A Strategy for Matching Noise Magnitude and Texture Across CT Scanners of Different Makes and Models

by

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Graduate Program in Medical Physics
Duke University

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Donald P Frush

Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the Graduate Program in Medical Physics in the Graduate School of Duke University

2012
ABSTRACT

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Abstract

Purpose: The fleet of x-ray computed tomography systems used by large medical institutions is often comprised of scanners from various manufacturers. An inhomogeneous fleet of scanners could lead to inconsistent image quality due to the different features and technologies implemented by each manufacturer. Specifically, image noise could be highly variable across scanners from different manufacturers. To partly address this problem, we have performed two studies to characterize noise magnitude and texture on two scanners: one from GE Healthcare and one from Siemens Healthcare. The purpose of the first study was to evaluate how noise magnitude changes as a function of image quality indicators (e.g., “noise index” and “quality reference mAs”) when automatic tube current modulation is used. The purpose of the second study was to compare and match reconstruction kernels from each vendor with respect to noise texture.

Methods: The first study was performed by imaging anthropomorphic phantoms on each scanner using a clinical range of scan settings and image quality indicator values. Noise magnitude was measured at various anatomical locations using an image subtraction technique. Noise was then modeled as a function of image quality indicators and other scan parameters that were found to significantly affect the noise-image quality indicator relationship.
The second study was performed by imaging the American College of Radiology CT accreditation phantom with a comparable acquisition protocol on each scanner. Images were reconstructed using filtered backprojection and a wide selection of reconstruction kernels. We then estimated the noise power spectrum (NPS) of each image set and performed a systematic kernel-by-kernel comparison of spectra using the peak frequency difference (PFD) and the root mean square error (RMSE) as metrics of similarity. Kernels that minimized the PFD and RMSE were paired.

**Results:** From the first study, on the GE scanner, noise magnitude increased linearly with noise index. The slope of that line was affected by changing the anatomy of interest, kVp, reconstruction algorithm, and convolution kernel. The noise-noise index relationship was independent of phantom size, slice thickness, pitch, field of view, and beam width. On the Siemens scanner, noise magnitude decreased non-linearly with increasing quality reference effective mAs, slice thickness, and peak tube voltage. The noise-quality reference effective mAs relationship also depended on anatomy of interest, phantom size, age selection, and reconstruction algorithm but was independent of pitch, field of view, and detector configuration.

From the second study, the RMSE between the NPS of GE and Siemens kernels varied from 0.02 to 0.74 mm. The GE kernels “Soft”, “Standard”, “Chest”, and “Lung” closely matched the Siemens kernels “B35f”, “B43f”, “B46f”, and “B80f” (RMSE<0.07 mm, PFD<0.02 mm⁻¹). The GE “Bone”, “Bone+”, and “Edge” kernels all matched most
closely to Siemens “B75f” kernel but with sizeable RMSE and PFD values up to 0.62 mm
and 0.5 mm\(^{-1}\) respectively. These sizeable RMSE and PFD values corresponded to
visually perceivable differences in the noise texture of the images.

**Conclusions:** From the first study, we established how noise changes with changing
image quality indicators across a clinically relevant range of imaging parameters. This
will allow us target equal noise levels across manufacturers. From the second study, we
concluded that it is possible to use the NPS to quantitatively compare noise texture
across CT systems. We found that many commonly used GE and Siemens kernels have
similar texture. The degree to which similar texture across scanners could be achieved
varies and is limited by the kernels available on each scanner. This result will aid in
choosing appropriate corresponding kernels for each scanner when writing protocols.
Taken together, the results from these two studies will allow us to write protocols that
result in images with more consistent noise properties.
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X-ray computed tomography (CT) technology has advanced to a point of unprecedented clinical utility and has become an invaluable tool with an ever-growing number of clinical applications [1-10]. Large medical centers often purchase CT scanners from a variety of manufacturers. An inhomogeneous fleet of CT scanners may result in inconsistent image quality unless examination protocols are carefully defined to accommodate differences in CT models. Achieving consistent image quality across manufacturers is a challenging task due to differences in the implementation of CT technology. For example, every major CT vendor has developed a tube current modulation algorithm that adapts the X-ray exposure to patients of different sizes. These proprietary algorithms all work differently and employ a unique nomenclature and set of input parameters [11]. Therefore, in order to achieve consistent image quality, it is necessary to understand how imaging parameters (both generic and proprietary) affect image quality on each manufacturer’s CT platform.

Image noise is one common metric used to evaluate image quality with noisy images being an indication of poor quality. Noise can be characterized by its magnitude and its texture. Noise magnitude refers to random fluctuations of pixel values in a homogenous region of interest (ROI) and is measured by taking the standard deviation...
of pixel values within that ROI. Noise texture refers to correlations between adjacent pixel values that are manifest by the grainy appearance of CT images. These correlations are largely affected by the image reconstruction process and are highly dependent on the convolution kernel employed during reconstruction. Noise texture may be characterized in terms of the noise power spectrum (NPS), which gives the spatial frequency content of noise within an ROI [12].

We performed two studies to characterize noise magnitude and texture for two different commercial CT platforms: one from GE Healthcare, and one from Siemens Healthcare. For both scanners, noise magnitude was characterized as a function of several imaging parameters by imaging anthropomorphic phantoms and using an image subtraction technique to measure noise. Noise texture was characterized by imaging the American College of Radiology (ACR) CT accreditation phantom and measuring the NPS of uniform images reconstructed with many convolution kernels from each scanner. Convolution kernels that gave similar NPS' were then paired. A detailed report of each study is presented in chapters 2-3 of this thesis.

The results of the first study make it possible to achieve images that have similar noise magnitude across both scanners by using automatic tube current modulation. The results of the second study allow us to match convolution kernels that produce images with similar texture across both scanners. Thus, the results of these two studies taken together can be used as tools to assist in the design of examination protocols by
informing the radiologist and physicist as to what settings on each scanner are expected to produce images with similar noise magnitude and texture.
2 Noise Magnitude

2.1 Background

2.1.1 Automatic Tube Current Modulation

Both advances in technology and increased clinical utility have resulted in an increase in the number of CT studies performed in the United States. Subsequently, the radiation dose received by patients due to CT examinations has increased drastically since the technology’s inception in the 1970s [13-14]. This drastic increase in patient dose has prompted researchers and manufacturers to investigate dose reduction strategies. One such strategy is the use of automatic tube current modulation (ATCM). ATCM techniques attempt to reduce dose and maintain image quality for patients of different shapes and sizes by dynamically adapting the X-ray tube current for specific patients [15-18]. These techniques are analogous to automatic exposure control techniques used in traditional radiography. In CT exams using ATCM, the user targets a level of image quality by setting an image quality indicator (e.g., noise index or quality reference effective mAs). The CT system then uses the size and X-ray attenuation properties of the patient to modulate the tube current (i.e., photon fluence) in order to create images of desired quality as denoted by the image quality indicator [11]. Generally, the purpose of
modulating the tube current based on patient size and shape is to control the photon fluence at the detectors [16-17]. In CT, there is an inverse relationship between image noise and the square root of fluence. Therefore, these ATCM systems are attempting to control quantum noise according to the selected image quality indicator and it is reasonable to think of an image quality indicator as a surrogate for expected noise. This means that the choice of tube current has effectively been replaced by the choice of image noise. One advantage of this approach is that a technologist doesn’t need to manually adjust the tube current for different sized patients because the ATCM algorithm will automatically adjust the tube current to accommodate different patient sizes and attenuation properties within a patient habitus [19].

