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A Novel Phantom for Characterization of Dual Energy Imaging Using an On-Board Imaging System

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Abstract

Dual-energy (DE) imaging using planar imaging with an on-board imager (OBI) is being considered in radiotherapy. We describe here a custom phantom designed to optimize DE imaging parameters using the OBI of a commercial linear accelerator. The phantom was constructed of lung-, tissue- and bone-equivalent material slabs. Five simulated tumors located at two different depths were encased in the lung-equivalent materials. Two slabs with bone-equivalent material inserts were constructed to simulate ribs, which overlap the simulated tumors. DE bone suppression was performed using a weighted logarithmic subtraction based on an iterative method that minimized the contrast between simulated bone- and lung-equivalent materials. The phantom was subsequently used to evaluate different combinations of high-low kV x-ray pairs of images based on the signal-difference-to-noise ratio (SDNR) metric. The results show a strong correlation between tumor visibility and selected energy pairs, where higher energy separation leads to larger SDNR values. To evaluate the effect of image post-processing methods on tumor visibility, an anti-correlated noise reduction (ACNR) technique and adaptive kernel scatter correction method were applied to subsequent DE images. Application of the ACNR technique approximately doubled the SDNR values, hence increasing tumor visibility, while scatter correction had little effect on SDNR values. This phantom allows for quick image acquisition and optimization of imaging parameters and weighting factors. Optimized DE imaging increases soft tissue visibility and may allow for markerless motion tracking of lung tumors.

Keywords

dual energy imaging; quality assurance; custom phantom

1. Introduction

Recently, there has been a significant clinical interest in lung tumor tracking during radiotherapy delivery (Booth et al 2016, Booth et al 2016a, Nuytens et al 2006, Shirato et al 2003, Nelson et al 2007, Xu et al 2008, Lin et al 2009, Rottmann et al 2010, Lewis et al 2010). By tracking the tumor during the respiratory cycle, the multi-leaf collimators may be modified in order to minimize the total volume of required lung irradiated. This concept of motion tracking is critical in stereotactic body radiotherapy (SBRT) and standard radiotherapy, both with and without concurrent chemotherapy, as several studies have

demonstrated that increased volumes of normal lung irradiated are correlated with symptomatic clinical radiation pneumonitis (Barriger et al 2012, Graham et al 1999, Rodrigues et al 2004, Schallenkamp et al 2007, Matsuo et al 2012).

There are several methods being considered for tracking including magnetic resonance imaging (MRI) (Cerviño et al 2011), x-ray imaging of anatomic surrogates (Cerviño et al 2009, van der Weide et al 2008), surface marker tracking (Dong et al 2012) and fiducial-based approaches (Nuyttens et al 2006, Shirato et al 2003, Nelson et al 2007, Persson et al 2013, Hagmeyer et al 2016, Booth et al 2016). Among these, x-ray-based tracking of fiducials implanted in close proximity to the tumor is the most common one (Nuyttens et al 2006, Shirato et al 2003, Nelson et al 2007, Persson et al 2013, Hagmeyer et al 2016, Booth et al 2016). However, such approaches are not without an increased risk of morbidity. In a retrospective analysis, it was demonstrated that computed tomography (CT) fluoroscopy-guided percutaneous fiducial marker placement in the lung carries a significant risk of pulmonary hemorrhage and pneumothorax (Trumm et al 2014). Additionally, fiducial marker migration may be significant within the lung (Nuyttens et al 2006, Shirato et al 2003, Nelson et al 2007).

Markerless tumor tracking using fluoroscopy may provide an alternative to fiducial-based techniques. Using template tracking methods, it has been shown that localization of <3 mm can be achieved (Xu et al 2008, Lin et al 2009, Rottmann et al 2010, Lewis et al 2010). However, in cases where the tumor overlaps the bone on individual images, tracking errors of up to 5 mm may occur (Lewis et al 2010). In these cases, dual energy (DE) imaging may be used to better visualize the tumor and improve tracking accuracy (Block et al 2014, Patel et al 2015). The DE imaging process involves obtaining planar x-ray images at both high (i.e., 120 kVp) and low (i.e., 60 kVp) energies. Using a weighted-logarithmic subtraction (WLS), a third planar image is created that suppresses bone and enhances soft tissue/tumor (Block et al 2014, Patel et al 2015).

