel, the algorithm can compute the entire set of unknowns. The current art in the dosimetry community is to segment the images and then use the segmented information to construct homogenous organ models to be used in the computations [6-14]. In our work, rather than setting up a relationship between a gray scale and an organ, we set up relationships between the voxel gray scales and attenuation coefficients specific to that voxel. This has been done by assuming that there are only four radiologically distinct tissues in the human body, namely adipose, skeletal muscle, spongiosa, cortical bone and attenuation coefficients for all others can be written as a combination of the attenuation coefficients of these radiologically distinct tissue types. For example, cortical bone is quite distinct due to its elemental composition and relatively high density. Spongiosa and cartilage have physical densities much higher than the average as well. Adipose and yellow marrow have physical densities below 1.0 g/cm\(^3\). The other tissue types have similar elemental compositions that have densities a little above 1.0 g/cm\(^3\). Even under these conditions, some of the tissues are expected to interact with photons at interaction rates very close to each other. This can easily be inferred from the linear attenuation plots in figure 1. Attenuation data in figure 1 have been generated by XCOM using tissue compositions from ICRU-44 [15]. As it is seen figure 1, cortical bone stands out alone.
Although adipose and muscle have different compositions and physical densities, attenuation coefficients are surprisingly close to each other. Therefore, photon-tissue interaction rates should be very close to each other as well. A simple survey of Visible Human Project [16] frozen data set from the head section shows that adipose provides a gray scale level around 965, skeletal muscle 1060, spongiosa 1475 and cortical 2450. Body variations and CT equipment settings can affect these values. Therefore, this approach is open to more sophisticated methods that can determine the individual specific gray scale values of distinct tissue types. Irregularity of the tissue boundaries, tissue heterogeneities, systematic noise and having a tissue border passing through the middle of a pixel are among causes of the variations in the gray scale levels. Profiles in figure 3 that were extracted from the image in figure 2 clearly show those fluctuations. The locations of these profiles are shown in figure 2. Rather than trying to come up with a new set of attenuation coefficients for a given tissue type, tissue variability has been accounted for by mixing distinct tissue attenuation coefficients based on the gray scale values. For example, skeletal muscle and adipose tissue attenuation coefficients vary about 14, 9, 9 and 9 % at 50, 100, 150 and 200 keV respectively. In the light of such small variations, using mixing coefficients and accounting for tissue variability should be more realistic compared to homogenous organ assumption.

FIGURE 2. Visible Human frozen data set c_vml100 with profile positions marked.
FIGURE 3. 12 bit gray scale profiles taken from c_vml10 in figure 2.

In using CT images as a model, we have adopted a common approach and stacked the images. Gray scale of the voxel has been determined by averaging the gray scales of the pixels involved in the formation of the voxel. Visible Human data set images are made up of 512x512 pixels and pixel resolution is 0.53 mm x 0.53 mm with a 1.0 mm distance between images. In our case, we have used 1.06 mm x 1.06 mm x 2 mm voxels with 12 bit gray scale values. Although gray scale range for 12 bit images is 0-4095, the maximum gray scale value in Visible Human CT images is around 2500. In 12 bit images, gray scale value 0 corresponds to black and 4095 corresponds to white. As stated above, we determined the interaction coefficients for a specific voxel by using mixing coefficients matching to the gray scale value specific to that voxel. These coefficients are shown in figure 4. For example, linear attenuation coefficients for a gray scale value of 1150 are obtained by summing muscle and spongiosa coefficients after they were multiplied by mixing coefficients 0.783 and 0.217 obtained from figure 4. Background gray scale values in the CT images were usually less than 100. Therefore, we assumed that this gray scale value should represent the air. Interaction coefficients in the 100-965 range are obtained by using only adipose tissue coefficients with the corresponding mixing ratio because air coefficients are assumed to be zero. If the gray scale is larger than 2450, that voxel is assumed to represent 100% cortical bone.
Approach described above can be implemented for industrial CT data as well. Gray scale values corresponding to homogenous components will be pretty much constant except for the fluctuations due to system noise and reconstruction algorithm. Gray scale values will deviate from the mean values significantly at the component interfaces and external boundaries where the pixel does not fit the boundary exactly. Gray scale for such a pixel will be computed based on data coming from two different material types. For an external boundary case, gray scale will represent material and air but two different materials for an internal boundary. If a mixing ratios database as in figure 4 is constructed for such an assembly, interaction coefficients can easily be computed for borderline voxels.

RESULTS

We demonstrated the idea by using the head section of the frozen Visible Human data set. CT data have been stacked into a $4 \times 10^6$ voxel 3D structure. An 24 cm x 24 cm ideal detector was placed right next to the object. Computations provided 3D absorbed dose distributions. 2D distributions were extracted the 3D data set for display purposes. One of these 2D dose distributions is given in figure 5 for lateral irradiation geometry. The left distribution represents the primary beam only and does not include photon scattering. The right distribution includes both primary and scattered beam components. As it is very obvious from a comparison of two distributions, scattered photon flux deposits a significant amount of energy into the medium. One other point about the distribution is the resolution. Due to the very small size of the voxels, it is quite easy to distinguish a lot of features in the distributions. Figure 6 displays a 256x256 pixel image formed on the ideal detector. The left images in these figures represent primary beam only cases where the scattered flux component has not been included into calculations. The right images include both primary and scattered flux components. These images have been formed by logarithmic energy fluxes that were scaled to fit into 8-bit 0-255 gray scale range. The third set of results shows flux profiles incident upon an ideal detector. Those profiles are displayed in figure 7. The left graphic in figure 7 displays lateral case uncollided flux profiles that are the center columns of the two-dimensional flux distributions on the detectors. The profiles in the right graphic belong to the scattered photon fluxes for various energy groups.
CONCLUSIONS

We developed an algorithm that can utilize CT data for simulations in both industrial and medical radiography. The algorithm is capable of handling all physics of the x-ray tube energy range and it is based on the deterministic integral transport equation. Modeling has been handled by forming three dimensional voxel structures by stacking up the CT slices. Each voxel was handled separately rather than correlating each voxel to a specific organ/material through a laborious segmentation and image-processing step. This eliminates the need to segment the human CT data to determine the organ or component boundaries in a CT slice. As it has been shown this approach provides an alternative to solid modeling/mesh generation procedure that can be done through CAD packages. It has also been shown that a very complex problem domain can easily be introduced into a simulation program through the algorithm described in this article.
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REFERENCES