SIMULATION AND MODELING FOR UHR-MDCT AND PHOTON-COUNTING CT

by

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Abstract

New CT technologies, such as ultra-high resolution multi-detector CT (UHR-MDCT), and photon-counting CT, open the potential for visualizing bone microarchitecture and enables material decomposition with a single scan. UHR-MDCT comes with many challenges – image quality varies with the position of the object in the field-of-view. Visualizing trabecular structures and quantifying bone health using biomarkers becomes a difficult task under in the presence of radial, azimuthal, and longitudinal blur. PCCT, being the talk of the show in 2022, boasts superior image resolution and noise properties. This new technology, however, is unable to escape from scatter. The problem becomes compounded due to the availability of energy channels. Scatter distribution behaves differently in different energy channels and varies depending on object composition and position. Applications of PCCT, namely, material decomposition, become inaccurate in the presence of scatter.

Software simulation for UHR-MDCT was created to study the extent of the non-stationary blurring effect caused by detector integration time and focal spot size. Quantifying the extent of image blurring will help optimize the application of trabecular metrics from UHR-MDCT to assess bone health.

The distribution of scatter in energy channels for PCCT was investigated through Monte-Carlo scatter simulations in phase space. Scatter in energy channels were qualitatively and quantitatively assessed for phantoms of various bone and water compositions. Material decomposition for two basis materials: bone and water were performed in projection domain and the bias of estimated line integrals in the presence of single channel scatter were assessed. This scatter study enables improvements in the accuracy of tissue composition and contrast agent quantification in PCCT.

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Chapter 1: Introduction

1.1 Computed Tomography – An Overview

X-ray computed tomography (CT) is a crucial medical imaging modality encompassing a wide range of clinical applications. Since the introduction of CT technology in 1970s from Allan M. Cormack and Godfrey N. Hounsfield, CT devices have shaped medical communities worldwide. Many important milestones in medicine began to be realized following the advent of CT, pre-surgical planning, robotic assisted surgery, and 4D cardiac angiography, to name a few.

CT has and still is indispensable in hospitals. The highly reduced imaging time compared to other imaging modalities such as MRI makes CT preferable for patients of all age groups, including children. CT also has the advantage that anesthesia or sedatives are not required. [5] In 2018 alone, over 75 million scans were performed in the United States. [6] In 2022, this number is projected to grow up to 85 million scans a year.

CT devices have been advancing since its commercialization in the late 1970s. From an initial pencil-beam prototype to fourth generation multidetector CT (MDCT), which enables the collection data over a wide field-of-view (FOV) with a single rotation. Different acquisition techniques have emerged with efforts spearheaded by scientific and medical communities, examples include CT scanners with high-resolution and fast acquisition speed, dual-source, dual-energy scanners with the capability to differentiate materials, as well as artifact reduction algorithms in both projection and image domain. [7] These developments would not have been possible without elaborate computer simulations, since collecting CT data from scanners alone does not yield sufficient information for CT hardware or algorithm development. To tackle CT challenges, such as improving existing hardware, or developing new pipelines to be used in clinical applications, a sufficiently capable CT simulation framework allowing parameters of
interest to be tested must be utilized. This thesis presents the application of such a simulation framework to two of the new CT technologies: UHR-MDCT and PCCT.

1.2 Ultra-High Resolution Multi-Detector CT (UHR-MDCT)

The recently developed Aquilion Precision UHR-MDCT scanner (Canon Medical Systems) boasts a small pixel size interchangeable between 0.25mm and 0.50mm spanning over multiple detector rows, greatly improving image spatial resolution. [8], [9] One application of UHR-MDCT is that its high resolution and small focal spot area enables improved visualization of trabecular bone. This is useful since being able to quantify the trabecular microstructure opens the possibility to clinically assess for fracture risk, osteoporosis, and early osteoarthritis. [10], [11] Another application of UHR-MDCT allows for the evaluation of severely calcified coronary arterial lesions. Latina et al. has reported higher diagnostic confidence scores for scans taken with UHR-MDCT compared to conventional CT. [12]

Since UHR-MDCT boasts superior spatial resolution, image assessment metrics performed on UHR-MDCT merits an in-depth discussion, and has been investigated by Hernandez. [9] The authors reported its spatial resolution varies depending on the location of the object within the field-of-view (FOV). Such effects were attributed to physical hardware - spatial resolution can be impacted by detector pixel pitch, focal spot size, and rotation of the gantry. Hernandez has reported major blurring in three directions, radial and azimuthal blurring within the axial plane (XY plane), and longitudinal blurring along the slices in the Z-direction. [9]

Part of this thesis investigates the blurring effects brought about by CT hardware limitations in the context of trabecular bone quantification at different locations in the FOV. An advanced software simulation, written in Matlab, assesses the location dependent impact to spatial resolution due to variations in gantry rotation speeds, detector integration time, and focal spot sizes.
1.3 Photon-Counting CT (PCCT)

Photon-Counting detectors (PCD) is an emerging CT sensor technology touting its ability to count individual incident photons and record its respective energy, something that cannot be achieved with the conventional energy integrating detectors (EID). PCDs have shown tremendous progress and promising results in the last decade, leading to the recent clinical introduction of photon-counting CT (PCCT). [13]

By binning the photons according to their energy, PCD provides a new dimension to the CT data. In other words, for a given number of energy bins (channels), there would be a corresponding number of sets of projections. This new set of data, which was not previously acquirable for a single EID, opens the possibility for material decomposition, plaque/bone removal, as well as virtual monoenergetic imaging. [13] Leng et al. has shown that PCCT provides accurate iodine quantification for concentrations of 2–20 mg of iodine per milliliter at different phantom sizes using virtual monoenergetic images (40-140 keV at steps of 10 keV) derived from multiple energy channels. [14]

Major advantages of PCCT include increased contrast-to-noise ratio, increased radiation dose efficiency, rejection of electronic noise, as well as reduction in beam-hardening and metal artifacts. Since PCD is a semiconductor technology that focuses on direct detection of x-rays rather than conversion of x-ray to optical photons through a scintillator, increase in spatial resolution is possible with smaller pixel pitch. [9]

This thesis develops an advanced simulation framework to model scatter in PCCT. The simulation framework enables us to investigate the accuracy of material decomposition under the impact of scatter in a PCD. A novel software simulation framework written in Matlab was made to model the behavior of a PCD with multiple energy channels. Scatter was simulated using a phase space Monte-Carlo (MC) approach that stored the energy of photons. An extended application of these simulations is to apply the outcome to material decomposition and using model-based algorithms. Parameters such as anti-scatter grid (ASG), bowtie, detector curvature, scatter and scatter denoising were programmatically implemented.
into the pipeline with the option to be turned on or off, so that the impacts to projections, reconstructions, as well as material decomposition from each of these parameters could be explored.

1.4 Thesis Overview and Outline

1.4.1 Thesis Statement

In the last several decades, x-ray CT has seen rapid development, as evidenced by the recent introduction of UHR and PCCT. Each new technology introduces image quality tradeoffs and technical challenges that have not been considered in the previous generations of CT. The thesis demonstrates how advanced computer simulations can be used to elucidate such tradeoffs and develop mitigation strategies, focusing on non-stationary spatial resolution in UHR-MDCT and the effects of scatter in PCCT material decomposition.

1.4.2 Thesis Outline

This thesis is organized as follows. Chapter 2 is split into four sections and describes the backbone and simulation process that makes up the experiments involving UHR-MDCT and PCCT. Section 2.1 delineates the building blocks that make up the advanced CT simulation software, including projection of primary (un-scattered), radiation, MC scatter, and various components of CT hardware that require a more complex modeling approach. Section 2.2 describes the functionalities specific to UHR-MDCT simulation, which was developed on top of the simulation framework described in Section 2.1. Section 2.3 presents functionalities of the simulation specific to modeling photon-counting detectors. Lastly, Section 2.4 describes material decomposition for photon-counting CT.

Chapter 3 presents experimental results using the simulation methods described in Chapter 2 for UHR-MDCT and PCCT. Section 3.1 presents the characterization of non-stationary blur in UHR-MDCT. Section 3.2 presents the validation of the MC phase space model. Sections 3.3 and 3.4 delineates the characterization of scatter in PCCT. Qualitative and quantitative studies of scatter in energy channels, and
effects of bowtie scatter in material decomposition are the focus in Sections 3.3 and 3.4, respectively. Section 3.5 presents the results for material decomposition of body phantoms in the presence of scatter.