To enhance the bone suppression capabilities of DE imaging in the thorax, x-ray source parameters (kVp, mAs) need to be optimized. This parameter optimization requires a standardized methodology that can be routinely performed and verified for quality assurance (QA) purposes. To accomplish this goal, a phantom that simulates the chest anatomy is required. However, to our knowledge, there are no commercial phantoms that meet the specifications for optimizing planar DE parameters in the radiotherapy setting. The goal of this study is to describe a phantom that was designed and constructed for the purposes of characterizing and optimizing planar DE imaging on the on-board imager (OBI) of a linear accelerator. Measurements are performed to compare and validate this phantom against previous studies.

2. Material and Methods

2.1 Dual Energy Subtraction

DE subtraction requires acquisition of two radiographic images obtained at different x-ray energies i.e., 120 kVp and 60 kVp (Bushberg et al 2011). Brody et al (1981) showed the possibility of combining two x-ray images in a certain proportions so that one material (high

or low Z) is subtracted while the other remains. As an example of this technique, consider high and low mono-energetic photon beams irradiating a phantom composed of two homogeneous materials such as bone and soft tissue. The intensity of each beam, as it strikes the imaging detector, is given by (Brody et al 1981):

$$I_L = I_L^0 \cdot e^{-\mu_L^{Soft} \cdot t_{Soft} - \mu_L^{Bone} \cdot t_{Bone}} \quad (1)$$

$$I_H = I_H^0 \cdot e^{-\mu_H^{Soft} \cdot t_{Soft} - \mu_H^{Bone} \cdot t_{Bone}} \quad (2)$$

where μ and t represent the attenuation coefficient and thickness of each material, respectively. The intensities of individual pixels produced from the high and low energy images are given by I_H and I_L , respectively. In order to remove bone, a weighted logarithmic subtraction of the two images can be performed to highlight soft tissue (Bushberg et al 2011, Brody et al 1981). This method, results in the following equation (Bushberg et al 2011, Brody et al 1981):

$$DE = \ln I_H - w_s \ln I_L \quad (3)$$

In the above equation $\ln$ is the natural logarithm, and w_s , is a constant required to produce the soft tissue image, for a particular energy pair. When w_s approaches the theoretical value

of $\frac{\mu_H^{Bone}}{\mu_L^{Bone}}$, an optimal image is created that removes all residual bone. However, clinical x-

ray sources are not mono-energetic and the spectrum along with the attenuating properties of the patient may not be well-known. Hence, a computational method (described in Section 2.4) is required to select the optimal weighting factor.

2.2 Phantom

To study the bone suppression capabilities of a planar DE imaging in the lung it is essential to have a phantom that simulates tumors hidden behind bony anatomy. To simulate this anatomy, tumors must be embedded in a material that mimics lung. Also, on the x-ray image, the tumor should be overlapped by the projection of anterior and posterior bones (ribs). It is also important to simulate various tumor dimensions at different depths. Hidden targets allow for the assessment of bone suppression capabilities of the imaging system and various depths may be utilized to evaluate possible scatter contributions.

To investigate DE imaging on the linear accelerator, we designed and built a customized phantom using various tissue equivalent materials to simulate bone, lung, soft tissue, and tumors. Simulated components were made from Average Bone (AB, $\rho = 1.6 \text{ g/cm}^3$), Lung-Inhale (LAA, $\rho = 0.31 \text{ g/cm}^3$), Plastic Water – Low Range (PWL, $\rho = 1.03 \text{ g/cm}^3$) and Soft

Tissue Gray (STG, $\rho = 1.2 \text{ g/cm}^3$) purchased through CIRS Inc. (Norfolk, VA). The phantom was constructed with 16 cm of lung equivalent material, consisting of 4 slabs that are each 4 cm thick. These lung-equivalent slabs are sandwiched at the top and bottom by 2 cm slabs of soft tissue equivalent material (20 cm total). Additional layers of tissue equivalent material (increments of 2 cm) are available to simulate larger patients, as shown in Figure 1, right.

