Statistical model based iterative reconstruction in clinical CT systems. Part III. Task-based kV/mAs optimization for radiation dose reduction

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Purpose: For a given imaging task and patient size, the optimal selection of x-ray tube potential (kV) and tube current-rotation time product (mAs) is pivotal in achieving the maximal radiation dose reduction while maintaining the needed diagnostic performance. Although contrast-to-noise (CNR)-based strategies can be used to optimize kV/mAs for computed tomography (CT) imaging systems employing the linear filtered backprojection (FBP) reconstruction method, a more general framework needs to be developed for systems using the nonlinear statistical model-based iterative reconstruction (MBIR) method. The purpose of this paper is to present such a unified framework for the optimization of kV/mAs selection for both FBP- and MBIR-based CT systems.

Methods: The optimal selection of kV and mAs was formulated as a constrained optimization problem to minimize the objective function, Dose(kV,mAs), under the constraint that the achievable detectability index $d'(kV,mAs)$ is not lower than the prescribed value of d'_R for a given imaging task. Since it is difficult to analytically model the dependence of d' on kV and mAs for the highly nonlinear MBIR method, this constrained optimization problem is solved with comprehensive measurements of Dose(kV,mAs) and $d'(kV,mAs)$ at a variety of kV–mAs combinations, after which the overlay of the dose contours and d' contours is used to graphically determine the optimal kV–mAs combination to achieve the lowest dose while maintaining the needed detectability for the given imaging task. As an example, d' for a 17 mm hypoattenuating liver lesion detection task was experimentally measured with an anthropomorphic abdominal phantom at four tube potentials (80, 100, 120, and 140 kV) and fifteen mA levels (25 and 50–700) with a sampling interval of 50 mA at a fixed rotation time of 0.5 s, which corresponded to a dose (CTDI_{vol}) range of [0.6, 70] mGy. Using the proposed method, the optimal kV and mA that minimized dose for the prescribed detectability level of $d'_R = 16$ were determined. As another example, the optimal kV and mA for an 8 mm hyperattenuating liver lesion detection task were also measured using the developed framework. Both an *in vivo* animal and human subject study were used as demonstrations of how the developed framework can be applied to the clinical work flow.

Results: For the first task, the optimal kV and mAs were measured to be 100 and 500, respectively, for FBP, which corresponded to a dose level of 24 mGy. In comparison, the optimal kV and mAs for MBIR were 80 and 150, respectively, which corresponded to a dose level of 4 mGy. The topographies of the iso- d' map and the iso-CNR map were the same for FBP; thus, the use of d' - and CNR-based optimization methods generated the same results for FBP. However, the topographies of the iso- d' and iso-CNR map were significantly different in MBIR; the CNR-based method overestimated the performance of MBIR, predicting an overly aggressive dose reduction factor. For the second task, the

developed framework generated the following optimization results: for FBP, kV = 140, mA = 350, dose = 37.5 mGy; for MBIR, kV = 120, mA = 250, dose = 18.8 mGy. Again, the CNR-based method overestimated the performance of MBIR. Results of the preliminary *in vivo* studies were consistent with those of the phantom experiments.

Conclusions: A unified and task-driven kV/mAs optimization framework has been developed in this work. The framework is applicable to both linear and nonlinear CT systems such as those using the MBIR method. As expected, the developed framework can be reduced to the conventional CNR-based kV/mAs optimization frameworks if the system is linear. For MBIR-based nonlinear CT systems, however, the developed task-based kV/mAs optimization framework is needed to achieve the maximal dose reduction while maintaining the desired diagnostic performance. © 2015 American Association of Physicists in Medicine. [<http://dx.doi.org/10.1118/1.4927722>]

Key words: CT, iterative reconstruction, radiation dose reduction, x-ray tube potential, tube current

1. INTRODUCTION

Despite its tremendous benefits in clinical imaging practices, x-ray computed tomography (CT) has increased ionizing radiation dose *per capita* since its introduction in the 1970s.¹ While the small but nonzero risk associated with low level ionizing radiation (<100 mSv) remains a highly controversial topic, it is always wise to reduce radiation dose to minimal required level for a given imaging task.