Chapter 4 offers a discussion of the non-stationary effects in UHR-MDCT, and bias in measured attenuation and estimated path lengths in material decomposition in PCCT. Chapter 5 peers into potential future studies for the new UHR-MDCT and PCCT technologies.
Chapter 2: Methods

2.1 X-Ray Simulation Fundamentals

This section describes the functional blocks that make up the framework for a CT simulator. Our CT simulation pipeline consists of various functional blocks together in sequence, including ray-tracing primary projection and MC scatter. We also incorporate various features that can be switched on or off. Examples are flat vs curved detector, focal spot area and detector integration time, phase space scatter, anti-scatter grid (ASG), and scatter denoising. The advanced CT simulation tool was written in Matlab with the aid of the CudaTools package developed by Dr. Alejandro Sisniega [15] to implement GPU accelerated computing for MC scatter, forward and backprojections.

2.1.1 Simulation of Primary Radiation

Forward projection is the generation of a two-dimensional image from a three-dimensional object - it can be thought of as shining a beam of light onto an object with a screen behind it. [16] The light intensity that appears on the screen, after experiencing attenuation by the object path length and material, is the forward projection. Instead of visible light, CT projection is formed by x-ray radiation incident on the object. Normalized projections are computed by dividing the output from the detector by its air scan, i.e. a scan without the object. Projections make up the basis of radiography and fluoroscopy. [16] In tomography, multiple projection views are taken around the object, the requirement is to collect sufficient views to be able to reconstruct cross-sections or slices of the imaged object. [17] The projections acquired in CT consist of attenuated primary radiation and scatter. We first describe the algorithms used for primary simulation.

The x-ray intensity based on the attenuation of x-ray flux for a path length follows the Beer-Lambert law:

\[ I = I_0 \int Q(E) D(E) \exp \left( - \sum_i \mu_i(E)L_i \right) dE \]  

(2.1.1)
\( I_0 \) represents the total number of emitted x-rays. \( Q(E) \) is the area-normalized x-ray source spectrum in the form of a probability density function (PDF). \( D(E) \) is the energy-dependent detector response, primarily the quantum efficiency for x-ray detectors. \( \mu_i(E) \) is the energy-dependent linear attenuation coefficient for the \( i \)th material. \( L_i \) is the path length of the \( i \)th material in the object that the x-ray path (from source to detector pixel) intersects.

In some cases, it is beneficial to consider a simpler – although unrealistic - case of a monoenergetic projection, where it is assumed that the spectrum consists of a single discrete energy \( e \):

\[
I = I_0 Q(e) D(e) \exp \left( -\sum_i \mu_i(e)L_i \right)
\]  
(2.1.2)

Normalized intensity after dividing the output of detector by the air scan can be written as:

\[
I = \frac{I_0 \int Q(E) D(E) \exp \left( -\sum_i \mu_i(E)L_i \right) dE}{I_0 \int Q(E) D(E) dE}
\]  
(2.1.3)

Normalized signal facilitates the conversion from intensity to attenuation. A properly normalized signal should have intensity value between 0-1. For a PCD, the calibration to predict pixel-to-pixel variations within a detector bank is a topic of investigation spearheaded by Dr. Katsuyuki Taguchi, since the problem is compounded by physical effects of pulse pileup, charge sharing, K-escape x-rays, Compton scatter, and possibly fluctuating energy thresholds under different photon flux. [18], [19]

The polyenergetic nature of the x-ray beam leads to a physical phenomenon known as beam hardening. The effects of beam hardening can be explained by the lower penetrating power of the lower energy photons compared to higher energy photons. In other words, lower energy photons are preferentially removed from the beam while higher energy photons remain. [16] The effective energy of the spectrum behind the object shifts towards higher effective energy. Since lower energy photons are removed and do not contribute to image contrast, it is a standard practice to add filters with high-Z materials in front of the x-ray source to harden the beam so that the deposited dose to the patient is lessened. Filtration also has the benefit to reduce beam-hardening artifacts in the image. Such artifacts manifest as dark streaks or shading.
in between highly dense materials such as bone or metallic implants present in the object. They are typically corrected by interpolating the polyenergetic projection values to monoenergetic projection values calculated from water path lengths at the effective energy of the spectrum. [20]

Figure 2.1.1 displays an example between reconstruction using monoenergetic projections and polyenergetic projections. Zooming in to the bone inserts in the polyenergetic image on the right shows distinct beam-hardening artifacts, specifically shading and streaking in between any two inserts. The image on the left, reconstructed with monoenergetic projections, do not display these beam-hardening artifacts in comparison.

Forward projections in the simulation employs a GPU accelerated ray-tracing method based off Siddon, which evaluates the radiological path (from source to detector pixel) through a three-dimensional array representing the object for each material $i$ and its respective path length $L_i$ in Equation 2.1.1. [21] System geometry consisting of parameters: source-to-detector distance (SDD), source-to-axis distance (SAD), number of views, location of the detector with respect to the source through piercing point, is set into computer memory. Detector dimensions and pixel size are specified. The phantom is created by assigning voxel values corresponding to the percentage density of a material. Area-normalized spectrum $Q(E)$ in discrete 1 keV bins and detector response $D(E)$ are also loaded in computer memory. After ray-tracing iis
completed for each material, the resulting material line integrals $L_i$ are used to calculate x-ray intensities with Equation 2.1.1.

**2.1.2 Simulation of Scattered Radiation**

Scatter is a physical product of photon interaction, it is unwanted in CT scans since it biases the magnitude of the projection, contributing to cupping artifacts [22] and loss of contrast in the reconstructed images. [23] Attempts have been made to estimate the spatial distribution and magnitude of scatter to correct for cupping artifacts. One of the most effective methods to achieve scatter rejection is the use of anti-scatter grids (ASG), placed flush against the pixels on the detector. ASG is an important component in our CT simulation.

Anti-scatter grid is employed in most, if not all CT systems developed this decade. The efficacy of ASG at reducing scatter has been thoroughly investigated and validated. [24], [25]. ASGs are made of lamellae interspaced between the detector pixels, typically made of hyper-attenuating material such as lead or tungsten. Scattered photons with trajectory deviating from the path of the primary photons will in theory be attenuated by the lamellae so that scattered radiation become negligible at the detector.

ASGs are typically characterized by their lamellae spacing in units of line pairs, lamellae thickness, and lamellae height. Figure 2.1.2 displays two ASG configurations. 1D grid configuration involves lamellae placed parallel to either the rows or channels of the detector. Scattered photon with trajectory parallel to the grid remain unattenuated, while photons travelling at an angle experience attenuation, often complete attenuation with high-Z materials such as lead or tungsten. 2D grid configuration on the other hand, has lamellae placed along both row and columns of the pixel, essentially creating a wall around the pixel. 2D grids have the benefit of rejecting most of the scatter photon, the downside is that the transmission of the primary photons will also be significantly reduced.
To incorporate the effect of the ASG on the primary x-rays, our simulator uses a grid transmission factor that represents the fraction of primary photons completely attenuated by the ASG:

\[ ASG = \frac{D}{D + d} \]  

(2.1.4)

\( ASG \) is the transmission factor, a fraction between 0-1. \( D \) is the length of the pixel not covered by the lamellae exposed to the flux of the photons. \( d \) is the thickness of lamellae. This model was suggested by Kyriakou and Kalender, which specifies that the signal behind the ASG is binary, either the photon passes without interaction or is completely absorbed by the scatter grid material. [27]

Primary projection intensity considering transmission factor \( ASG \) is given by the following modification of Equation 2.1.1:

\[
I = I_0 \int Q(E) \cdot D(E) \cdot ASG \cdot \exp \left( - \sum_i \mu_i(E)L_i \right) dE
\]

(2.1.4)

To investigate the distribution of scatter and the effects of ASG on the scattered photons, we apply GPU-accelerated MC simulations. The MC software requires setting the CT geometry, segmenting the phantom volume into its respective material components, collimating the beam, and specifying the number of photons to simulate. Figure 2.1.3 (a) demonstrates an example of the output from the Monte-Carlo scatter simulation. A pure-water elliptic cylindrical phantom of 400 mm x 240 mm x 600 mm is placed with in the FOV at the center of the gantry. The short-axis view was simulated varying number of photons: \(10^5\), \(10^7\), \(10^9\). The time it takes to run one simulation is proportional to the number of photons. The tradeoff
with MC simulations is between the number of photons and the noise in scatter distribution. Scatter
distribution with higher number of photons, e.g., $10^9$ are considered gold-standard in our simulations and
appear noiseless, distributions with $10^5$ photons appear unusable in comparison.