2.1.2 Optimizing Protocols Using Automatic Tube Current Modulation

The mandate to keep radiation exposure as low as reasonably achievable (ALARA) requires one to smartly design and optimize CT protocols. Some clinical tasks, such as pediatric lung nodule detection, are particularly sensitive to image quality. Previous work by Li et al show the possibility of predicting radiologist performance using physical image quality metrics for the specific task of pediatric lung nodule detection [20]. In order for studies such as this to be useful, we need to know how to use scan settings to target specific noise levels. As described above, ACTM techniques make targeting specific noise levels a possibility. The complication is that different
manufacturers apply ACTM differently and use different image quality indicators as inputs to their proprietary algorithms.

### 2.1.3 Purpose of Study

The purpose of this study was to quantitatively assess the relationship between actual noise and image quality indicators across imaging parameters in the context of the two specific commercial CT platforms in question, GE and Siemens. Both CT platforms are capable of simultaneous longitudinal (z-axis) and angular (x-y) modulation. Simultaneous modulation has been shown to decrease dose compared to systems using only angular modulation or no modulation [21]. On the GE scanner, the ACTM algorithm is called “SmartmA” and its image quality indicator is called “noise index” (NI). One selects a NI and specifies minimum and maximum tube current (mA) levels. NI is expected to reflect the noise in the central region of a uniform phantom. The SmartmA algorithm will attempt to produce images with noise equal to the selected NI, independent of kVp, patient size, and prospectively chosen reconstructed slice thickness [11]. Therefore, one would expect actual image noise to scale linearly with noise index and be independent of kVp, patient size, and prospective slice thickness. On a Siemens scanner, the ACTM algorithm is called “CARE Dose 4D”. Its image quality indicator is called “quality reference effective mAs” (Q). Q represents the mean effective tube current-time product (mAs) used on a reference patient. The system adapts the tube current in real time according to Q and individual patient size and attenuation.
properties [19]. The Siemens ATCM algorithm does not alter the tube current according to any reconstruction parameters nor does it attempt to achieve constant noise levels across patients of different sizes. Given such a design, and known physics of CT imaging, one would expect actual image noise to be inversely related to Q and be dependent on reconstruction parameters and patient size. The goal of this study was to assess how actual noise in a patient image varies as a function of NI and Q across imaging parameters.

2.2 Materials and Methods

2.2.1 Materials

We imaged two anthropomorphic phantoms, representing an adult male (73 kg) and a one-year-old (10 kg) patient (ATOM, models 701 and 704, Computerized Imaging Reference Systems, Inc., Norfolk, VA), on a 64-slice scanner (Discovery CT 750 HD, GE Healthcare, Waukesha, WI) and a 128-slice scanner (SOMATOM Definition Flash, Siemens Healthcare, Germany).

2.2.2 Scan Settings

A clinical range of imaging parameters was chosen in order to investigate the relationship between image quality indicators and measured noise. The parameters of interest were helical pitch factor, peak tube voltage (kVp), beam collimation or detector configuration, slice thickness (t), reconstructed field of view (FOV), reconstruction algorithm, and the convolution kernel (reconstruction filter). Siemens’ CARE Dose 4D
modulation algorithm works slightly differently for different patient age categories (e.g., adult or pediatric). Thus the effect of selecting different patient categories was explored on the Siemens scanner.

Because of scan time restraints and the large number of parameters investigated, data were not collected for every combination of parameters. Further, some acquisitions were not possible due to limitations on the output of the X-ray tubes. Data were collected by first choosing a reference protocol based on clinical settings. The phantom was then imaged at various values of the system’s image quality indicator using this reference protocol. We then altered the reference protocol, one parameter at a time, each time imaging with several image quality indicator values. This allowed for the systematic exploration of the effect each parameter has on the noise-image quality indicator relationship. Table 1 shows the values used for the various scan parameters with the reference protocol underlined. On the GE system, the minimum and maximum tube current (mA) were set to their lowest and highest values to ensure the required mA (as determined by the SmartmA algorithm) was not clipped during the scan. The scan coverage started at the top of the lungs and ended in the abdomen in order to include a range of anatomical and attenuation variations. Each scan was repeated and duplicates were subtracted to remove anatomy (i.e., signal) (Figure 1).
Table 1: Scan parameters used in the noise magnitude study

<table>
<thead>
<tr>
<th>Make/Model:</th>
<th>GE/Discovery CT750 HD</th>
<th>Siemens Definition Flash</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phantom:</td>
<td>Adult Male, One Year Old</td>
<td>Adult Male, One Year Old</td>
</tr>
<tr>
<td>Image Quality Indicator:</td>
<td>Noise Index: 6, 9, 11.57, 16, 19, 22</td>
<td>Quality Reference eff. mAs: 30, 60, 75, 120, 150, 200, 300</td>
</tr>
<tr>
<td>Pitch Factor:</td>
<td>0.969, 0.984, 1.375</td>
<td>0.8, 1.4</td>
</tr>
<tr>
<td>kVp:</td>
<td>80, 100, 120, 140</td>
<td>80, 100, 120, 140</td>
</tr>
<tr>
<td>Beam Collimation (mm):</td>
<td>40 (64x0.625), 20 (32x0.625)</td>
<td>38.4 (128x0.6), 38.4 (32x1.2)</td>
</tr>
<tr>
<td>Slice Thickness (mm):</td>
<td>0.625, 1.25, 2.5, 5.0</td>
<td>0.6, 1.0, 3.0, 5.0</td>
</tr>
<tr>
<td>Reconstructed FOV (mm):</td>
<td>150, 340</td>
<td>150, 340, 400</td>
</tr>
<tr>
<td>Reconstruction Algorithm:</td>
<td>FBP2, 30% ASIR3</td>
<td>FBP, IRIS4</td>
</tr>
<tr>
<td>Convolution Kernel:</td>
<td>Standard, Bone, Soft, Detail</td>
<td>B31f, I31f</td>
</tr>
<tr>
<td>Age Category</td>
<td>N/A</td>
<td>Adult, Pediatric</td>
</tr>
</tbody>
</table>

2.2.3 Noise Measurement Methodology

Three square regions of interest (ROI) were defined for each series, one in the mediastinum, one in the lung, and one in the abdomen (Figure 1). Noise magnitude (pixel standard deviation) within each ROI was measured on the subtracted images over multiple slices and averaged. This average noise value was then divided by the square root of two in order to account for the noise added as a result of the subtraction process.

---

1 The physical number of detector rows is 64 but the use of a z-axis flying focal spot allows double sampling resulting in 128 data channels.
2 FBP is filtered back projection.
3 ASIR is Adaptive Statistical Iterative Reconstruction.
4 IRIS is Iterative Reconstruction in Image Space.
(i.e., error propagation). The standard deviation and coefficient of variation (COV) of noise across slices was also recorded. The number of slices measured in each image series was dependent on the slice thickness of that series because a constant axial length of ~6 cm was considered for each volume ROI. The in-slice size of the ROI depended on the FOV and the phantom scanned of that particular series. ROI sizes varied between 360-1000 pixels, corresponding to 1-4 cm².