Among various strategies for radiation dose reduction, x-ray tube potential (kV) and tube current-rotation time product (mAs) optimization is an important means to avoid unnecessary x-ray exposures to patients.^{2–14} For a given patient size and diagnostic imaging task, there is usually an optimal combination of tube potential and mAs to achieve the desired image quality with the least amount of radiation dose. For example, iodinated contrast-enhanced CT exams for small-sized patients are usually performed at relatively low tube potential (e.g., 80 kV) to improve the contrast between iodinated and noniodinated soft tissues, which often allows noisier images to be tolerated. For large patients, however, the optimal tube potential could be 120 kV or higher for several reasons, including reduction of structured noise streaks caused by photon starvation, mitigation of metal artifact, and so on. Usually when low kV scans are prescribed, a higher mAs is needed to compensate for the drop in photon fluence rate. In practice, this kV–mAs trade-off is often limited by the maximal mA of the tube-generator assembly. As a result, both kV and mAs should be taken into account in the optimization procedure. In general, there is no optimal kV or mAs that is universally applicable to all clinical scenarios: the optimal selections of kV and mAs depend on the clinical imaging tasks, patient sizes, and properties of the CT systems.

For conventional filtered backprojection (FBP)-based quasilinear CT systems, a variety of kV/mAs optimization methods and clinical validation studies have been reported.^{2–13} For example, Kalender *et al.* used the dose-weighted contrast-to-noise ratio (CNRD) as the criterion for kV optimization.¹¹ In this method, the noise standard deviation is assumed to be inversely proportional to mAs; thus, the dose normalization procedure removes the dependence of image quality on mAs. Therefore, the tube potential that maximizes CNRD yields the optimal kV. For contrast-enhanced CT exams,

Yu *et al.* developed an automatic kV selection method using the contrast-to-noise ratio (CNR) of iodinated lesions as the figure of merit to optimize the kV selection; in addition to that, maintaining the noise standard deviation in the background tissue below a specified level was introduced as an additional criterion for kV optimization.¹³ This method, referred to as iCNR_NC, takes into account not only properties of the iodinated lesions but also the background image quality. For a desired iCNR_NC level, the relative adjustments in radiation dose level at different kVs were compared, and the optimal kV was chosen as the one requiring the lowest dose. In these published methods, the assumption of system linearity significantly reduces the workload of the optimization process. This can be attributed to the fact that spatial resolution and noise texture have negligible dependence on kV and mAs. Under this condition, zero-frequency analysis usually serves the purpose of scan parameter optimization.

Recently, statistical model-based iterative reconstruction (MBIR) methods have been introduced into clinical CT systems to reduce radiation dose and/or improve image quality.^{15–18} The introduction of spatial smoothness prior model as a regularizer to suppress image noise, the use of statistical weighting of the projection data to suppress structured noise streaks, and the use of iterative reconstruction work jointly to accomplish low noise and low streak CT reconstruction at reduced radiation dose levels. However, these operations in MBIR may also introduce strong nonlinearities into CT imaging systems. As a result, several assumptions used in the previous kV/mAs optimization methods may be violated. For example, it has been found that the spatial resolution of MBIR images depends on both radiation dose and local contrast levels.^{19–24} Dependence of noise properties on image contrast has also been found in several studies.^{20,21,23,25–29} With these nonlinear characteristics, the CNR-based kV/mAs optimization framework is not justified and may lead to unacceptable optimization results in clinical practice.

The purpose of this work is to develop a unified kV/mAs optimization framework for both linear and nonlinear CT imaging systems to address the aforementioned challenges introduced by the nonlinear MBIR method. Modern signal detection theory represented by local frequency-dependent detectability analysis was incorporated into the optimization framework, and isodetectability and isodose contours

generated from extensive phantom experiments at different kV–mAs combinations were used to graphically solve the kV/mAs optimization problem. The framework is applicable to both MBIR-based nonlinear CT systems and FBP-based linear CT systems. The classical CNR-based optimization methods have been proven to be a special case of the presented unified optimization framework. Both an *in vivo* animal study and a human subject study have been used to demonstrate how the developed optimization framework can be used in clinical scenarios.