Figure 2.1.3 (a) Left: Total-counts normalized scatter distribution, short-axis view of a pure water elliptic
cylindrical phantom measuring 400 mm x 240 mm x 600 mm. Monte-Carlo scatter simulated at $10^5$, $10^7$, $10^9$
photons. Distribution with less noise is apparent for higher photon count. (b) Right: Center profile of scatter
distribution in (a), corresponding to $10^5$, $10^7$, $10^9$ photons.

In order to conduct experiments in a timely manner, and to direct our studies so that they conform to
acceptable runtime in clinical settings, MC simulations were run at a lower $10^7$ photons per view in
comparison to our gold-standard at $10^9$ photons. The scatter distributions were then denoised with a 2D
gaussian kernel. The full-width-half-max (FWHM) of the kernel was chosen to best match the gold
standard scatter distribution based on preliminary tests using a small number of projection views.

MC simulation employs an analytical grid model from Day and Dance. [28] For a scattered photon of a
given energy and direction, a transmission factor is calculated considering the number of lamellae that the
photon intersects for a focused grid. This transmission factor is multiplied to scatter count at the detector
pixel. Analytical grid models were available for both flat and curved detector configurations. Grid
lamellae are focused to a distance, usually the SDD, scatter photons with trajectories that do not fall
within the focus of the lamellae are attenuated by the transmission factor.
2.2 UHR-MDCT Simulation Framework

To investigate the effects of image blurring and to obtain an understanding of image quality in UHR-MDCT, a framework for simulating UHR-MDCT was created. The results of the simulation were validated against image assessment metrics from Boone et al, where the authors described measurements taken from the Canon Aquilion Precision CT. [9]

2.2.1 Modeling of UHR-MDCT Components and Non-Stationary Blur

UHR-MDCT simulation first starts with forward projection. Selectable pixel sizes specified by the Canon Aquilion Precision CT were implemented into the simulation: normal resolution “NR” (0.5 x 0.5 mm), high resolution “HR” (0.25 x 0.5 mm), super high resolution “SHR” (0.25 x 0.25 mm). [9] UHR-MDCT specific effects that cause azimuthal, radial, and longitudinal blurring such as focal spot size, gantry rotation speed, and detector integration time were implemented into the framework. Initialization parameters such as geometry (piercing point, SDD, SAD, view angles), object volume (object dimension, voxel size), detector (detector dimension, pixel size, response), and spectrum were set into computer memory. The spectrum was generated using a TASMIC model from Spektr 3.0, normalized by its area. [29]

Object voxel size was chosen so that sufficient sampling was obtained for all pixels on the detector. A general rule is to ensure that the magnification $M$ between voxel and pixel size is correctly applied.

$$M = \frac{SDD}{SAD} \quad (2.2.1)$$

Voxels were set to sizes that are smaller than the pixel size divided by the magnification factor to avoid sampling artifacts. As an extra step of caution, during the forward projection process, a flag in the software allows the detector dimensions to be upsampled to multiple times its original dimension. At this discretization level, the rays traced from the source to each pixel should be sufficient to capture the composition of the phantom.
The effects caused by detector integration time - azimuthal blurring was implemented into the framework. As the gantry holding the source and detector rotates around the object in a standard circular geometry, the detector will acquire frames continuously. The movement of the gantry within the time that a frame is captured causes azimuthal blurring in the image. A simplified drawing of this effect is depicted in Figure 2.2.1.

![Figure 2.2.1](image)

**Figure 2.2.1** Simplified diagram illustrating the effects of detector frame integration time during gantry rotation. The circle represents the gantry path. An arc is illustrated exaggerating the coverage of a detector view during rotation. \( t \) presents the time it takes for the gantry to traverse the arc. On the right, the arc is divided into multiple projections of finer angles to simulate azimuthal blurring effects.

The number of frames acquirable in the single rotation depends on the allowable specifications of the detector or electronic hardware. The CT manufacturer may also engineer their hardware such that the CT technologist may not have access to changing the number of frames per rotation. The time that the detector accumulates signal for one frame is referred in this chapter as “detector integration time”. It is implemented in the simulation by forward projecting a multiple of number of total specified views, then taking the average of all projections that fall within the range of the single view. For example, if 360 frames is captured for a rotation, corresponding to 1 degree per frame, then the forward projection is simulated for 360\( n \) frames so that within the one-degree coverage, \( n \) projections are averaged into one projection. For this experiment, the number of frames captured per gantry rotation time (0.35, 0.50, 1.50 s/rot were available) for the Canon Aquilion Precision was undisclosed, therefore this parameter was estimated through MTF curves reported by Boone et al. [9] It was hypothesized that with increasing distance away from the isocenter, we should see greater azimuthal blur.
We investigated the effects of radial and longitudinal blurring due to focal spot sizes. Canon Aquilion Precision allows for six focal spot sizes (0.4 x 0.5 mm, 0.6 x 0.6 mm, 0.6 x 1.3 mm, 0.8 x 1.3 mm, 1.0 x 1.4 mm, 1.6 x 1.4 mm). The simulation accomplishes this by modeling an array of singular point sources, each referred to as a “Sourcelet”. A diagram illustrating this concept is shown in Figure 2.2.2, where X-Y axes span the axial plane, and the Z-axes represent the slices.

![Figure 2.2.2](image)

**Figure 2.2.2** An array of Sourcelets (single point sources in the simulation) dispersed uniformly within a focal spot area specified by lengths in the X and Z axes. The array emulates focal spot size defined by the Canon Aquilion Precision CT.

Sourcelets populate the focal spot area uniformly. Specifiable parameters for the Sourcelet consist of the dimensions of the focal spot area, the number of point sources in the X and Z direction within the focal spot area, and tilt angle of the focal spot area due to angulation of the anode. The spatial distribution of the Sourcelets is by default uniform across the focal spot area, can also be changed to quadratic distances by changing a flag in the simulation. Sourcelet model allows the simulation of radial blurring effects caused by focal spot sizes. This model also allows us to investigate the blurring caused by focal spot elongation, where the projection of the longitudinal (Z) axis of the focal spot impacts the spatial resolution in the axial plane (X-Y plane).

Detector curvature parameters were implemented in the simulation pipeline to model curved detector hardware typical in MDCT, including Canon Precision. Curvature is by default set to the source-to-detector distance (SDD) of the geometry and modifiable to other values. To model the curved detector, a flat detector system is first assumed. Each pixel on the flat detector is traced back along the trajectory of the ray (from the source to the flat detector pixel) until the ray intersects with the plane of the curved
detector, shown in Figure 2.2.3. Pixel value on the flat detector is then copied (or interpolated, if needed) into the curvature detector pixel array at the intersecting location on the curve.

Figure 2.2.3 Implementation of a curved detector by copy or interpolating pixel values from a flat detector system through the ray that intersects both the curved and flat detectors.

2.2.2 Experimental Studies on the Impact of Non-Stationary Blurs in UHR-MDCT Bone Imaging

An experiment to investigate and quantify blurring in trabecular bone scans by shifting the object away from the center was conducted. UHR-MDCT simulation utilized a standard circular geometry with 1440 views for 360 degrees of gantry rotation, corresponding to 0.25 degrees per view. Source-to-axis distance was 500 mm and axis-to-detector distance was 500 mm. Magnification factor was 2. A curved detector with curvature of 1000 mm (equivalent to SDD) of dimensions 2000 x 32 pixel and pixel pitch of 0.25 mm isotropic was used to generate projections. Forward projections were upsampled to four times the detector dimensions to minimize discretization effects. Time-integration azimuthal blur was simulated by upampling the number of views to 5 times. 7200 views were simulated within 360 degrees, each 0.25 degree view comprises of a summation of 5 views, the average was computed after the summation. Longitudinal and radial blur was simulated by employing focal spot sizes of 0.4 x 0.5 mm (X and Z directions), a 5 x 5 array of Sourcelets was spaced uniformly within the focal spot area, anode angle was set to 0 degrees.
Figure 2.2.4 displays the trabecular bone models used in the UHR-MDCT simulation. The models were obtained from a tunable model provided by our collaborators at FDA. Four regions representing trabecular bone of varying sparsity and thickness were used. The regions measured 100 x 100 x 100 voxels; voxel size was 0.3 mm isotropic for all bones.