Figure 1: Example image of the adult phantom with a subtracted image showing the location of the lung and mediastinum ROIs.

2.2.4 Modeling Noise vs. Noise Index and Noise vs. Quality Reference Effective mAs

Noise data were analyzed to determine the dependency of scan and reconstruction parameters on the noise-image quality indicator relationship. For each CT system, noise was assumed to be a function of its image quality indicator and the parameters that were found to have a significant affect that relationship. For both systems, the analysis was done using a least squares fit technique (Matlab, 2010;
The specific mathematical model used for each system was based on the design of each manufacturer’s ATCM algorithm and will be presented in with the results of this study. All parameters that were found to have a significant affect on the noise-image quality indicator relationship were incorporated into the models. To determine if a particular parameter had a significant effect on the noise-quality indicator relationship, either the percent difference, COV, or a paired t-test was used depending on the number of comparable noise values. For parameters with only a few comparable noise values, if the percent difference or COV was greater than the average percent error of the measurements, the parameter was deemed to have a significant affect. For parameters with many comparable noise values, if the paired t-test (JMP Pro 9, 2010, SAS Institute Inc., Cary, NC) resulted in a p-value less than 0.05, that parameter was deemed to have a significant impact on the noise-quality indicator relationship.

2.3 Results

Each vendor implements ATCM in a different way and therefore the results from each scanner will be reported separately. There was however consistent findings about the uncertainty associated with each noise measurement that should be mentioned initially. First, changing the location within a particular anatomical region (Figure 2) or changing the ROI size was found to have little effect on the noise measurement. Overall variations due to ROI size (from 400 to 1600 pixels), and location (variable within the anatomical region) were 3% and 8% respectively.
Figure 2: Example of noise distribution in the mediastinum and lung\textsuperscript{5}

Second, the standard deviation associated with each noise measurement was larger for noisier images. Average standard deviation was 0.6 HU and the maximum was 2.6 HU. The average COV was 9% and the maximum was 19%. The error bars for noise measurements shown on subsequent plots represent one standard deviation.

\textsuperscript{5} Although the image shown here is un-subtracted, the values displayed were measured from subtracted images.
2.3.1 GE

2.3.1.1 Noise vs. Noise Index

Figure 3: Plot of noise in the mediastinum against NI in the adult phantom under reference conditions\(^\ast\). The dashed line shows points where NI is equal to noise.

On the GE system, noise increased linearly with NI for every set of scan parameters. Figure 3 shows an example of the noise-NI relationship for the reference protocol. This result confirms Equation 1. The noise-NI relationship was found to be independent of phantom size (<7% difference), slice thickness (<5% difference), pitch (<4% difference), FOV (<7% difference), and beam width (<4% difference) and dependent on anatomy of interest, kVp, convolution kernel, and the reconstruction

\(^\ast\) Reference conditions are 120 kVp, pitch of 1.375, 40 mm beam collimation, slice thickness of 5 mm, reconstructed with a 34 cm FOV using FBP and the standard filter.
algorithm (Figures 4-5). The dependence of the noise-NI relationship on anatomy of interest, kVp, convolution kernel, and reconstruction algorithm was statistically significant using the criteria described in at the end of section 2.2.4.

Figure 4: Bar graphs of noise in the mediastinum against NI showing the effect of (a) slice thickness (t), (b) kVp, (c) pitch, (d) FOV, (e) beam width, (f) phantom size, (g) convolution kernel, and (f) reconstruction algorithm on the noise-NI relationship. Each plot represents an alteration with respect to the reference technique by one parameter. The reference parameters are underlined in the legend of each plot.
For a given image series, lung noise was 31% lower and abdomen noise was 25% higher compared to mediastinum noise measured in the same image series. The plots in Figure 5 illustrate this point.

Figure 5: Plot of (a) lung noise and (b) abdomen noise against mediastinum noise for acquisitions on the GE scanner. Each data point represents a different image series, but for a given data point, the noise values being compared were measured from the same image series. These plots provide a way to translate mediastinum noise to lung and abdomen noise.

Given the design of the SmartmA algorithm, and the results presented above, the noise-noise index relationship was best described by

$$\sigma = \sigma_{\text{ref}} \cdot A = \alpha \cdot NI \cdot A,$$

Eq. (1)

where $\sigma$ is the noise under conditions of interest, $\sigma_{\text{ref}}$ is the noise under reference conditions, $\alpha$ is a fitting constant that equals 0.936, NI is the noise index, and A is an adjustment factor to account for deviations from reference conditions. The adjustment
factor, $A$, was found by taking ratios of noise under conditions of interest to noise under reference conditions and describes the dependency of the noise-NI relationship on kVp, anatomy of interest, convolution kernel, and reconstruction algorithm. Adjustment factors were calculated for each affecting parameter so that an overall adjustment factor could be a multiplication of the parameter based adjustment factors as

$$ A = A_{\text{Anatomy}} \cdot A_{\text{kVp}} \cdot A_{\text{Kernel}} \cdot A_{\text{Algorithm}}. $$

Eq. (2)

These adjustment factors are tabulated in Table 2.

**Table 2: Adjustment factors used to estimate noise on the GE scanner for a given protocol governed by Equations 1,3**

<table>
<thead>
<tr>
<th>$A_{\text{kVp}}$</th>
<th>80 kVp</th>
<th>100 kVp</th>
<th>120 kVp</th>
<th>140 kVp</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.08</td>
<td>1.02</td>
<td>1.00</td>
<td>0.94</td>
<td></td>
</tr>
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<table>
<thead>
<tr>
<th>$A_{\text{Anatomy}}$</th>
<th>Med.</th>
<th>Lung</th>
<th>Ab.</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00</td>
<td>0.69</td>
<td>1.25</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$A_{\text{Kernel}}$</th>
<th>Soft</th>
<th>Standard</th>
<th>Detail</th>
<th>Chest</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.81</td>
<td>1.00</td>
<td>1.23</td>
<td>1.35</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$A_{\text{Algorithm}}$</th>
<th>FBP</th>
<th>30% ASIR</th>
<th>-</th>
<th>-</th>
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<tbody>
<tr>
<td>1.00</td>
<td>0.84</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 2.3.1.2 Goodness of Fit

The model described by Equations 1, 2 fits closely to measured data. In comparing predicted noise with measured noise, the average residual magnitude was

---

7 The adjustment factors for different kernels were calculated using the images from the ACR phantom described in chapter 3.
0.46 HU (5%) with a maximum at 2.5 HU (18%). The root mean square of residuals was 0.7 HU. Residual magnitude was generally larger for noisier images while less noise images resulted in higher percent errors. Take note that the adjustment factors listed in Table 2 pertain only to the range of values studied for a given parameter. The factors should not be directly extrapolated to other parameter values.