The phantom consists of 5 different clinically relevant simulated spherical tumors made from soft tissue gray material, with diameters ranging from 0.5 - 2.5 cm, in increments of 0.5 cm. The simulated tumors are encapsulated in lung equivalent material at depths of 2 cm and 14 cm from the anterior surface of the lung material. Bone equivalent material, in the shape of a cylinder to simulate ribs, is inserted in solid water slabs and placed at the top of the phantom. By overlapping the simulated bones and tumors, bone suppression in DE images can be evaluated.

2.3 Experimental Setup

Fluoroscopic image sequences were acquired from the TrueBeam (Varian, Palo Alto, CA, USA) using the iTools Capture (Varian) software and a Matrox Imaging (Matrox Imaging, Dorval, Quebec, Canada) frame grabber card. The TrueBeam OBI (Varian) consists of a kV x-ray source and an amorphous silicon flat-panel detector (Figure 2). The source-to-isocenter distance is 100 cm, while the detector-to-isocenter distance is 50 cm. Images are encoded in 16 bit unsigned-integer having dimensions of 1024×768 and a pixel size of 0.388 mm (2×2 binned). The frame grabber saves images in a proprietary XIM file format used by Varian which contains a header object and raw image data. The header object contains information about the linac settings, including the x-ray tube current and energy. Images were acquired at x-ray tube settings ranging from 50 to 140 kVp with 10 kV increments. The exposure time was fixed such that the total mAs for low kVp settings (40-90 kVp) is 0.4 mAs and for high kVp settings (100-140 kVp) is 0.1 mAs. The mAs settings were selected to minimize differences in air exposure between the high- and low-energy beams. DE images were created for all possible high/low combinations using Equation 3.

2.4 Weighting Factor

Following image acquisition, XIM files were loaded into in-house software written in MATLAB (MathWorks, Natick, MA, USA) to create bone suppressed images. The optimal value of the soft-tissue weighting factor was determined using an iterative technique (Hoggarth et al 2013). Briefly, a 10×10 pixel region of interest (ROI) was placed in the simulated bone equivalent material and another in the neighboring lung-equivalent background region. The value of w_s in Equation 3 is increased from 0 to 1 in increments of 0.01, and DE images were created for each weighting factor. The optimal value of w_s occurs when the relative contrast between ROIs in the bone and background regions is minimized in the resulting DE image. The weighting factor is expected to be different for each unique energy pair due to spectral variations. Therefore, a unique weighting factor was computed for each combination of energies.

2.5 Optimal Energy Pair Selection

To determine the optimal energy pair that enhances visibility of a tumor hidden under a bony structure, various energy pairs were evaluated. The signal-difference-to-noise ratio (SDNR) adapted from (Williams et al 2007) is used to quantify tumor visibility following WLS and is given by:

$$SDNR = \frac{|S_{tumor} - S_{back}|}{\frac{1}{2} \cdot \sqrt{(\sigma_{tumor}^2 + \sigma_{back}^2)}} \quad (4)$$

where S_{tumor} and S_{back} represent mean pixel values within the ROIs of simulated tumor and background in the subsequent DE image, respectively. Similarly, σ_{tumor}^2 and σ_{back}^2 are intensity variances within the same ROIs reflecting noise. The SDNR was calculated using a 10×10 pixel ROI placed within the center of each target and neighboring bone-equivalent background region. The same ROIs were used for all acquisitions. The smallest simulated target (5 mm diameter) was not clearly visible, and thus was excluded from the study. The uncertainty associated with each calculation was estimated using various SDNR measurements across the fluoroscopic sequences. The SDNR values for all possible kV x-ray pairs were compared and the optimal energy pair that corresponded to the highest SDNR was noted.