![Figure 2.2.4 Trabecular bone models, cropped to 100 x 100 voxels. Each sample represents different trabecular thicknesses and densities, simulating osteoporotic and normal trabecular bones.](image)

### 2.3 PCCT Simulation Framework

#### 2.3.1 Modeling of Primary Radiation in PCCT

The response for a CdZnTe (CZT) photon-counting detector was investigated. In literature, a comprehensive approach to modeling a CZT detector involves fluorescence X-rays, primary electron path, charge diffusion, charge repulsion, charge trapping, and various other physical effects. [30]–[33] The scope of this experiment is much simpler in comparison. The detector is considered an attenuating
material of a given thickness, allowing a fraction of incident photons that were unattenuated to be captured by the detector electronics.

The detector response $D(E)$ as a function of energy can be written as the fraction of photons that remains unattenuated by the detector material at a given thickness:

$$D(E) = W(E) \cdot \left( 1 - e^{-\mu_{DET}(E) \cdot L} \right)$$  \hspace{1cm} (2.3.1)

$W(E)$ is the weight applied to each discrete energy. For an energy integrating detector, $W(E) = E$. For a photon-counting detector, $W(E) = 1$ since it is the individual photon counts that make up the output of the detector, not the integrated energy of the photons. $\mu_{DET}(E)$ is the linear attenuation of the detector material as a function of energy. $L$ is the thickness of the detector. [29]

Linear attenuation for CZT from 1 to 150 keV was generated using NIST X-Ray Mass Attenuation Coefficient database [34] and Spektr 3.0. CZT density was 5.80 g/cm³. The detector response for a 2mm thick CZT detector is displayed in Figure 2.3.1 with linear attenuation generated from both NIST and Spektr 3.0.

![CZT Detector Response S(E)](image)

**Figure 2.3.1** 2mm thick CZT photon-counting detector response for energies 1-150 keV generated from two sources of linear attenuation – NIST and Spektr 3.0.

It should be noted that for most of the simulations involving PCD, perfect detector response is assumed so that investigations in single channel reconstructions and accuracy in material decomposition from single channel data can be simplified.
Polyenergetic projections in energy channels were explored. Instead of integrating the entire spectrum, integration was computed for energies that fall into the threshold of each energy channel. Notation from Equation 2.1.4 is used in the following equation to represent normalized projection per energy channel:

$$I_\kappa = \frac{I_0 \sum_{e_{\kappa,\text{min}}}^{e_{\kappa,\text{max}}} Q(e) \cdot D(e) \cdot ASG \cdot \exp(-\sum \mu_i(e)L_i)}{I_0 \sum_{e_{\kappa,\text{min}}}^{e_{\kappa,\text{max}}} Q(e) \cdot D(e) \cdot ASG} \tag{2.3.2}$$

For $\kappa$ energy channels, $\kappa$ number of forward projections were computed, each energy channel encompasses a segment of the spectrum from $e_{\kappa,\text{min}}$ to $e_{\kappa,\text{max}}$.

### 2.3.2 Modeling of Scatter in PCCT

We investigated the impact of scatter in individual energy channels. MC scatter simulations in phase space was used to model scatter distribution in energy channels for a PCD. In phase-space, the energy of each individual photon is stored. Output from this simulation is a collection of scatter distribution for each discrete energy (1-150 keV) within the range defined by the source spectrum. To obtain the distribution for each channel, a summation is taken for distributions that fall within the range of energies defined by the channel. An example of the distribution is shown in Figure 2.3.2. Scatter for three energy channels: 26-35 keV, 51-65 keV, 86-120 keV, generated with different number of photons and denoising is presented. Figure 2.3.3 displays the scatter distribution profile across the center row of the detector for $10^7$ photons with and without denoising, and $10^8$ photons as the gold-standard.
Figure 2.3.2 Scatter distribution from Monte-Carlo phase space simulation for a short-axes of a 400 mm x 240mm abdominal sized pure water phantom, in three energy channels 25-34 keV, 50-64 keV, 80-120 keV. Scatter distribution is total count normalized, simulated at $10^7$ low number of photons and $10^9$ photons representing the gold-standard. $10^7$ photon distribution is denoised using a Gaussian kernel of 39 x 39 pixels. $10^9$ gold-standard distributions were not denoised.

Figure 2.3.3 Scatter profile across the center row of the detector for distributions in Figure 2.3.2. $10^7$ profiles without denoising is substantially noisier than the $10^9$ gold-standard profiles (without denoising).

To conduct experiments in a timely manner, scatter simulations were conducted at $10^7$ photons. Shown in the distribution in Figure 2.3.2 and the profile in Figure 2.3.3, $10^7$ photon distribution without denoising is substantially noisier than the gold standard with $10^9$ photons. Monte-Carlo phase space runtime increases linearly with the number of simulated photons. Simulating with $10^9$ photons takes roughly 100 times the runtime with only $10^7$ photons. We denoise the $10^7$ photon distribution by convolving the distribution for all channels with a Gaussian kernel. After denoising, the distribution closely follows the gold-standard. It
is noted that greater kernel FWHM tend to suppress the spatial features inherent to scatter distributions, therefore it is important to select a suitable kernel FWHM that preserves spatial features and at the same time removes noise as much as possible.

For all PCCT studies in this thesis, scatter simulations were conducted at $10^7$ photons for speed and to simulate time-sensitive clinical settings. All $10^7$ photon distributions were denoised using a Gaussian kernel.

### 2.4 Material Decomposition

#### 2.4.1 Material Decomposition Algorithm

We describe a material decomposition model that takes energy channel data from a photon-counting detector to estimate path lengths of basis materials. In theory, for $\nu$ basis materials, there needs to be at least $\nu$ number of energy channel data to obtain solutions for the system of equations. Path lengths of $\nu$ basis materials can be estimated through solving the inverse defined by the discretized polyenergetic forward model for all pixels $J$. [35], [36]

$$y_j = \mathbf{B} \exp(-\mathbf{M}\mathbf{\pi})$$ (2.4.1)

$y_j$ is a vector containing the measured projections for every pixel $j$, where $j = 1, ..., J$. For $\kappa = 1, ..., K$ energy channels, the measurement per pixel per channel is $y_{j,\kappa}$:

$$y_j = \begin{bmatrix} y_{j,1} \\ \vdots \\ y_{j,K} \end{bmatrix}$$ (2.4.2)

$\mathbf{\pi}_j$ is a vector of path length at pixel $j$, and $\pi_{j,\nu}$ is the vector of path length per pixel $j$ and per material $\nu$:

$$\mathbf{\pi}_j = \begin{bmatrix} \pi_{j,1} \\ \vdots \\ \pi_{j,\nu} \end{bmatrix}$$ (2.4.3)
The $B$ matrix comprises of the scaling defined by the source spectrum $q_k(\epsilon)$ (per energy channel), detector response $d_k(\epsilon)$ (per energy channel) and anti-scatter grid constant $\alpha$ (constant throughout all energy channels), also interpreted as the scaling to the number of photons due to source, quantum efficiency, and primary attenuation due to anti-scatter grid. The range of energies in keV in each energy channel is denoted by $\epsilon = 1, ..., E$.

$$B = \begin{bmatrix} q_1(1) & d_1(1) & \alpha & \cdots & q_1(E) & d_1(E) & \alpha \\ q_K(1) & d_K(1) & \alpha & \cdots & q_K(E) & d_K(E) & \alpha \end{bmatrix}$$  \hspace{1cm} (2.4.4)

The $M$ matrix contains column vectors of the linear attenuation for $\nu = 1, ..., V$ basis materials as a function of energies grouped into energy channels:

$$M = \begin{bmatrix} \mu_1(1) & \cdots & \mu_V(1) \\ \vdots & \ddots & \vdots \\ \mu_1(E) & \cdots & \mu_V(E) \end{bmatrix}$$  \hspace{1cm} (2.4.5)

In the simulation, each pixel corresponds to a single ray that is traced from the source location to the pixel location, intersecting basis materials by a path length. $y$ matrix describes the collection of rays traced to all pixels on the detector. We formulate the objective function for the non-linear optimization problem to minimize for the path lengths of basis materials for all pixels simultaneously using data from energy channels:

$$\arg\min_\pi \|\vec{y} - Bexp(-M\pi)\|^2$$  \hspace{1cm} (2.4.6)

Where $\vec{y}$ is the measured projections. In the simulation, $\vec{y}$ is calculated using the forward model described in Equation 2.4.1. The objective function minimizes for optimal $\pi$ path lengths. A gradient-based method with line search was employed to solve the non-linear optimization problem, described in Liu et al. [36] No volume conservation or non-negativity constraints were put in place. We allow estimates of the bone path lengths to be negative to compensate for the overestimation of water path lengths.

