

# Investigations on bone representation in voxelized patient models for estimation of scatter profiles in cone-beam CT

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**Abstract**—To improve the clinical value of cone-beam CT in both C-arm CT and conventional diagnostic CT, it is essential to improve the quantitative accuracy of attenuation values. Scatter is a major patient-specific, non-linear, physics effect that affects quantitative accuracy of the CT attenuation values when improperly corrected for. Recently, practical methods have emerged for patient-specific scatter correction. These methods rely on the use of voxelized patient models wherein bone representation poses challenges. In this work, we investigate the impact of bone representation on monoenergetic images and scatter profiles. Our early results indicate that many materials should be used to represent bones. However, this number needs not be proportional to the number of bone voxels; 200 materials may be largely sufficient with negligible impact on computational cost for Monte-Carlo transport with GEANT4. We also show that including or not bone marrow within the bone representation results in a small but non-negligible effect on scatter profiles (about 4%).

## I. INTRODUCTION

Obtaining quantitatively accurate attenuation values in cone-beam CT is an essential, yet challenging, goal to improve the clinical value of C-arm CT, as well as that of conventional diagnostic CT. Patient-specific, non-linear, physics effects such as beam hardening and scatter are major factors that affect realization of this goal. In this work, we are interested in the representation of bones for patient-specific estimation of scatter profiles. See [1] for a recent investigation that we conducted on analyzing the effects of bone on patient-specific beam hardening errors within the lung parenchyma.

Two practical methods have recently emerged for patient-specific estimation of scatter profiles, one using the Boltzmann transport equation [2], and another one using deep learning convolution networks [3]. A common aspect of these methods is that realistic models of the patient anatomy are needed, either directly for the patient being imaged [2] or indirectly to produce reliable training data [3]. Such models are typically called “voxelized patient models”.

A voxelized patient model is a volume of voxels regularly and finely distributed on a 3D Cartesian grid, where each voxel value specifies the patient tissue present at the spatial location of the voxel in terms of mass density and chemical composition. From such a model, it is possible, using tabulated values for atomic cross sections, to evaluate the linear attenuation

coefficient for photon absorption at any photon energy, as well as to evaluate scatter and dose deposition events, all at any location within the patient. Voxelized patient models suitable for organ-specific estimation of CT radiation dose were first introduced in [4] and proved valuable for such estimation in many subsequent publications, including, e.g., [5].

Most often, the starting point used to create a voxelized patient model is a series of axial CT images obtained from a 120 kV scan. Although soft tissues can be well modeled, representation of bones from such images is particularly difficult. There are three issues that affect this representation. First, the spatial resolution is far too poor to rigorously separate bone material from bone marrow within the bones; only a composite material can be modeled. Second, there is no unique definition for such a composite material from a 120 kV scan. Third, a spatially varying composite material definition is necessary to reflect real patient anatomy.

In the DeMarco model [4], [5], bones were represented using four material options; these four materials shared the same chemical composition but differed in terms of mass density. In [6], the issue of bone representation was extensively discussed and two richer models were suggested, one in which each local bone value is modeled as cortical bone with a spatially varying mass density, and another one in which each local bone value is modeled as a linear combination of bone marrow and cortical bone, which induces spatial variations in both mass density and chemical composition. Although such models are much richer, it was also acknowledged that they could not be practically used with Monte-Carlo transport software like GEANT4 (used here) and MCNP (used in [4], [5]) as these programs are not amenable to efficiently using a number of materials proportional to the number of voxels. Categorization into a finite number of options was considered necessary, but the number of options can be much larger than that used in the DeMarco model.

In this work, we investigate bone representation using these various model options, with the two models of [6] referred to as the bone-only and the bone-mixture models along with an integer that specifies the number of categories the models are divided into.

## II. EXPERIMENTAL SET-UP

### A. Patient data selection

While we plan on expanding our investigations to cover various biological variables (such as sex and body mass index) and anatomical sites (such as the head and the pelvis),

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the investigations reported here are focused on chest CT images of a single female patient. The scan was acquired at 120 kV, and was reconstructed with a slice thickness of 3 mm. See Fig. 1 for visual appearance of the patient anatomy. To convert the HU values of the CT images into physical attenuation values, it was necessary to select an energy level that is representative of the source-detector energy spectrum involved. Using dual energy measurements through a 20cm phantom water equivalent phantom without and with a bone insert, we established this energy level to be 78.5 keV.