2.3.2 Siemens

2.3.2.1 Noise vs. Quality Reference Effective mAs

Figure 6: Plot of noise in the mediastinum against Q in the adult phantom under reference conditions.\(^8\)

---

\(^8\) Reference conditions are 120 kVp, pitch of 0.8, 32.8 mm beam width with flying focal spot, 5 mm slice thickness, and reconstructed with a 34 cm FOV using FBP and the B31f convolution kernel.
On the Siemens scanner, noise decreased with increasing Q for every set of scan parameters. Figure 6 shows an example of this for the reference protocol. The trend seen in Figure 6 follows the form of Equation 2. As Figures 7 and 8 show, the noise-Q relationship did not depend on helical pitch factor (<6% difference), FOV (<5% difference), or detector configuration (<8% difference) but did depend on slice thickness, kVp, phantom size, patient age selection, anatomy of interest, and reconstruction algorithm. The dependence of the noise-Q relationship on slice thickness, kVp, phantom size, patient age selection, anatomy of interest, and reconstruction algorithm was statistically significant using the criteria described in at the end of section 2.2.4.
Figure 7: Bar graphs of noise in the mediastinum against Q showing the effect of (a) slice thickness (t), (b) kVp, (c) pitch, (d) FOV, (e) detector configuration\(^9\), (f) phantom size, (g) patient age selection\(^9\), and (f) reconstruction algorithm on the noise-Q relationship. Each plot represents an alteration with respect to the reference technique by one parameter. The reference parameters are underlined in the legend of each plot.

\(^9\) These noise values were measured on the one-year-old phantom.
For a given image series, lung noise was 27% lower and abdomen noise was 24% higher compared to mediastinum noise measured in the same image series. The plots in Figure 8 illustrate this point.

![Figure 8: Plot of (a) lung noise and (b) abdomen noise against mediastinum noise for scans on the Siemens scanner. Each data point represents a different image series, but for a given data point, the noise values being compared were measured from the same image series. These plots provide a way to translate mediastinum noise to lung and abdomen noise.](image)

Given the design of the CARE Dose4D algorithm, and the results presented above, the noise-Q relationship was best described by

\[ \sigma = A \cdot \sigma_{\text{ref}} = A \cdot \frac{e^{\alpha}}{(Q \cdot t)^{\beta} \cdot kVp^\gamma}, \]

Eq. (3)

where \( \sigma, \sigma_{\text{ref}}, \) and \( A \) are the same as in Equation 1, \( \alpha, \beta, \) and \( \gamma \) are fitting constants, \( Q \) is the quality reference effective mAs, \( t \) is the slice thickness in mm, and \( kVp \) is the peak kilovoltage of the X-ray tube. The fitting constants \( \alpha, \beta, \) and \( \gamma \) were found using a linear least squares fit to the natural log of noise. The adjustment factor, \( A, \) was found by
taking ratios of noise under conditions of interest to noise under reference conditions and describes the dependency of the noise-Q relationship on the anatomy of interest, phantom size, patient age selection, and reconstruction algorithm. Adjustment factors were calculated for each affecting parameter so that an overall adjustment factor could be a multiplication of the parameter based adjustment factors as

$$A = A_{\text{Anatomy}} \cdot A_{\text{Phantom}} \cdot A_{\text{Age}} \cdot A_{\text{Kernel}} \cdot A_{\text{Algorithm}}.$$

Eq. (4)

These adjustment factors found are tabulated in Table 3 along with the values of the fitting constants $\alpha$, $\beta$, and $\gamma$. The form of Equation 3 is vastly different from that of Equation 1 due to the difference in the design of each manufacturer’s ATCM algorithm.
Table 3: Fitting constants and adjustment factors needed to calculate expected noise for a given protocol on the Siemens scanner using Equations 2,4

<table>
<thead>
<tr>
<th>Anatomy</th>
<th>Med.</th>
<th>Lung</th>
<th>Ab.</th>
<th>-</th>
<th>-</th>
<th>-</th>
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<tbody>
<tr>
<td>A_Anatomy</td>
<td>Adult</td>
<td>1.00</td>
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<td>-</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>A_Age</td>
<td>Adult</td>
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<td>0.69</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
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<th>B18f</th>
<th>B20f</th>
<th>B22f</th>
<th>B23f</th>
<th>B25f</th>
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<tbody>
<tr>
<td>0.61</td>
<td>0.60</td>
<td>0.77</td>
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<tr>
<td>0.75</td>
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<td>0.90</td>
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<td>1.69</td>
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<td>2.47</td>
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<tr>
<td>5.32</td>
<td>3.94</td>
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<table>
<thead>
<tr>
<th>Algorithm</th>
<th>FBP</th>
<th>IRIS</th>
<th>-</th>
<th>-</th>
<th>-</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>A_Algorithm</td>
<td>1.00</td>
<td>0.60</td>
<td>-</td>
<td>-</td>
<td>-</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
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<td>12.52</td>
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<td>1.44</td>
<td>-</td>
<td>-</td>
<td>-</td>
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</tr>
</tbody>
</table>

A brief explanation of the age adjustment factor \(A_{age}\) is warranted. When entering patient information on the Siemens scanner, the technologist chooses the relative age of the patient (e.g., adult or pediatric). That choice changes the attenuation curves used by the system to modulate the tube current and therefore affects noise. This effect is reflected by \(A_{age}\). This implies that for the same phantom and scan settings, expected noise may be different depending on the choice of an adult or pediatric patient.

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The adjustment factors for different kernels were calculated using the images from the ACR phantom described in chapter 3.
2.3.2.2 Goodness of Fit

The model described by Equations 3, 4 fits closely to measured data. In comparing predicted noise with measured noise, the average residual magnitude was 0.7 HU (9%) with a maximum at 5.7 HU (53%). The root mean square of residuals was 1.1 HU. Similar to results on the GE scanner, residual magnitude was larger for noisier images while less noisy images results in higher percent error. Take note that the adjustment factors listed in Table 3 pertain only to the range of values studied for a given parameter. The factors should not be directly extrapolated to other parameter values.

2.4 Discussion

The results presented thus far show how noise changes as a function of NI and Q across many imaging parameters for two common brands of CT scanners. To our knowledge, similar assessments have not been reported before. Equations 1-4 could be useful in protocol optimization by targeting a tolerable noise level for a given set of scan parameters and for a given clinical task. For example, observer studies can quantitatively show how radiologist performance for specific tasks is related to physical metrics of image quality such as noise [20]. Equations 1-4 relate noise to image quality indicators and other image acquisition settings. Therefore, using Equations 1-4 in conjunction with the results of observer studies helps one predict radiologist performance for a given set of image acquisition settings. Translating image acquisition
settings to radiologist performance is necessary in order to optimize protocols. Further, achieving equal noise levels across scanners from these two manufacturers can be more easily achieved using the results of this study. For a given set of scan settings, one can use Equations 1-4 and select NI and Q values that will result in images with similar noise magnitude for patient sizes that are similar to the sizes of the phantoms used in this study.