We investigate the path length accuracy after adding scatter to the simulated measured projections.
2.4.2 Simulation Study on the Impact of Scatter in PCCT Material

Decomposition

A simplified abdominal phantom was used in the study, shown in Figure 2.4.1(a). The ellipsoidal cylinder phantom comprises of water measuring 400 mm by 240 mm, and is extended to cover the entirety of the cone angle (at 8cm and 16cm collimation measured at isocenter) in the z-axis. Six inserts made of bone and water mixtures were added inside the body of water. Bone and water mixture inserts of 20 mm diameter were created at various bone densities to simulate osteoporotic to cortical bone. The volume fraction of bone and water for these inserts are listed in Table 2.4.1. The density of 100% volume fraction bone is 1920 mg/mL for reference. An insert modeling the spine was created with cortical density at 1920 mg/mL and trabecular density at 100 mg/mL.

A simplified phantom modeling the head was also used, shown in Figure 2.4.1(b). The head phantom contains mostly water, measuring 180 mm by 240mm, with six bone and water mixture inserts with volume fractions listed in Table 2.4.1. The phantom is extended to cover the entirety of the cone angle in the z-axis.

Figure 2.4.1 (a) Left: Phantom imitating a human abdomen. Six bone-water mixture inserts of densities 50, 100, 150, 200, 300, 400 mg/mL are placed in an array configuration in the water bath. A spine insert made up of cortical from pure bone and trabecular of bone density 100 mg/mL is present. View 0 deg indicate the short-axis projection. View 90 deg indicate long-axis projection. (b) Right: Phantom imitating a human head. Six bone-water mixture inserts of densities 50, 100, 150, 200, 300, 400 mg/mL are placed in an array configuration in the water bath. Skull made of pure bone at 1920 mg/mL measuring 4.5 mm thick surrounds the water bath. View 0 deg indicate the short-axis projection. View 90 deg indicate long-axis projection.
Table 2.4.1 Summary of volume fraction of bone and water for the six bone inserts present in the head and abdominal phantoms. Attenuation of the mixtures at effective energy (120 kV TASMIC + 0.2 mm Cu filtration) is shown.

<table>
<thead>
<tr>
<th>Bone Insert #</th>
<th>Bone Density (mg/mL)</th>
<th>Fraction of bone in mixture</th>
<th>Fraction of water in mixture</th>
<th>Attenuation of mixture at effective energy (mm⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>0.0260</td>
<td>0.9740</td>
<td>0.0211</td>
</tr>
<tr>
<td>2</td>
<td>100</td>
<td>0.0521</td>
<td>0.9479</td>
<td>0.0221</td>
</tr>
<tr>
<td>3</td>
<td>150</td>
<td>0.0781</td>
<td>0.9219</td>
<td>0.0231</td>
</tr>
<tr>
<td>4</td>
<td>200</td>
<td>0.1042</td>
<td>0.8958</td>
<td>0.0241</td>
</tr>
<tr>
<td>5</td>
<td>300</td>
<td>0.1562</td>
<td>0.8438</td>
<td>0.0260</td>
</tr>
<tr>
<td>6</td>
<td>400</td>
<td>0.2083</td>
<td>0.7917</td>
<td>0.0280</td>
</tr>
</tbody>
</table>

The simulations involved a photon-counting flat detector with 900 x 320 pixels and 1.00 mm isotropic pixel size was utilized. The detector assumed a perfect response and the signal was binned into five energy channels: 25-34 keV, 35-49 keV, 50-64 keV, 65-79 keV, 80-120 keV. Source spectrum employed a 120kV TASMICS with 0.2 mm copper filtration, normalized by its area. 30:1 anti-scatter grid was employed. ASG in primary is simulated using a binary model from Kyriakou and Kalender. [27] For this grid, the ASG constant (from Equation 2.3.2) was 0.75. Phantom was realized using a 0.5mm isotropic voxel grid. Head phantom spans 600 x 600 x 600 voxels and the abdominal phantom spans 900 x 900 x 600 voxels. The phantom was placed at the center of the gantry. Projection matrices were generated for 720 views within 360 degrees. The beam collimation for scatter was set to either 8cm or 16cm at isocenter to investigate the effects of collimation on the accuracy of line integral estimates.

The simulation pipeline for the material decomposition experiment was as follows. Monte-Carlo scatter simulations in phase space were computed for 90 views at 10⁷ photons with denoising, which was later interpolated in the angular domain to 720 views. Path length matrix \( \mathbf{\pi} \) for water and bone basis materials were computed from phantoms made of values representing fractional densities, see Table 2.4.1. \( \mathbf{y}, \mathbf{B}, \mathbf{M} \) matrices from Equation 2.4.6 were created based on source spectrum with energy channel thresholding, photon-counting detector response, anti-scatter grid, linear attenuation of bone and water. The objective function, where the measured projection containing scatter \( \mathbf{s} \), with scatter correction \( \mathbf{s} \), is formulated:
\[
\arg\min_\pi \| (\mathbf{y} + \mathbf{s}) - (\mathbf{B}_\text{exp}(\mathbf{M}\pi) + \mathbf{s}) \|^2
\]  \hspace{1cm} (2.4.7)

Scatter correction was applied to the experiment in Section 3.4 to investigate the accuracy of material decomposition after scatter correction in the presence of bowtie scatter.

The objective was minimized for each view, and it was run for 720 views. Up to 2000 iterations were allowed for each view. A stopping condition was implemented by checking whether the differences between the previous and current objective function is within a threshold.

Once the line integral estimates for water and bone were obtained, they were sent into the reconstruction pipeline to create material separated images and virtual monoenergetic images at effective energy of the spectrum, so that we can analyze the attenuation bias for each bone-water mixture insert after decomposition. The reconstruction pipeline loads the line integral estimates for bone and water.

Projections in line integral domain are filtered using the FDK filter. Filtered projection were backprojected to create an image.

Virtual monoenergetic images (VMI) were generated through:

\[
\mu = f_{\text{Bone}} \mu_{\text{Bone}}(E_{\text{EFF}}) + f_{\text{H2O}} \mu_{\text{H2O}}(E_{\text{EFF}})
\]  \hspace{1cm} (2.4.8)

where \( f_{\text{Bone}} \) and \( f_{\text{H2O}} \) are fractions of pure bone and water per voxel, respectively, obtained from the reconstructions of the base material projections. \( \mu_{\text{Bone}}(E_{\text{EFF}}) \) and \( \mu_{\text{H2O}}(E_{\text{EFF}}) \) are linear attenuation of bone and water at effective energy of the spectrum.
Chapter 3: Results

3.1 Characterization of the Effects of Non-Stationary UHR-MDCT

Blur in Trabecular Bone Imaging

In this section, the results from the UHR-MDCT simulations are presented. In particular, non-stationary blurring for UHR-MDCT due to focal spot size and time-integration are the focus of this experiment.

The four trabecular samples in Figure 2.2.4 were used as phantoms for the UHR-MDCT simulation. Figure 3.1.1 displays the output of the “Dense 1” bone sample from UHR-MDCT simulation. Labels are in the format of \([X \ Y \ Z]\) mm shifts away from the axis center. At the center of gantry (label \([0 \ 0 \ 0]\)), trabeculae appear dilated due to blurring from the focal spot (settings 0.4 mm x 0.5 mm) and detector pixels. The dilation agrees with the expected outcome from the effects of focal spot size – a point stimuli undergoing blurring from focal spot size would be dilated to the area of the focal spot size. When the object is shifted in the Y-direction by 40mm (label \([0 \ 40 \ 0]\)), the trabeculae suffer from strong azimuthal blurring tangent to the direction of the gantry rotation, due to frame time-integration. The shift in the Y-direction by 75mm (label \([0 \ 75 \ 0]\)) and 110mm (label \([0 \ 110 \ 0]\)) displays more significant effects of azimuthal blurring. The simulation results agree with the findings from Boone et al. that as the object moves away from the center, azimuthal blurring due to time-integration become accentuated. [9] Shifting the object off center diagonally by 110 mm (label \([78 \ 78 \ 0]\)) results in visible azimuthal blurring tangent to the path of the gantry rotation. Visually inspecting the output from UHR-MDCT simulation at the center of gantry, trabecular branches can no longer be associated with the original CT scan due to dilation, which shows the difficulty of UHR-MDCT at resolving trabecular structures even at the highest resolution settings.