### B. Voxelized patient models

We considered three voxelized patient models. The first model followed the approach of [4], [5]: all tissues were represented using 17 materials with material index 0 for air and material indices 13 through 16 for the four bone materials. The range of HU spanned by each material is shown in Fig. 2. In particular, the four bone materials were distributed over the range of [152,1560] HU; this wide range conveys the complexity of representing bone. Fig. 3 shows one sagittal slice through the voxelized patient model using color-coded display.

The second and third models were modifications of the first model. We changed the description of the voxels covering the bones using the two suggestions of [6], which we refer to as the bone-only and the bone-mixture models. For these modifications, we considered categorization into 20, 200 and 2000 materials. Pre-testing assessed that 2000 materials incurs a 3% increase in computational cost for our scatter simulations based on GEANT4. Fig. 4 shows one sagittal slice through these two modifications of the first voxelized patient model, again using color-coded display.

### C. Scatter experiments

Scatter profiles were estimated using GEANT4. We simulated an 80 keV X-ray source randomly transmitting photons towards a 36 cm x 36 cm region in the detector plane, located at 120cm from the X-ray source, while the source to center distance was 75cm. The scatter events were recorded over a 42 cm x 42 cm region centered over the same point within the detector plane. The number of transmitted photons was 4,000,000. The simulation was carried out for two source locations (anterior-posterior and lateral). To mitigate noise, each simulation was repeated 100 times and their results were averaged over these 100 repetitions. When mentally dividing the 36 cm x 36 cm region into pixels of size 0.64 mm, it can be said that 12 photons were, in average, transmitted towards each detector pixel. Hence, in our experiment, a count of 2 scattered photons hitting a location within the 42 cm x 42 cm region refers to a scatter-to-primary ratio of 0.17.

## III. RESULTS

### A. Monochromatic images

To assess model accuracy, we converted the voxelized patient models into monochromatic CT images at 78.5 keV. The result is shown in Fig. 5. Comparing with Fig. 1, it is

clear that the first model yields bone that are too attenuating compared to the original CT attenuation values, whereas the other two models yield attenuation values for the bones that are seemingly identical and more satisfying. For a more quantitative assessment, we examined a region of interest centered on a vertebra, as shown in Fig. 6. It can be seen that the two modified models provide highly similar results and these closely match the original CT images.

To appreciate the difference between the bone-only and the bone-mixture representation of voxels containing bones, it is necessary to examine images at other energy levels. Specifically, one might expect that the bone-only model results in higher attenuation values at lower keV level as more calcium is present in this model. Fig. 7 shows this expectation to be indeed correct. In a less predictable manner, Fig. 7 also shows that the bone-mixture model yields higher attenuation values at higher keV level; this difference is induced by the different chemical compositions involved.

### B. Scatter profiles

Figure 8 shows a 2D histogram of scatter events observed on the detector. As expected, scatter has a smooth appearance. Nevertheless the variations can be non-negligible, particularly in the anterior-posterior view direction. Such variations are enough to create challenges for the problem of achieving quantitative attenuation values in image reconstruction, as illustrated in [7].

Fig. 9 shows the effect of using 20 versus 200 versus 2000 materials to represent the bones. It appears clear that 20 materials can be a little too small, but 200 materials provides converged plots with negligible impact on computational cost.

Fig. 10 shows the impact of choosing the bone-only versus the bone-mixture model for estimation of scatter. It can be seen that the overall shape of the profiles remain the same, but the magnitude is impacted by a spatially varying factor of about 4%.

## IV. CONCLUSIONS

We presented early results investigating the effects of bone representation on scatter profiles estimated using Monte-Carlo transport through voxelized patient models. We observed that it is critical to use a large number of materials to represent the bones. However, this number needs not be proportional to the number of voxels in the model. In our experiments, 200 materials appear largely sufficient with the convenience that such a number has negligible impact on computational cost when using GEANT4. We also observed that there are small but non-negligible effects resulting from including or not bone marrow in the bone representation. More investigations are needed to see how these results are impacted by biological variables, anatomical sites, and scanning parameters.

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