2. METHODS AND MATERIALS

2.A. General strategy

Without loss of generality, we have assumed the tube rotation time is fixed in each study. Therefore, the optimization of the mAs is reduced to the optimization of the mA alone. The diagnostic performance of lesion detection is quantified by the task-based detectability index, $d'(\text{kV}, \text{mA})$, which is a function of both kV and mA values. In the proposed unified kV/mA optimization framework, the kV and mA should be selected to minimize the radiation dose function, $\text{Dose}(\text{kV}, \text{mA})$, while ensuring the corresponding detectability, $d'(\text{kV}, \text{mA})$, is not lower than the prescribed detectability d'_R for a given imaging task. In other words, the scan parameters are chosen by solving the following constrained optimization problem:

$$\arg \min_{\text{kV}, \text{mA}} \text{Dose}(\text{kV}, \text{mA}), \quad \text{s.t.} \quad d'(\text{kV}, \text{mA}) \geq d'_R. \quad (1)$$

In Eq. (1), “s.t.” denotes “subject to” and the subscript R denotes “prescribed.” The prescription of the desired detectability level d'_R should follow the as low as reasonably achievable (ALARA) principle³⁰ and should be done by radiologists or other physicians who use CT images to perform clinical diagnosis.

Using the detectability index d' rather than CNR in kV/mA optimization has several potential advantages: first, it depends on the nature of the diagnostic imaging task (e.g., lesion shape and size); second, it takes noise texture and spatial resolution into account; third, it allows for the introduction of anthropomorphic modeling of the human visual system into the optimization pipeline. For example, the measurement of detectability index for the non-prewhitening model observer with eye filter and internal noise (NPWEi)^{31,32} requires knowledge of the imaging task, system noise power spectrum (NPS), the internal noise fluctuation in the human visual system, and the inherent bandpass nature of the eye. Recently, studies have demonstrated good correlations between the NPWEi model observer and human observer in MBIR.³³ Note

that in this paper, it was not our intention to compare the performance of different model observers for a given imaging task. Instead, we focused on the development of the needed task-based kV/mA optimization framework, and thus chose to use the NPWEi model as our starting point without further justification throughout the paper. In the NPWEi model, the detectability d' is calculated as follows:

$$[d'(\text{kV}, \text{mA})]^2 = \frac{\left[\int |S(f, \text{kV}, \text{mA})|^2 |E(f)|^2 df \right]^2}{\int \left[\text{NPS}(f, \text{kV}, \text{mA}) |S(f, \text{kV}, \text{mA})|^2 |E(f)|^4 + N_{\text{in}} \right] df}, \quad (2)$$

where f denotes spatial frequency, E denotes the eye filter, N_{in} denotes the internal noise, and S denotes the detection task function represented in the output image, which is given by filtering the input task function W with the optical transfer function (OTF) of the imaging system,

$$S(f, \text{kV}, \text{mA}) = C(\text{kV}) \cdot W(f) \cdot \text{OTF}(f, \text{kV}, \text{mA}). \quad (3)$$

In Eq. (3), C denotes the image contrast between Hypothesis I (lesion present) and Hypothesis II (lesion absent). Since the contrast may be energy dependent, C has an argument of kV. $W(f)$ represents the frequency decomposition (Fourier transform) of the difference between Hypotheses I and II. The modulus of the OTF is the well-known modulation transfer function (MTF).

2.B. Application to the FBP-based quasilinear CT imaging systems

For FBP-based linear CT systems, several justified approximations can be used to simplify the calculation of d' in the NPWEi model. The first one is to neglect the x-ray energy dependence and tube current dependence in OTF, i.e.,

$$\text{OTF}(f, \text{kV}, \text{mA}) \approx \text{OTF}(f). \quad (4)$$

The second approximation is to consider the NPS as a separable function, decoupling the frequency dependence from kV and mA,

$$\text{NPS}(f, \text{kV}, \text{mA}) \approx \sigma^2(\text{kV}, \text{mA}) \cdot \text{NNPS}(f). \quad (5)$$

In Eq. (5), $\sigma^2(\text{kV}, \text{mA})$ denotes noise variance that is dependent on kV and mA selection, and the spatial frequency dependence of the NPS is included only in the normalized NPS (NNPS). Possible sources of errors for these two approximations in Eqs. (4) and (5) include x-ray scatter, beam hardening, electronic noise, and other nonlinear processes in the CT imaging chain.