Figures 3.1.2, 3.1.3, 3.1.4 presents the output from the UHR-MDCT simulation for trabecular sample labeled “Dense 2”, “Sparse 1”, “Sparse 2”, respectively. Increased intensity in azimuthal blurring is
observed in all three trabecular ROIs as the object is shifted away from the center. Azimuthal blurring direction are also in agreement with the observations in Figure 3.1.1 – direction is tangent to the circular path of gantry. Dilation of the trabeculae due to focal spot and pixel size was observed in all objects placed at the center of the gantry. It was expected with tightly packed trabecular structures, no branches could be delineated because of the focal spot size. [1]

**Figure 3.1.1** UHR-MDCT simulation output for “Dense 1” trabecular sample moved to various distances within the FOV. Simulations exhibit dilation of the trabecular due to focal spot and pixel size, and azimuthal blur due to detector integration. Labels represent moving the object [X Y Z] mm distances from the center of gantry.

**Figure 3.1.2** UHR-MDCT simulation output for “Dense 2” trabecular sample moved to various distances within the FOV. Simulations exhibit dilation of the trabecular due to focal spot and pixel size, and azimuthal blur due to detector integration. Labels represent moving the object [X Y Z] mm distances from the center of gantry.
Figure 3.1.3 UHR-MDCT simulation output for “Sparse 1” trabecular sample moved to various distances within the FOV. Simulations exhibit dilation of the trabecular due to focal spot and pixel size, and azimuthal blur due to detector integration. Labels represent moving the object [X Y Z] mm distances from the center of gantry.

Figure 3.1.4 UHR-MDCT simulation output for “Sparse 2” trabecular sample moved to various distances within the FOV. Simulations exhibit dilation of the trabecular due to focal spot and pixel size, and azimuthal blur due to detector integration. Labels represent moving the object [X Y Z] mm distances from the center of gantry.

3.2 PCCT Characterization – Scatter in Energy Channels

This section describes the results obtained from the investigation of scatter for a photon-counting detector in energy channels for a water cylinder phantom of diameter 300 mm. Scatter spectrum behind the object, SPR distribution, and SPR magnitudes for various collimation widths were the focus of this experiment.

Figure 3.2.1 displays the primary spectrum and the scatter spectrum behind the center of a water cylinder of diameter 300 mm. The units on display are in air-normalized photon counts. The energy channels on
display are 26-35 keV, 36-50 keV, 51-65 keV, 66-85 keV, 86-120 keV. The primary was generated with Spektr 3.0 and an attenuation of water path length 300 mm was applied to the spectrum. Characteristic radiation spikes can be seen in the primary spectrum. Scatter on the other hand, was generated with MC phase space simulations at $10^{10}$ photon counts. The scatter spectrum did not exhibit similar magnitude compared to the primary. Note that a 30:1 anti-scatter grid has been applied to both scatter and primary. Scatter is more prominent in the lower two energy channels compared to the primary, suggesting that images generated from low channel data will experience the most cupping artifacts. It is also plausible that the scatter in lower channels may compromise the accuracy of material decomposition.

![Primary and Scatter Spectrum](image)

**Figure 3.2.1** Air-normalized x-ray spectra of primary and scatter behind a 300 mm diameter water cylinder. Scatter was simulated with 8cm collimation.

![Figure 3.2.2](image)

**Figure 3.2.2** (a) Left: Scatter distribution of 26-35 keV and 86-120 keV channels of a 300 mm diameter water cylinder. (b) Right: Center profile of scatter distribution of 26-35 keV and 86-120 keV channels of a 300 mm diameter water cylinder. Collimation was 8cm at isocenter.
Figure 3.2.3 SPR distribution of 26-35 keV and 86-120 keV channels of a 300 mm diameter water cylinder. Figure 3.2.2 (a) displays the scatter distribution for the lowest and highest energy channels behind the 300 mm water cylinder, Figure 3.2.2 (b) displays the scatter profile across the center row of the detector. Figure 3.2.3 presents the SPR spatial distribution for the lowest and highest energy channels behind the 300 mm water cylinder with 8 cm collimation at isocenter, using the scatter distribution in Figure 3.2.2. In the lowest energy channel (26-35 keV), the distribution is concentrated towards the center of the water cylinder and has a magnitude roughly 400 times the magnitude of the highest energy channel. The SPR distribution is also much wider for the highest energy channel than the lowest energy channel.

Figure 3.2.4 Boxplot of the SPR of a diameter 300 mm water cylinder within a 21 x 21 pixel ROI at the center of the detector for five energy channels, for three collimation widths 2 cm, 8 cm, 16 cm.
Figure 3.2.4 displays the SPR within a 21 x 21 pixel ROI for three collimation 2 cm, 8 cm, 16 cm at isocenter in all five energy channels. An exponential decrease in SPR is observed from the lowest to the highest energy channel. The impact of scatter, as mentioned previously, is highest in the lower energy channels. The results conform to the expected outcome that wider collimation produces higher scatter magnitude, as shown in Figure 3.2.4 that the SPR for 16cm collimation is greater than the 8cm collimation case for all energy channels.

3.3 PCCT Characterization – Effect of Bowtie Scatter

In this section, the results comprising of bowtie scatter distributions and the accuracy of material decomposition in the presence of bowtie scatter are presented. Scatter causes spectral distortion and specifically, scatter originating from the bowtie is investigated. Scatter and SPR distribution behind an aluminum bowtie and water cylinders of diameter 150 mm and 300 mm are the focus of this investigation. The aluminum bowtie phantom used in this experiment is shown in Figure 3.3.1. An expanded version of this investigation has been submitted to SPIE Medical Imaging 2023 and will be published in conference proceedings. [4]

![Figure 3.3.1](image)

**Figure 3.3.1** Aluminum bowtie designed for this study. Thickness of bowtie is 83 mm. Top of the bowtie is placed 48 mm away from the point source.

Figure 3.3.2 (a), (b) displays the scatter profile across the center of the detector with 8cm collimation at isocenter for an aluminum bowtie and a water cylinder of 150mm and 300mm, respectively, for five energy channels of the photon-counting detector. Aluminum bowtie was placed 48 mm away from the point source and the cylinder was placed at the center of gantry. The plots in these figures are zoomed in
to capture the differences in scatter magnitude sections shadowed by the water cylinder (columns 300-600 for 150 mm diameter cylinder, columns 120-780 for 300 mm diameter cylinder). Comparing the scatter distribution of a water cylinder without a bowtie in Figure 3.2.2 to scatter distribution with the bowtie, at the periphery of the cylinder, scatter profile forms a peak that would not exist without the presence of bowtie. For three different collimations: 4 cm, 8 cm, 16 cm at isocenter, we observe increasing scatter magnitudes within the sections shadowed by both the 150 mm and 300 mm water cylinders. The results align with the expected outcome that as the beam collimation widens, scatter magnitude increases. This increase in scatter magnitude for wider collimations was also observed outside the periphery of the cylinder for all energy channels. In particular, at the sections shadowed by the water cylinder for the lowest energy channel (25-34 keV), the scatter profile is rather flat, and becomes increasingly round as the energy increases.

Figure 3.3.2 (a) Left: Scatter profile of a 150 mm diameter water cylinder in the presence of bowtie scatter for three collimations 4 cm, 8 cm, 16 cm. (b) Right: Scatter profile of a 300 mm diameter water cylinder with a bowtie for three collimations 4 cm, 8 cm, 16 cm.

We have measured the SPRs for two cases: (i) scatter generated by the object and the bowtie (denoted below as Bowtie+Object), and (ii) scatter generated by only the object, bowtie acting only as an
attenuator (denoted below as Object-Only). We found that the SPR for Bowtie+Object is higher than for Object-Only for all object sizes in all energy channels. In particular, the greatest discrepancy between the two cases is observed in higher energy channels – for example, we observed a 20-30% increase in scatter for Bowtie+Object compared to Object-Only in the 50-64 keV and 80-120 keV channels for the 300 mm object. This increase in SPR is likely due to x-rays that scattered in forward directions in the bowtie and did not undergo any additional scattering events in the object, thus maintaining relatively high energy.

To quantify the impact of bowtie scatter on material decomposition, we embedded wedge-shaped Ca inserts into the center and periphery of the water cylinder. The inserts provide a range of path lengths to measure the accuracy of the decomposition.