2.4.1 GE: SmartmA

Results on the GE scanner are mostly consistent with the design of SmartmA modulation [11]. That is, the system was able to modulate the tube current to achieve images of similar noise for different slice thicknesses, pitches, and phantom sizes. Changing kVp, however, did slightly affect the noise-NI relationship. The kVp dependence of the noise-NI relationship is not consistent with the design of SmartmA and will be discussed below. Noise in several anatomical locations can be predicted from the selection of NI. An important caveat is that the SmartmA algorithm modulates the tube current based on the prospectively chosen reconstructed slice thickness. This implies that changing the slice thickness prospectively could have a large impact on patient exposure while a retrospective reconstruction at a different slice thickness should result in a change in noise as predicted by known physics principles; i.e., the noise is roughly inversely proportional to the square root of slice thickness [22].
2.4.2 GE: kVp

As mentioned above, on the GE scanner, changing the kVp did affect the noise-NI relationship. However, as Table 2 suggests, the effect of changing kVp was small compared to other factors. This effect is probably negligible compared to other changes in image quality that happen as a result of changing kVp. In other words, two images acquired at different kVp, but with identical noise magnitude, do not necessarily have the same image quality. For example, low kVp scans generally have better contrast [23] but are more prone to streak artifact.

2.4.3 GE: Beam Width

Figure 4e shows that decreasing the beam collimation width from 40 mm to 20 mm has little effect on the noise-NI relationship. However, the selection of beam width has other implications on image quality. For example, for a narrower beam to achieve the same scan coverage, total scan time must be longer. The more time the scan takes, the greater the risk of introducing motion artifact. Also, over-beaming and over-scanning are increased with narrower beam [24-26]. This means that narrower beams are generally associated with lower dose efficiency. On the other hand, a wider beam will result in short scan times but will also introduce more detected X-ray scatter. Increased scatter degrades image quality [27].
2.4.4 Convolution Kernel

It is important to note that neither the SmartmA nor CARE Dose4D algorithms alter the tube current according to the prospectively chosen convolution kernel. Therefore, the choice of convolution kernel had a large impact on the noise-image quality indicator relationship (Figure 4g). The choice of convolution kernel not only affects noise magnitude but also affects the texture of the noise as described by the NPS. For example, Boedeker et al have shown that images with the same noise magnitude but different NPS appear to have different noise texture [28]. Such images do not necessarily have the same diagnostic image quality. Also, different manufacturers have different reconstruction algorithms and use different convolution kernels. Thus, the noise texture as described by the NPS must be considered in conjunction with noise magnitude in evaluating image quality. An extensive study looking at the differences in noise texture between GE and Siemens kernels will be presented in chapter 3 of this thesis. As noted in the footnotes of Table 2 and Table 3, $\text{A}_{\text{Kernel}}$ values were calculated using images of the ACR phantom (acquired for the study described in chapter 3) instead of the CIRS phantoms used in this study. Preliminary comparison of $\text{A}_{\text{Kernel}}$ values calculated using images of the ACR phantom with $\text{A}_{\text{Kernel}}$ values calculated using images of the CIRS phantoms show that they agree within ~10%.
2.4.5 Iterative Reconstruction

ASIR (Adaptive Statistical Iterative Reconstruction) and IRIS (Iterative Reconstruction in Image Space) are both iterative reconstruction techniques that have been shown to reduce noise for the same dose compared to filtered back projection [29-32]. The results presented in Figure 4h and Figure 7h are consistent with other studies. This result was expected given that neither SmartmA nor CARE Dose4D alters the tube current according to use of iterative reconstruction. Note that the ASIR algorithm allows for a specified amount of blending between pure ASIR images and FBP images reconstructed with the same raw data. The ASIR images analyzed in this study were thirty percent blended (i.e., 30% ASIR, 70% FBP). Further noise reduction would be expected for a higher percent of ASIR but a recent observer study by Mievele et al suggests that if ASIR is used above fifty percent, subjective image quality can actually decrease [29]. The IRIS algorithm does not have the option to blend with FBP images.

2.4.6 Siemens: CARE Dose4D Summary

The results from the Siemens scanner are consistent with the design of CARE Dose4D modulation [11], and Eq. (3) is consistent with known physics principles of CT imaging. Namely that noise should decrease with increasing kVp and mAs. In contrast to SmartmA, CARE Dose4D does not alter the tube current modulation profile according to the prospective reconstructed slice thickness. As such, changing slice thickness affects expected noise and, therefore, the noise-Q relationship. For this reason, Equation 1
(SmartmA) has no dependence on slice thickness while Equation 3 (CARE Dose4D) does. The effect of changing slice thickness and kVp on the noise-Q relationship is accounted for in Eq. (3).

2.4.7 Siemens: Flying Focal Spot

The results from the Siemens scanner show that for the same beam width, double sampling (made possible by use of a z-axis flying focal spot) had little effect on the noise-Q relationship (Figure 7e). Double sampling can be compared to halving the width of each detector row. This means that each projection measurement is noisier because the total X-ray fluence per projection is cut in half. However, double sampling results in twice as many projections. Thus the net X-ray fluence in a fixed axial length is unchanged and noise in the reconstructed images is unaffected.

2.4.8 Siemens: Patient Size and Age

This study showed that on the Siemens scanner, images of the one-year-old phantom had less noise compared to images of the adult phantom acquired with identical scan settings (Figure 7f). This implies that the noise-Q relationship is dependent on patient size. Further, our results show that if you scan the same phantom, but change the selected patient age from adult to pediatric, the modulation algorithm will produce images with less noise (Figure 7g). Thus the noise-Q relationship is also dependent on the relative patient age (adult or pediatric) chosen by the user. The size and patient age dependencies of the noise-Q relationship were expected and, given the
design of CARE Dose 4D, highlight an important distinction between SmartmA and CARE Dose 4D. As described before, SmartmA attempts to produce images with the same noise levels for patients of different size and shape, whereas CARE Dose 4D attempts to maintain constant diagnostic image quality across patient sizes. Diagnostic image quality is based on clinical assessment. This approach is based on the principle that different sized-patients require different levels of noise to maintain adequate diagnostic image quality [33]. The consequence of such an approach is that for identical Q, the system will produce images with less noise for smaller patients and more noise for larger patients. For this reason a phantom size adjustment factor (A_{phantom}) was needed to characterize the noise-Q relationship. Such an approach to ACTM may be justified by the fact that images of pediatric patients are more prone to breathing artifact and they often lack soft tissue contrast. Therefore, less noise can be tolerated in pediatric images.

2.4.9 Anatomical Location

The difference in noise between the mediastinum, lung, and abdomen observed on both systems is not by the design of either SmartmA or CARE Dose4D but is due to the difference in average attenuation path length through these tissues. In the back projection reconstruction process (ignoring effects of filtering), the variance of a pixel in the reconstructed image is proportional to the sum of variances of all the projections through that pixel [16]. The variance of a single projection is proportional to the
attenuation path length of that projection. Thus, on average, projections through pixels in the lungs (abdomen) have shorter (longer) attenuation path lengths when compared to the attenuation path lengths of projections through pixels in the mediastinum. This leads to images with non-uniform noise. When using Equations 1-4 to calculate expected noise, the anatomy of interest should be an important consideration.