The SDNR values were normalized using the dose to the skin surface calculated by combining individual doses of high- and low-energy images. To estimate the surface dose of each single energy exposure, the empirical formula developed by (Block et al 2014) was used which computes the dose as a function of mAs, kVp and source-to-skin distance (SSD) as follows:

$$Dose(mGy) = 0.115 \cdot mAs \cdot kVp^{2.047} \cdot SSD^{-2.023} \quad (5)$$

Throughout this analysis, the SSD value was fixed at 90 cm.

2.6 Scatter Correction

To reduce scatter contributions, a computationally-based scatter correction algorithm developed by Varian (Sun and Star-Lack 2010) was utilized. In this approach, the scatter component in the image is equivalent to a blurred version of the primary signal and is estimated using a convolution of kernels. This method uses adaptive kernels whose shapes vary depending on the local thickness of the object and thus result in better models of the scatter contributions from realistic OBI systems. This algorithm is integrated with standard iTool Reconstruction (Varian) software. A batch file using MATLAB (MathWorks, Natick, MA, USA) was created that sends instructions to iTools and applies the scatter correction. To investigate the effects of the scatter correction on the resulting tumor visibility, the scatter correction method was applied to the individual component images (i.e., each high and low energy image of the pair considered for subtraction). Then, weighted log-subtraction

(Bushberg et al 2011, Brody et al 1981) was performed using the scatter corrected images, and the SDNR values were calculated.

2.7 Noise Reduction

While DE imaging is effective in removing anatomical noise it increases the quantum noise within the image. To reduce this noise, the anti-correlated noise reduction (ACNR) algorithm was utilized which takes advantage of the fact that quantum noise in the soft-tissue image and bone-only image are anti-correlated (Warp and Dobbins 2003, Richard and Siewerdsen 2008). Briefly, to remove noise in the soft-tissue DE image, the ACNR algorithm first applies a high-pass filter (HPF) to the bone-only image (I_{Bone}^{HPF}) (Warp and Dobbins 2003). This effectively removes anatomical structures leaving quantum noise. A noise-reduced soft-tissue image was formed by subtracting weighted I_{Bone}^{HPF} from the soft-tissue image:

$$I_{Soft}^{ACNR} = I_{Soft}^{DE} - w_e \cdot I_{Bone}^{HPF} \quad (6)$$

Warp and Debbins, (2003) discussed a method to quantitatively obtain w_e by minimizing quantum noise in the image. Briefly, to compute the optimal w_e value, a 75×75 pixel ROI was placed on the lung region of I_{Soft}^{ACNR} and the variance was calculated for each w_e that increased from 0.1 to 1.0 in increments of 0.01. An optimal value of w_e is selected that produces the minimum variance within the ROI. For selected energy pairs the optimal w_e was found to be between 0.3 and 0.4.

3. Results

In this study, we described the use of a novel phantom that was designed and built for optimizing DE imaging parameters using the OBI of a TrueBeam (Varian) linear accelerator. The results of this analysis, and its validation against previous studies (Williams et al 2007, Hoggarth et al 2013), are presented in Figures 3–8.

3.1 Weighting factor

Figure 3 depicts the weighting factor optimization (w_s) using the iterative method for the 140-60 kVp pair. The relative contrast between the bone and lung regions as a function of the weighting factor is a convex function with a global minimum ($0 < w_s < 1$). The weighting factors obtained with iterative method ranged from 0.52 (for 140-60 kVp pair) to 0.96 (100-90 kVp pair). Figure 4 shows the weighting factors for several x-ray kV pairs. The weighting factors (w_s) were determined experimentally using Equation 3 and the iterative technique described in Section 2.4. This ratio decreases as the difference in DE energies increases. For example, consider a fixed low-energy image setting such as 90 kVp. As shown in Figure 4, increasing the kVp setting of high-energy image reduces the weighting factor. That is, a lower weighting factor is required for image pairs that have a large energy separation.