Tables 3.3.1 and 3.3.2 quantify the estimated bone path lengths obtained using a projection-domain approach similar to that in Section 2.4 for the 8cm and 16cm collimations, respectively. Path lengths for the ideal scatter correction shows no bias between the true and estimated path lengths (see first and second columns). Estimated bone path lengths without any scatter correction displays significant discrepancies compared to estimated path lengths with ideal scatter correction (see second and fourth columns). At 6 mm true path length, we observe negative estimated bone path lengths in case without any scatter correction, which is typical of the outcome of material decomposition in the presence of scatter. Scatter correction that ignores the bowtie scatter shows appreciable residual errors for both collimations.
<table>
<thead>
<tr>
<th>True Path Length (mm)</th>
<th>Ideal Scatter Correction (mm)</th>
<th>Object-Only Scatter Correction (mm)</th>
<th>No Scatter Correction (mm)</th>
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<tr>
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<tr>
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<td>25.00</td>
<td>23.78</td>
<td>15.65</td>
</tr>
</tbody>
</table>

Table 3.3.1 Estimated Ca path lengths from Ca wedges embedded into the center of a 300 mm diameter water cylinder. Collimation was 8 cm. Object-only scatter correction refers to scatter generated only by the object (bowtie was acting only as an attenuator).

<table>
<thead>
<tr>
<th>True Path Length (mm)</th>
<th>Ideal Scatter Correction (mm)</th>
<th>Object-Only Scatter Correction (mm)</th>
<th>No Scatter Correction (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.00</td>
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<tr>
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<td>19.39</td>
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Table 3.3.2 Estimated Ca path lengths from Ca wedges embedded into the center of a 300 mm diameter water cylinder. Collimation was 16 cm. Object-only scatter correction refers to scatter generated only by the object (bowtie was acting only as an attenuator).

3.4 PCCT Application – Two-Material Decomposition with Energy Channels

In this section, results from the material decomposition experiment for the abdominal and head phantoms from Figure 2.4.1 are presented. The attenuation biases in the reconstruction from the line integral estimates are focuses for this experiment.
Figure 3.4.1 (a) Left: Center profile of the bone line integral estimates from material decomposition for the abdominal phantom (Figure 2.4.1 (a)) at the short body axis (view 0 deg) with three cases: no scatter, added scatter at either 8cm or 16cm collimation. (b) Right: Center profile of the bone line integral estimates from material decomposition for the abdominal phantom (Figure 2.4.1 (a)) at the long body axis (view 90 deg) with three cases: no scatter, added scatter at either 8cm or 16cm collimation.

Figure 3.4.2 (a) Left: Center profile of the water line integral estimates from material decomposition for the abdominal phantom (Figure 2.4.1 (a)) at the short body axis (view 0 deg) with three cases: no scatter, added scatter at either 8cm or 16cm collimation. (b) Right: Center profile of the water line integral estimates from material decomposition for the abdominal phantom (Figure 2.4.1 (a)) at the long body axis (view 90 deg) with three cases: no scatter, added scatter at either 8cm or 16cm collimation.

Figure 3.4.1(a), (b) depicts the center profiles taken through the abdominal phantom projection for bone line integral estimates from the two-material decomposition for 0 degree and 90 degrees views, respectively. Three cases of line profiles were obtained from line integral estimates with scatter for 8cm and 16cm collimation, and without scatter. Viewing the abdominal phantom from 0 degrees, the peaks represent estimated path lengths for the spinal insert. The lower two peaks at the periphery of the profile correspond to bone-water mixture inserts. For the scatter free case, the gradient based optimization
successfully found exact solutions for the path length of bone. For cases with scatter, path lengths for bone were underestimated for regions of spinal insert, bone-water mixture insert, as well as sections without any bone. We see a trend that with higher scatter magnitude (8cm collimation to 16cm collimation), bone line integrals become significantly more underestimated. For sections that were originally with zero bone line integrals in the scatter-free case, impact of scatter in material decomposition creates negative values for bone line integral estimates. In other words, the crevasse in the solution space of the objective function shifts into the negative region as scatter is added to the projections. The shift towards negative becomes more significant as scatter magnitude increases.

Figure 3.4.2 (a), (b) displays the center profiles of the abdominal phantom projection for water line integral estimates for 0 degree and 90 degree views, respectively. The water line integrals are the counterparts to the bone line integrals, making up the full path length of the phantom. The water line integrals are in opposite agreement to bone line integrals under the effects of scatter – as scatter magnitude increases, water line integrals become more overestimated. This is to compensate for the underestimation of bone line integrals.

![Figure 3.4.2](image)

**Figure 3.4.3** (a) Left: Center profile of the bone line integral estimates from material decomposition for the head phantom (Figure 2.4.1 (b)) at the long body axis (view 0 deg) with three cases: no scatter, added scatter at either 8cm or 16cm collimation. (b) Right: Center profile of the bone line integral estimates from material decomposition for the head phantom (Figure 2.4.1 (b)) at the short body axis (view 90 deg) with three cases: no scatter, added scatter at either 8cm or 16cm collimation.
Figure 3.4.4 (a) Left: Center profile of the water line integral estimates from material decomposition for the head phantom (Figure 2.4.1 (b)) at the long body axis (view 0 deg) with three cases: no scatter, added scatter at either 8cm or 16cm collimation. (b) Right: Center profile of the water line integral estimates from material decomposition for the head phantom (Figure 2.4.1 (b)) at the short body axis (view 90 deg) with three cases: no scatter, added scatter at either 8cm or 16cm collimation.

Figure 3.4.3 (a), (b) displays the center profiles taken across the head phantom projection for bone line integral estimates for 0 degree and 90 degree views, respectively. Though more subtle than the line integral estimate discrepancies between scatter-free and scatter cases for the abdominal phantom, the head phantom shows similar agreement trends where cases with scatter have underestimated bone path lengths, especially at the three peaks at the center of the 0 degree view representing the bone-water mixture inserts. Figure 3.4.4 (a), (b) shows the center profiles across the head phantom projection, for water line integral estimates. Discrepancies are also in agreement with the trend found in the abdominal water line integral estimates. Case with scatter at 16cm collimation is observed with the highest overestimation of water line integrals.

Reconstructing estimated bone line integrals result in a bone only image of the phantom in units of bone fraction. Bone fractions are taken from the center of six bone-water mixture inserts with 13 x 13 voxel ROIs, the mean of the ROI is displayed in Figure 3.4.5 (a) for the head phantom and Figure 3.4.5 (b) for the abdominal phantom for the six inserts with bone densities of 50, 100, 150, 200, 300, 400 mg/mL. It was expected that for the case without scatter (ground truth bone fraction), the line integral estimates increased linearly as the bone density increases. This was observed in both the head and abdominal
phantoms. For cases with scatter (8cm and 16cm collimation), there is a discrepancy from the linear trend starting at 200 mg/mL. As the scatter magnitude increased, bone line integrals become more underestimated, resulting in less bone fraction in the reconstruction.

![Graph showing bone fraction vs bone density](image)

**Figure 3.4.5** (a) Left: Quantifying effects of scatter in material decomposition. 5 x 5 voxel ROI selected within the six bone inserts of various densities for the reconstructed image from bone line integral estimates for the head phantom. Reconstructed images are in units of bone fraction. (b) Right: Quantifying effects of scatter in material decomposition. 5 x 5 voxel ROI selected within the six bone inserts of various densities for the reconstructed image from bone line integral estimates for the abdominal phantom. Reconstructed images are in units of bone fraction.

Virtual monoenergetic images at effective energy of the spectrum were reconstructed from estimated bone and water line integrals using Equation 2.4.8. Figure 3.4.6 (a) displays the abdominal VMI with its horizontal profile across the center of the phantom in Figure 3.4.6 (b) for cases with scatter (8cm and 16cm collimation). The units of HU are with reference to the attenuation of water at effective energy of the spectrum. Similar to the bone fraction analysis presented in Figure 3.4.5, VMI with scatter at 8cm collimation show greater HU inside the three bone-water than VMI with scatter at 16cm collimation mixture inserts, indicating that the bone line integrals become severely underestimated with increasing scatter magnitudes. The head phantom VMI is shown in Figure 3.4.7 (a) along with its vertical profile across the center of the image in Figure 3.4.7 (b). Difficult to visualize with the scaling in Figure 3.4.7 (b), HU within the two inserts also show the underestimation of bone line integrals as scatter magnitude increased with collimation from 8cm to 16cm.
Figure 3.4.6 (a) Left: Virtual monoenergetic image created from water and bone line integral estimates for the abdominal phantom. Image was created with estimates containing scatter at 8cm collimation. Right: Center profile (along the horizontal) across the VMI reconstructed with line integral estimates containing scatter at both 8cm and 16cm collimation cases for the abdominal phantom.