2.4.10 Limitations

This study was limited in two ways with respect to available resources. First, only two anthropomorphic phantoms of drastically different size were available. Further data is needed to characterize the response of the CARE Dose 4D algorithm to patients of many different sizes. This limitation restricts the range of patient sizes over which it will be possible to achieve consistent image quality across these two CT scanners. Second, only two CT manufacturers were considered. Because implementation of ATCM varies greatly across manufacturers, the results reported in this study can only be used to predict noise if using SmartmA or CARE Dose 4D. Another limitation is that not every possible factor that could affect noise was considered. For example, modulation strength is a CARE Dose 4D parameter that determines the lookup table used to relate effective mAs to attenuation. This parameter can be selected as ‘weak’, ‘average’, or ‘strong’ and controls the degree to which the tube current is adjusted for patient size [33]. The effect of changing modulation strength on image quality has been previously considered by other researchers but was not explored in this study [34].
2.5 Conclusions

For the SmartmA tube current modulation algorithm on the GE system, expected noise is a linear function of noise index. The slope of this function can be adjusted to account for differing anatomy, kVp, convolution kernels, and reconstruction algorithms. This function is not affected by phantom size, slice thickness, collimated beam width, pitch, or FOV. For the CARE Dose 4D tube current modulation algorithm on the Siemens system, expected noise can be modeled as a power function of quality reference effective mAs, slice thickness, and kVp. This function can be further adjusted to account for differing anatomy, phantom size, patient age selection, convolution kernel, and reconstruction algorithm. This function is independent of pitch, FOV, and detector configuration settings. This work will allow one to target specific noise levels to in order to optimize protocols and produce images with consistent noise magnitude across scanners from different manufacturers.\footnote{The work presented in this chapter is currently under review for publication in the American Journal of Roentgenology.}

\footnote{The work presented in this chapter is currently under review for publication in the American Journal of Roentgenology.}
3

Noise Texture

3.1 Background

Noise magnitude by itself is insufficient to fully characterize the noise properties of CT images. As demonstrated by Figure 9, images with the same noise magnitude but different noise texture may not have the same image quality [28]. Therefore, it is necessary to consider noise texture when evaluating image quality in CT.

![Figure 9: Images of the contrast to noise ratio (CNR) and low contrast resolution (LCR) sections of the ACR phantom for four different kernels. Noise and contrast (and therefore CNR) is held relatively constant across these four image sets.](image)

3.1.1 Noise Correlations in CT Images

White noise refers to completely random pixel values. This means, in a uniform region of the image, the value of one pixel is independent of other surrounding pixels. In
CT, the noise at the detector is generally assumed to be white and is described well by Poisson (counting) statistics. During the backprojection step of the reconstruction process, each detector signal is backprojected through a reconstruction matrix to form the final image. Thus the signal at a single detector contributes to many pixel values in the final image. This implies that although the raw detector signal is white, the pixel values in the final image are not independent. In other words, CT images contain spatially correlated noise. These correlations are manifest by the grainy texture common in CT images.

3.1.2 Quantifying Texture: The Noise Power Spectrum

The NPS gives the noise power as a function of spatial frequency and is calculated by taking the Fourier Transform of uniform images. The NPS has long been used as a metric of image quality in CT [12, 35-38]. Images with coarse texture have an NPS curve concentrated at low frequencies while images with finer texture have an NPS curve concentrated at higher frequencies. Images with white noise have a flat NPS with equal amplitude at all spatial frequencies (Figure 10). The integral of the NPS is equal to noise variance in the ROI from which the NPS was measured. Variance is the square of noise magnitude.
3.1.3 Convolution Kernels, Resolution, and NPS

As stated above, in a CT system, noise at the detector is assumed to be white until the reconstruction process introduces correlations. Backprojection reconstruction methods introduce an inherent radial (1/r) blurring into the reconstructed images. To reduce this 1/r blurring, raw projections are filtered before being backprojected [22]. The filters can operate equivalently in frequency space via multiplication or projection (sinogram) space via convolution. For this reason, they are often referred to as either reconstruction filters or convolution kernels. Convolution kernels are designed to
weight the frequency content of the projections. Therefore, the specific design of the kernel greatly influences the shape of the NPS and the texture of the final images. It follows that choosing different convolution kernels allows the user to somewhat control noise texture. Also, the ability to choose a specific kernel allows the user to exploit a fundamental tradeoff in CT between noise and resolution. In frequency space, most kernels (filters) follow the same basic ramp-up roll-off design. The ramp is designed to reduce the 1/r blurring mentioned above. The roll-off portion is highly variable and controls the high-frequency content of the image. Sharp kernels preserve more high frequency content and thus result in better spatial resolution. The penalty for high resolution is increased noise at high spatial frequencies. Soft kernels suppress high frequency content and offer reduced noise at the cost of lower spatial resolution [22].

3.1.4 Purpose of Study

The purpose of this study was to investigate how different reconstruction kernels, from the two commercial manufacturers in question, compare with respect to noise texture. Noise texture was characterized by computing the NPS from images reconstructed with many available convolution kernels from each scanner. Different kernels were then compared between GE and Siemens according to the shape of their respective NPS. The results presented here can aid in achieving consistent image quality, in terms of noise texture, across scanners from different manufacturers by informing the
user as to which reconstruction kernels are expected to produce images with similar texture.

### 3.2 Materials and Methods

We present a three step method of comparing kernels: 1) measuring the NPS from uniform images reconstructed with each kernel, 2) filtering the NPS with a human visual response function, and 3) comparing the filtered NPS curves using both the peak frequency difference (PFD) and the root mean square error (RMSE) as metrics of similarity. Kernels that minimized the PFD and RMSE were paired.

#### 3.2.1 Step 1: Measure the NPS

The ACR CT accreditation phantom (Gammex 464, Gammex, Inc., Middleton, WI) was imaged on both systems using the scan settings shown in Table 4. The images were reconstructed using a selection of available reconstruction kernels on each system. Images of the low contrast and the high contrast components of the ACR phantom were visually compared in terms of their relative resolution and noise.
Table 4: Scan settings used to image the ACR phantom

<table>
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<tr>
<th></th>
<th>GE Discovery CT750 HD</th>
<th>Siemens Definition Flash</th>
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</thead>
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<tr>
<td><strong>kVp:</strong></td>
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<td>120</td>
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<tr>
<td><strong>mAs:</strong></td>
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<td>200</td>
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<td><strong>Detector Configuration:</strong></td>
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<td><strong>Reconstructed FOV (mm):</strong></td>
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<tr>
<td><strong>Slice Thickness (mm):</strong></td>
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<td><strong>Reconstruction Algorithm:</strong></td>
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<tr>
<td><strong>Convolution Kernels:</strong></td>
<td>Soft, Standard, Detail, Chest, Lung, Bone, Bone+, Edge</td>
<td>B10f, B18f, B20f, B22f, B23f, B25f, B26f, B30f, B31f, B35f, B36f, B40f, B41f, B43f, B46f, B50f, B60f, B70f, B75f, B80f</td>
</tr>
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</table>

The 2D NPS was estimated by taking the square of the Fourier transform of ROIs in the uniform (water) section of the ACR phantom as

\[
NPS(u, v) = \frac{dx dy}{N_x N_y} \cdot |\mathcal{F}[I(x, y) - P(x, y)]|^2 ,
\]

Eq. (5)

where \(u\) and \(v\) are spatial frequency (mm\(^{-1}\)) in the x and y directions, respectively, \(dx\) and \(dy\) are pixel size (mm), \(N_x\) and \(N_y\) are the number of pixels in the x and y direction of an ROI, \(\mathcal{F}[]\) denotes the 2D Fourier transform, \(I(x, y)\) is the pixel value (HU) of the ROI at position \((x, y)\), and \(P(x, y)\) is a 2\(^{nd}\) order polynomial fit of \(I(x, y)\). Subtracting \(P(x, y)\) from \(I(x, y)\) removes any DC component and also reduces the influence of very low frequency non-uniformities in the image that are measured through the NPS; such non-uniformities, caused by scatter, dark current, non-uniform detector gain, or beam

\(^{12}\) The physical number of detector rows is 64 but the use of a z-axis flying focal spot allows double sampling resulting in 128 data channels.
hardening, are generally not considered noise in the context of image quality evaluation. They are usually non-stochastic in nature and, for the purpose of comparing reconstruction kernels, can be removed [28, 36].