Figure 5 shows both single energy images and the resulting DE image of the custom phantom with complete bone removal using the calculated weighting factor.

3.2 Optimal energy pair

Figure 6 shows the relationship between SDNR values and corresponding kV x-ray pairs. Energy pairs that have little energy separation were not able to suppress bone as the theoretical value of weighting factor approaches unity, and were excluded from the analysis. Of the 45 energy pair combinations, only 14 pairs (140-90, 140-80, 140-70, 140-60, 130-80, 130-70, 130-60, 120-80, 120-70, 120-60, 110-70, 110-60, 100-60, 90-60 and 80-60) that suppress bone are considered for further analysis. SDNR values for selected energy-pairs varied between 4.11 ± 0.25 to 1.97 ± 0.23 (target size = 25 mm), 3.94 ± 0.28 to 1.87 ± 0.17 (target size = 20 mm), 2.60 ± 0.25 to 1.08 ± 0.20 (target size = 15 mm) and 2.14 ± 0.27 to 0.94 ± 0.24 (target size = 10 mm). The percent difference between SDNR values for the simulated tumors located closer to the x-ray source (94 cm from the source) vs. those located further from the source (106 cm from the source) was ~5% depending on the simulated tumor size and energy pair. Generally, higher SDNR values were observed for the simulated tumors closer to the x-ray source with differences possibly due to varying degrees of scatter contribution.

The resulting energy pairs were ranked based on the SDNR values of the simulated tumors located closer to the x-ray source. Table 1 summarizes the SDNR and dose normalized SDNR values for the top 7 energy pairs. The top three candidates that produced the highest SDNR values were 140-60 kVp, 130-60 kVp and 120-60 kVp with SDNR values for the largest tumors of 4.11 ± 0.25 , 3.74 ± 0.21 and 3.42 ± 0.28 , respectively. After normalizing to dose, the ranking of the top three energy pairs (shown in Table 1) did not change and are within the statistical uncertainty of each other. Of note, the 140-60 kVp pair achieved the highest SDNR value and is consistent with previous results of Hoggarth et al (2013) and Williams et al (2007). Our study also revealed that the selection of the optimal energy pair is invariant across tumor sizes.

3.3 Scatter correction

Figure 7 shows an original 140 kVp image, scatter image and image after scatter correction. As described previously, the scatter correction was applied to the individual high and low kV images before performing weighted logarithmic subtraction. For the 140-60 kVp pair, the scatter corrected SDNR values were 3.32 ± 0.22 (target size = 25 mm), 3.08 ± 0.24 (target size = 20 mm), 1.90 ± 0.23 (target size = 15 mm) and 1.68 ± 0.27 (target size = 10 mm). These values are smaller than the SDNR values ($p < 0.0001$ for all targets) obtained before the scatter correction (Section 3.2) and the percent difference (absolute difference and uncertainty) is found to be 21.3% (0.79 ± 0.053), 24.5% (0.86 ± 0.058), 31.1% (0.70 ± 0.054) and 24.1% (0.46 ± 0.060) for 25, 20, 15 and 10 mm targets, respectively.

3.4 Noise Reduction

To quantify the effects of noise reduction methods on tumor visibility, SDNR values were evaluated before and after using the ACNR noise reduction technique. For the 140-60 kVp pair, the SDNR values for noise reduced images are 7.06 ± 0.47 (target size = 25 mm), 6.79

± 0.54 (target size = 20 mm), 4.23 ± 0.35 (target size = 15 mm) and 3.50 ± 0.39 (target size = 10 mm), higher than DE images before noise reduction. The percent difference (absolute difference and uncertainty) between noise reduced SDNR values and original SDNR values is found to be 52.8% (2.95 ± 0.084), 53.1% (2.85 ± 0.096), 47.7% (1.63 ± 0.068) and 48.2% (1.36 ± 0.075) for 25, 20, 15 and 10 mm targets, respectively ($p < 0.0001$ for all targets). As expected, this improvement is due to reduction of the standard deviations (σ_{Tumor} and σ_{Back}) in Equation 4. Importantly, the ranking of the top 3 energy pair candidates (140-60, 130-60, 120-60 kVp) has not changed after noise reduction (Figure 8).