Figure 3.4.7 (a) Left: Virtual monoenergetic image created from water and bone line integral estimates for the head phantom. Image was created with estimates containing scatter at 8cm collimation. Right: Center profile across the VMI (along the vertical) reconstructed with line integral estimates containing scatter at both 8cm and 16cm collimation cases for the head phantom.
Chapter 4: Discussion

Two new CT technologies were investigated in this thesis: UHR-MDCT and PCCT. UHR-MDCT is a useful imaging tool for investigating fine anatomical features, e.g., the microstructure of trabecular bone, which can potentially aid the assessment of osteoporosis and osteoarthritis. PCCT on the other hand, allows the differentiation of the energy of incident photons. Signals from individual energy channels enable material decomposition, which can be used for quantification of multiple exogenous contrast agents and accurate measurements of tissue composition.

Non-stationary blur in UHR-MDCT, specifically azimuthal and radial blurring when the object is moved away from the center of the gantry, was explored. A simulation tool to investigate non-stationary blur was built with parameters referenced from Canon Aquilion Precision CT. Trabecular bone samples representative of osteoporotic and normal trabecular bone were used as phantoms in this simulation. Azimuthal blur was direction-dependent and its effects were apparent as the object moved further away from the center of the gantry. Stronger effects of azimuthal blur were correlated to longer detector integration time. Radial blur due to focal spot and detector pixel exhibited dilation on trabecular structures. The UHR-MDCT simulation tools developed in this thesis are currently used to study the impact of non-stationary spatial resolution on texture biomarkers of bone. [1], [2]

PCCT investigation focused on quantifying scatter in energy channels, along with the impact of scatter to material decomposition. According to the SPR of a water cylinder, the lowest energy channel (26-35 keV) contains approximately 100 times the SPR of a higher energy channel (86-120 keV) at the center of the cylinder. Material decomposition in the presence of scatter was explored. Scatter underestimates bone line integrals and overestimates water line integrals, translating to biases in the virtual monoenergetic images. The severity of these material decomposition biases was quantified by the amount of scatter present in each energy channel. In the presence of a bowtie, without correct calibration to account for scatter coming from the bowtie, bias in bone line integral estimates remained present.
Chapter 5: Future Work

UHR-MDCT with its high-resolution scans, opens the possibility to quantitatively assess bone microarchitecture. Canon Aquilion Precision CT allows the visualization of details down to \(~150\ \mu\text{m}\), which approaches the size of the trabeculae. On-going work is underway for quantitative measurements and classification of bone microstructures, which translates to assessment of osteoporosis, osteoarthritis, and other bone disease.

Applications of PCCT are vast – the availability of single channel data enables applications such as material decomposition and virtual monoenergetic imaging. Since scatter is present in CT scans, even with a rigorous 30:1 ASG in place, there is a need to improve scatter correction algorithms to fully realize the potential benefits of PCCT in accurate material decomposition. Scatter distribution varies with object composition, position, and energy channels. MC simulations are effective at simulating scatter distributions and are useful for scatter corrections but suffer from long runtimes. Scatter denoising is a topic of interest. There is still much more work to be done to improve scatter correction algorithms.
References


# Curriculum Vitae

## EDUCATION

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<td>2021 - Current</td>
<td>Johns Hopkins University</td>
<td>MSE Biomedical Engineering – Imaging and Medical Devices</td>
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<td>Master’s Thesis: “Simulation and Modeling for UHR-CT and Photon-Counting CT”</td>
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<td>2019 - 2020</td>
<td>University of California, Irvine</td>
<td>Graduate Preparation Program (5 quarters) – Biomedical Engineering</td>
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<td>2014 - 2018</td>
<td>Hong Kong University of Science and Technology (HKUST)</td>
<td>BEng in Electronic Engineering</td>
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<td>2016 - 2017</td>
<td>École polytechnique fédérale de Lausanne, Switzerland</td>
<td>Exchange Program – Electronic Engineering</td>
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<td>2018</td>
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## RESEARCH EXPERIENCE

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| 2021 - Current| Johns Hopkins University, Quantis Laboratory (https://quantis.bme.jhu.edu) | - Research assistant under Dr. Wojtek Zbijewski  
- Computed tomography (CT) research – quantification of bone image quality, scatter, and artifact corrections utilizing CT simulation framework  
- Constructed a computed tomography bench station from basic components to aid next generation of CT experiments - wrote C++ software to control detector readout, x-ray source, platform stage, DAQ card  
- Collaborated with Canon Medical USA – planned, designed, and executed Monte-Carlo models and simulation pipelines for photon-counting CT using Matlab  
- Master’s thesis: Investigating effects of scatter in energy channels for a photon-counting detector, applications on two-material decomposition |
| 2019 - 2020   | University of California, Irvine - Beckman Laser Institute, Microvascular Therapeutics and Imaging Laboratory | - Designed and carried out Multi-Exposure Laser Speckle Contrast Imaging experiments – characterized perfusion of vessels  
- Programmed in Matlab to explore and fit non-linear functions to investigate trends and properties of laser speckle imaging results |
| 2016          | National Taiwan University of Science and Technology, Analog IC Laboratory | - Wrote and edited academic paper “2.5ps Bin Size TDC Converter” published in IEEE VLSI Issue 1 Vol. 25.  
- Utilized Verilog/VHDL to create time-to-digital converters with Altera Stratix IV and Altera DE0 FPGA development kits  
- Performed experiments using 81134A 3.34GHz Pulse Generator; Matlab, and Quartus for post-processing of results |
SCIENTIFIC PRESENTATIONS


GRADUATE LEVEL COURSES (Johns Hopkins University)

X-ray Imaging and Computed Tomography – Dr. Wojtek Zbijewski

- Learned CT physics: x-ray production and interaction, forward and back projection, apodization kernels, dosimetry, scatter, artifact correction techniques, material decomposition
- Implemented known-component model based iterative reconstruction to reduce artifacts caused by metal implants

Imaging Instrumentation – Dr. J. Webster Stayman

- Programmed CT backprojection algorithm based on Kak & Slaney in Matlab to reconstruct object slices from forward projections captured using a modern camera
- Developed auto-focus algorithm for modern cameras, utilized image quality assessment tools (line pair, MTF) to characterize spatial resolution for focused images
- Created and trained convolutional neural network to assign colors to greyscale images

Radiology for Engineers – Dr. J. H. Siewerdsen

- In-depth introduction to different modalities in medical imaging: CT, MRI, PET/SPECT, ultrasound, endoscopy, computer assisted surgery
- Shadowed surgeons at Johns Hopkins Hospital – C-Arm computer assisted pedicle screw insertion surgery
- Trained neural networks to segment images containing carcinomic skin lesions
- Slicer3D to perform deformable image registration of patient brains to a brain atlas

Introduction to Data Science for Biomedical Engineering – Dr. Brian Caffo

- Categorized and sorted large public COVID datasets using Tidyverse, created interactive COVID data dashboard using Shiny R
- Image classification using Keras Deep Learning module, coded in Python
- Semester Project: *AirDashboard* – Interactive web app displaying flight statistics written using R, Shiny, HTML ([https://github.com/ytai9109/AirDashboard](https://github.com/ytai9109/AirDashboard))

Introduction to MRI in Medicine – Dr. Siamak Ardekani

- Learned mathematical background in MRI: excitation, encoding, echo, fast MR imaging methods
- Applied diffusion tensor imaging techniques to brain MRI dataset in Matlab, color coding direction of perfusion in brain vessels, optimization for diffusion gradient subsets from large population of gradients

Principles of the Design of Biomedical Instrumentation – Dr. Nitish Thakor

- Learned process from circuit design to institutional approval for various biomedical devices: ECG, PPG, EMG
- Designed a game controller for disabled patients utilizing ultrasonic sensors

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TEACHING EXPERIENCE

2021 – 2022 Johns Hopkins University, Biomedical Engineering Practice and Innovation

- Course and lab assistant for Matlab, PPG, ultrasound modules
- Created and revised Matlab exercises to give students an introduction to Matlab
- Assisted students with devising suitable PPG data collection methods using laboratory equipment and analysis methods in Matlab

PROGRAMMING SKILLS

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VOLUNTEER ACTIVITIES

2021 – Current Youth Library Tutorial, Johns Hopkins University
2020 Food from the Heart, Singapore
2018 Jiangxi Service Trip, HKUST
2018 Nepal Service Trip, HKUST
2016 Leadership Development Program, Taiwan
2013 Organization Committee Volunteer for International Olympiad in Informatics, Australia