NPS measurements are inherently noisy. In order to minimize the uncertainty, we used an ensemble of ROIs (32x32 pixels per ROI), calculated the 2D NPS of each ROI, and then took the average across ROIs. Noise magnitude was recorded by computing the integral of this average 2D NPS. Next, a radially-averaged representation of the 2D NPS was deduced and the radially-averaged NPS was normalized to have an area of one.

3.2.2 Step 2: Filter NPS With the Human Visual Response Function

The radially-averaged, normalized NPS were filtered by the human visual response function, $V(f)$, to account for the variable perception of noise by a human observer at different spatial frequencies [39-42]. The filtered NPS is given by

$$NPS_{filtered}(f) = NPS_{measured}(f) \cdot |V(\rho)|^2,$$

$$\rho = f \cdot \frac{\text{FOV} \cdot R \cdot \pi}{D \cdot 180},$$

$$V(\rho) = \left| \eta \rho^{a_1} \cdot e^{-a_2 \rho^{a_3}} \right|^2,$$

where $f$ is radial spatial frequency (mm$^{-1}$) represented by the image, $\rho$ is the radial spatial frequency (cycles/degree) as seen by observer, FOV is the reconstructed field of view (mm), R is the viewing distance (mm), D is the size of the displayed image (mm), $\eta$
is a factor to normalize $V(\rho)$ to one at its maximum value, and parameters $(a_1, a_2, a_3)$ are $(1.5, 0.98, 0.68)$ [40]. Figure 11 shows the shape of the human visual response function for changing viewing distance and display size. For this study, a typical viewing distance of 40 cm and a display size 30 cm were assumed.

![Figure 11: Shape of the human visual response function when viewing a 22 cm reconstructed image for (a) changing display size at a fixed viewing distance of 40 cm and (b) changing viewing distance at a fixed display size of 30 cm.](image)

**3.2.3 Step 3: Compare and Match Kernels**

The filtered, radially-averaged, normalized NPS was computed for every convolution kernel. The peak radial frequency of each spectrum was also computed. The spectra of the kernels from both manufacturers were compared in terms of the peak frequency difference (PFD) and the root mean square error (RMSE). Low PFD and RMSE values imply similar spectra, and thus similar noise texture. Therefore, kernel pairs that minimized the PFD and RMSE were identified. Figure 12 summarizes the process of comparing kernels across manufacturers.
The focus of this specific study was on noise texture, however, as noted in section 3.2.2, we also recorded the noise magnitude from each kernel by integrating the 2D NPS. These noise magnitude values were used to calculate the $A_{\text{kernel}}$ adjustment factors reported in chapter 2.
3.3 Results

The NPS curves are shown in Figures 13-18. The shaded areas represent one standard deviation from the mean as calculated after averaging across ROIs and scaled by normalization. The coefficient of variation was, on average, about 10% for a given kernel and spatial frequency. Several Siemens’ kernels were found to yield nearly identical NPS (B10f-B18f, B22f-B23f, and B25f-B26f). For visual clarity, B18f, B23f, and B26f have not been included in Figure 15. Images of the high contrast resolution (HCR) and low contrast resolution (LCR-6mm rods) sections of the ACR phantom have been included for visual comparison. Note that noise magnitude is not constant across these images, the point of comparison being the noise texture.
Figure 13: (a) Idealized and (b) actual images of the high contrast resolution and low contrast resolution sections of the ACR phantom for standard GE kernels with (c) their respective NPS.
Figure 14: (a) Idealized and (b) actual images of the high contrast resolution and low contrast resolution sections of the ACR phantom for sharp GE kernels with (c) their respective NPS.
Figure 15: (a) Idealized and (b) actual images of the high contrast resolution and low contrast resolution sections of the ACR phantom for soft Siemens kernels with (c) their respective NPS.
Figure 16: (a) Idealized and (b) actual images of the high contrast resolution and low contrast resolution sections of the ACR phantom for standard-soft Siemens kernels with (c) their respective NPS.
Figure 17: (a) Idealized and (b) actual images of the high contrast resolution and low contrast resolution sections of the ACR phantom for standard-sharp Siemens kernels with (c) their respective NPS.
Figure 18: (a) Idealized and (b) actual images of the high contrast resolution and low contrast resolution sections of the ACR phantom for sharp Siemens kernels with (c) their respective NPS.

Every GE kernel was compared to every Siemens kernel to get PFD and RMSE values between each possible pair. Among all kernel pairs, the RMSE (PFD) values ranged from 0.02 mm (0.003 mm\(^{-1}\)) to 0.74 mm (0.74 mm\(^{-1}\)). Figures 19-20 show all PFD
and RMSE values overlaid on a color map for visual comparison. Kernel pairs that had minimal PFD and RMSE values were matched. A summary of these results is found in Tables 5-6. As there is not a single one-to-one correspondence between individual GE and Siemens kernels, it is necessary to consider one manufacturer as a reference and choose the closest matching kernels from the other. This has been done using GE as the reference in Table 5 and Siemens as the reference in Table 6. Among matched kernels, the minimum RMSE (PFD) values ranged from 0.02 mm (0.003 mm⁻¹) for closely matching kernels to 0.62 mm (0.45 mm⁻¹) for kernels that were not particularly similar.

Figure 19: Color map of PFD values between the NPS of GE and Siemens kernels. A low PFD between kernels implies that both kernels have maximum noise power at similar frequencies.
Figure 20: Color map of RMSE values between the NPS of GE and Siemens kernels. A low RMSE between kernels implies the overall shapes of the NPS curves are similar. Thus, dark blue squares show which Siemens kernels best match a given GE kernel and vice versa with respect to noise texture.