4. Discussion

In this study we described a phantom that was designed and built to optimize DE imaging parameters for radiotherapy applications. The overall design of the phantom allows for easy image acquisition, optimization of imaging parameters and weighting factors. The phantom allows physicists to develop standardized protocols and reproducible results, enabling its usage as part of a comprehensive quality assurance program.

The weighting factor (w_s) was optimized by minimizing the contrast between bone- and lung-equivalent materials. The theoretical value of the weighting factor is proportional to the ratio of the high kV bone attenuation coefficient relative to that of the low kV energy. The attenuation coefficient of bone decreases as the energy of the incident photon increases. As the separation between individual energies increases, the net result is a decreasing weighting factor. For a fixed low-energy setting, the weighting factor (w_s) decreases as high energy setting increases (Figure 4). Williams et al (2007) observed a similar trend in weighting factors where for a fixed low energy (60 kVp), the weighting factor decreased from 0.32 (for 120 kVp) to 0.28 (for 150 kVp). These results imply that the weighting factor (w_s) is directly related to the gap between x-ray spectra of high- and low-photon energies. Thus, changes in the weighting factor may be used to detect a change in x-ray spectra in DE imaging devices.

Selection of the optimal imaging technique is based on quantitative evaluation of simulated tumor visibility using SDNR measurements. SDNR values were ranked for different imaging techniques and different tumor sizes. As the separation between low-high kV x-ray settings were decreased, SDNR values gradually decreased. This trend was consistent across all tumor sizes (Figure 6). The top three kV imaging pairs that produced the highest SDNR values were 140-60 kVp, 130-60 kVp and 120-60 kVp, in decreasing order. Williams et al (2007) studied the selection of kV imaging pairs based on human performance tests, such as visualization tasks for soft and bony tissue. Their study showed, for the visualization of soft-tissue structures in the lung, 130-60 kVp x-ray energy pair provided optimal tumor visibility. A similar study (Hoggarth et al 2013) used brass strips and an anthropomorphic phantom with simulated tumors of 4 different sizes to determine the optimal mAs and kVp setting. They suggested that the 140-60 kVp x-ray energy pair was the optimal imaging pair based on SDNR measurement. The top candidates from our study are consistent with the results from both of these previous studies. Normalization of SDNR values by corresponding dose did not change the relative ranking of the top three imaging pairs, as shown in Table 1, and dose normalized SDNR values were within their measured uncertainties.

Of particular interest, our analysis demonstrated that scatter correction reduced SDNR values by 25.3% on average (see Section 3.3). However, the scatter correction may have benefits that are not quantified by the SDNR metric. These include improved uniformity across the image and better quantification of bone and tissue thicknesses. Thus, the impact of scatter correction needs further exploration.

To investigate effects of noise reduction on the visibility of simulated tumor, DE images were processed using the ACNR noise reduction method (Section 2.7). Richard et al (2008) demonstrated that ACNR significantly reduces noise in soft tissue DE images, relative to WLS method alone. Moreover, their study showed that modulation transfer function (MTF) of the soft tissue DE images processed using ACNR is similar to the original DE image MTF over all frequency ranges, indicating that ACNR does not reduce image resolution (Richard and Siewerdsen 2008). Our results demonstrated that ACNR noise reduction significantly improved SDNR values and hence, can be utilized as an image post-processing method to improve tumor visibility without decreasing image resolution.

The phantom developed for this study has provided a standardized means for optimizing DE imaging pairs and the subsequent weighting factor. The results from this study are consistent with those presented in the literature using other experimental arrangements (Williams et al 2007, Hoggarth et al 2013). In our own previous studies (Hoggarth et al 2013), we used a phantom consisting of pork ribs that were affixed to a commercial phantom along with simulated tumors that were custom-molded. The advantage of the current phantom is that the set up is reproducible and it simulates the patient geometry. Future enhancements to the phantom design include modifying the external shape in order to mimic the cross section of the human body. Additional modifications may also include the insertion of multiple ribs, and the use of 3D printed tumors based on patient data. In the current form, this phantom may be used as a part of a commissioning and quality assurance program for DE imaging on a linear accelerator.

5. Conclusion

Dual energy imaging is powerful method to reveal hidden lung tumors under bony structures in x-ray radiography. Although, it has been widely used in the diagnostic setting, its application has been limited in radiotherapy. By providing improved visualization of lung tumors, DE imaging using the OBI on a linac can enhance real-time tumor tracking and image-guided radiotherapy. Currently, implementation of fast-kV-switching x-ray source is being considered on the linac. Before this application is clinically available, DE imaging parameters and corresponding weighting factors need optimization. In this note we presented a custom phantom designed to optimize DE imaging parameters. We also described post-processing methods such as scatter correction and noise reduction. This phantom may be incorporated as part of a clinical quality assurance program.

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Figure 1.

Illustration of the custom phantom. The images on the left side and in the middle show a schematic diagram of the top and side view of the phantom. This phantom consists of 5 simulated spherical tumors with diameters ranging from 0.5-2.5 cm which are embedded in simulated lung material. A phantom slab with embedded cylinders constructed of bone-equivalent material (shown as dark gray, right figure) may be placed on the top and/or bottom to simulate the overlap of bone with tumor on x-ray projections. The phantom as constructed is shown on the right side of the figure.

Figure 2. Experimental setup for dual energy imaging on the Varian OBI. The custom phantom is positioned on the treatment table. The x-ray source of OBI is positioned at the top, while flat panel detector is below the couch.

Figure 3. Iterative method to determine optimal weighting factor (w_s). Each point represents the relative contrast between bone and background ROI. The optimal value of w_s for a particular energy pair is that which minimizes the relative contrast between these two ROI. Results for the 120-60 kVp energy pair are shown to demonstrate this method.

Figure 4.

Illustration of the weighting factor dependence on energy-pairs. The horizontal axis is the high energy setting. Corresponding low energies are demonstrated by distinct markers where circle, diamond, triangle and square represent 90, 80, 70 and 60 kVp settings. The vertical axis corresponds to the optimal weighting factor for dual energy subtraction.

Figure 5. X-ray image of the custom phantom. 140-kVp image (left), 60-kVp image (middle), and DE subtraction image (right) produced using Equation 3.

Figure 6. SDNR value for various energy pairs. The horizontal axis represents selected energy pairs. Square, triangle, circle and diamond markers represent SDNR values for 25, 20, 15 and 10 mm targets, respectively.

Figure 7.
Original 140 kVp image (left), scatter estimate (middle) and scatter corrected image (right)

Figure 8.

SDNR values for the 25 mm target before and after the noise correction method is applied. Square points represent values before noise reduction. Triangle points represent SDNR values after noise reduction. SDNR value have increased for all energy pairs after noise reduction.

Table 1

SDNR values normalized to imaging dose. First column - energy pairs for highest SDNR values, second column - SDNR values, third column - surface dose calculated using Formula 5 and last column - SDNR values normalized to surface dose. The order of the top candidates has not changed after dose normalization.

Energy Pairs (kVp)	SDNR	Imaging Dose (mGy)	Dose Normalized SDNR (mGy ⁻¹)
140-60	4.11 ± 0.25	0.054	76.3 ± 4.5
130-60	3.75 ± 0.21	0.050	75.6 ± 4.3
120-60	3.43 ± 0.28	0.045	75.4 ± 6.1
140-70	3.17 ± 0.23	0.062	50.8 ± 3.6
110-60	3.08 ± 0.24	0.042	74.0 ± 5.7
130-70	2.86 ± 0.24	0.058	49.5 ± 4.1
90-60	2.82 ± 0.22	0.074	38.3 ± 3.0