Table 5: Closest matching Siemens kernel for a given GE kernel

<table>
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<tr>
<th>GE</th>
<th>Siemens</th>
<th>Minimum RMSE (mm²)</th>
<th>Minimum</th>
<th>PFD</th>
<th>(mm⁻¹)</th>
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<tbody>
<tr>
<td>SOFT</td>
<td>B35f</td>
<td>0.02</td>
<td>0.01</td>
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<tr>
<td>STANDARD</td>
<td>B43f</td>
<td>0.02</td>
<td>0.00</td>
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<td></td>
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<tr>
<td>DETAIL</td>
<td>B46f</td>
<td>0.07</td>
<td>0.01</td>
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</tr>
<tr>
<td>CHEST</td>
<td>B46f</td>
<td>0.04</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LUNG</td>
<td>B80f</td>
<td>0.06</td>
<td>0.01</td>
<td></td>
<td></td>
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<tr>
<td>BONE</td>
<td>B75f</td>
<td>0.35</td>
<td>0.15</td>
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</tr>
<tr>
<td>BONE+</td>
<td>B75f</td>
<td>0.36</td>
<td>0.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EDGE</td>
<td>B75f</td>
<td>0.62</td>
<td>0.45</td>
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Table 6: Closet matching GE kernel for a given Siemens kernel

<table>
<thead>
<tr>
<th>GE</th>
<th>Siemens</th>
<th>Minimum RMSE (mm$^2$)</th>
<th>Minimum</th>
<th>PFD</th>
<th>(mm$^{-1}$)</th>
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<tr>
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<td>0.02</td>
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<tr>
<td>B25f</td>
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<tr>
<td>B26f</td>
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<td>B31f</td>
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<tr>
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<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>SOFT</td>
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<td>0.00</td>
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<tr>
<td>B40f</td>
<td>SOFT</td>
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<td>0.01</td>
<td></td>
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<tr>
<td>B41f</td>
<td>STANDARD</td>
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<td>0.01</td>
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<tr>
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<td>STANDARD</td>
<td>0.02</td>
<td>0.00</td>
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<tr>
<td>B45f</td>
<td>STANDARD</td>
<td>0.11</td>
<td>0.02</td>
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</tr>
<tr>
<td>B46f</td>
<td>CHEST</td>
<td>0.04</td>
<td>0.01</td>
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<tr>
<td>B50f</td>
<td>CHEST</td>
<td>0.17</td>
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<tr>
<td>B70f</td>
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<td>0.05</td>
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<tr>
<td>B75f</td>
<td>LUNG</td>
<td>0.20</td>
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<tr>
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<td>0.06</td>
<td>0.01</td>
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</tr>
</tbody>
</table>

3.4 Discussion

We have shown a method to systematically compare noise texture across convolution kernels from different manufacturers. The results of this study show the shape of the NPS curves for common convolution kernels available on modern GE and Siemens CT scanners. Using the PFD and RMSE as metrics of similarity, the data show the degree by which various GE and Siemens kernels are expected to produce images with similar noise texture. To our knowledge, such a comparison across manufacturers
has not been previously reported. These results can inform physicists and radiologists by allowing them to choose convolution kernels that will produce images with similar noise texture across manufacturers.

### 3.4.1 The Human Visual Response Function

The spectra were filtered with the human visual response function in order to make the texture comparisons more meaningful with respect to how an actual human observer perceives noise at different spatial frequencies. One consequence of filtering is that low frequency noise is deemphasized due to humans’ low visual response at very low frequencies [43]. Such filters have been used successfully as a part of mathematical human observer models such as a non-prewhitening matched filter with an eye filter (NPWE). These models have been shown to agree well with actual human observer performance for imaging tasks that are limited by correlated noise [40-42].

### 3.4.2 PFD and RMSE Values

It is important to note the value of the minimum PFD and RMSE values in Tables 5-6. These values indicate the degree by which two paired kernels are similar. There is a wide range of minimum PFD and RMSE values among kernels that were matched. For example, the Soft-B35f, Standard-B43f, Chest-B46f, and Lung-B80f pairs had very low minimum PFD (<0.02 mm⁻¹) and RMSE (<0.07 mm) values indicating that they all match closely. It can be expected that images reconstructed with these kernel pairs would have similar texture. On the other hand, Bone, Bone+, and Edge were all matched with B75f
but with high PFD (up to 0.45 mm$^{-1}$) and RMSE (up to 0.62 mm) values. This implies that the texture of images reconstructed with these kernels, though somewhat similar, is not identical. These quantitative results can be subjectively confirmed by visual examination of the images shown in Figures 13-18.

3.4.3 Limitations

Due to available resources, this study was limited to only two manufacturers. Further work is needed to characterize the noise texture for reconstruction kernels from other CT manufacturers. Also, the Siemens scanner offers many additional kernels that are used for different types of exams (e.g., body, head, etc...); however, we focused only on kernels intended to be used with body exams. Further, only images reconstructed with traditional filtered backprojection techniques were considered. As stated in section 2.4.5, iterative reconstruction algorithms have been shown to reduce noise for the same dose compared to filtered back projection [29-32]. Such reconstruction techniques produce images with unique noise texture and are generally non-linear which poses additional challenges. Despite these challenges, promising work have shown the possibility of adapting Fourier based, task specific, image quality metrics to evaluating appropriate dose reduction levels for several iterative reconstruction algorithms [44]. Our future work will include iterative reconstruction algorithms. Finally, despite the important tradeoff between noise and resolution, the focus of this work was on noise texture alone and only simple observational measurements of resolution were reported.
Future work is needed that includes both the resolution and noise as criteria for kernel selection.

### 3.5 Conclusions

The texture of noise, as described by the NPS, is highly dependent on the specific convolution kernel used during reconstruction. We have proposed and implemented a three-step technique to quantitatively compare and match kernels from different manufacturers with respect to noise texture. This led to a mapping between similar kernels (Tables 5-6) allowing the user choose the closest matching kernels from one manufacturer to another. For two major CT manufacturers, the degree by which two matching kernels are expected to produce images with similar noise texture was highly variable. The findings of this study can inform the selection of kernels across manufacturers.\(^{13}\)

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\(^{13}\) The work presented in this chapter is currently under review for publication in Medical Physics.
### Summary

<table>
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<th>Different Noise</th>
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<tr>
<td>Different Texture</td>
<td><img src="image" alt="c" /> <img src="image" alt="d" /></td>
<td><img src="image" alt="d" /> <img src="image" alt="c" /></td>
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</tbody>
</table>

**Figure 21:** Images of the LCR-6mm rods of the ACR phantom showing how differences in noise magnitude and texture are visibly manifested.

From a consistency standpoint, it is desirable to have images with similar noise magnitude and texture across scanners (Figure 18a). Images with either different noise magnitude (Figure 18b), different noise texture (Figure 18c), or different noise magnitude and texture (Figure 18d) can be avoided by using the results of the two studies presented in this thesis. From a practical standpoint, these results could be implemented as tools to help translate protocols from one manufacturer to another. Using Equations 1-4 and Tables 5-6, it would be possible to write corresponding
protocols that are expected to produce images with similar noise magnitude and texture. Further work is needed to create such tools and make them practical for radiologists and physicists to use. A possible future implementation could be a computer program with a graphical user interface in which the user enters the protocol information from one scanner, and the software automatically determines the best corresponding parameters on the other scanner.
References


44. B. Chen, S. Richard, O. Christianson, X. Zhou, and E. Samei, "CT Performance as a Variable Function of Resolution, Noise, and Task Property for Iterative
Reconstructions (IRIS & SAFIRE),” SPIE Medical Imaging, San Diego, California (2012).