Under these two approximations, Eq. (2) becomes

$$[d'(\text{kV}, \text{mA})]^2 = \frac{C^4(\text{kV}) \left[\int |W(f) \cdot \text{OTF}(f)|^2 |E(f)|^2 df \right]^2}{\sigma^2(\text{kV}, \text{mA}) C^2(\text{kV}) \int \text{NNPS}(f) |W(f) \cdot \text{OTF}(f)|^2 |E(f)|^4 df + \int N_{\text{in}} df}. \quad (6)$$

If the internal noise is further neglected, Eq. (6) can be simplified as the following concise formula:

$$[d'(\text{kV}, \text{mA})]^2 = \left[\frac{C(\text{kV})}{\sigma(\text{kV}, \text{mA})} \right]^2 \kappa^2, \quad (7)$$

where the factor κ is independent of both kV and mA,

$$\kappa^2 = \frac{\left[\int |W(f) \cdot \text{OTF}(f)|^2 |E(f)|^2 df \right]^2}{\int \text{NNPS}(f) |W(f) \cdot \text{OTF}(f)|^2 |E(f)|^4 df}. \quad (8)$$

The C/σ in Eq. (7) is simply the well-known CNR. Since the entire kV/mA dependence has been included in C/σ , using d' to optimize kV and mA is equivalent to using CNR to optimize kV and mA. In other words, maximizing $\text{CNR}/\sqrt{\text{Dose}}$ (CNRD, Ref. 11) is equivalent to minimizing dose for a specified d' in linear CT imaging systems.

2.C. Application to MBIR-based nonlinear CT imaging systems

For the nonlinear MBIR method, it has been demonstrated that the assumptions made in Eqs. (4) and (5) are severely violated: the image contrast (C) can no longer be decoupled from OTF, nor can mA or kV be decoupled from the NPS.^{19,22,23,25,29} As a result, the detectability index cannot be reduced to the simplified form in Eq. (6). Instead, its value must be assessed at different kV–mA combinations. Since there is no analytical expression available to describe the OTF and NPS dependence on kV and mA, the following procedures were developed to graphically solve for the kV/mA optimization problem formulated in Eq. (1):

1. Identify a diagnostic CT imaging task (lesion contrast, lesion size, patient size, etc.) and a corresponding surrogate (phantom).
2. Identify the prescribed detectability level (d'_R).
3. Perform CT scans of the phantom with a given kV/mA level. Other scan parameters should be consistent with clinical settings. Measure Dose(kV, mA) by recording the CTDI_{vol} value.
4. Repeat Step 3 N times to obtain an ensemble of independent image instances to calculate the detectability index d' .

5. Repeat Steps 3 and 4 at different kV–mA combinations to generate an iso- d' map and an isodose map.
6. Overlay the two maps; an example is shown in Fig. 1. Along the isoline of $d' \geq d'_R$, search the kV–mA combination that corresponds to the lowest dose.

The prescribed detectability level d'_R can be determined through human observer experiments using methods described in other studies.^{34–36}

2.D. Experimental phantom data acquisition

This study used an anthropomorphic abdominal phantom with models of adult liver, spleen, kidneys, various irregularly shaped focal lesions, and other structures (3D Abdominal Phantom, CIRS, Inc., Norfolk, VA). The size of the phantom was measured to be 26 cm along the left–right direction and 18 cm along the anterior–posterior direction. Figure 2 shows a photo of the phantom.

Two imaging tasks were studied in this work. Task A was defined as detecting a hypoattenuating zone in the liver [Fig. 2(b)]. The effective diameter of the lesion is 17 mm. The exact materials of this “lesion” and other components of the phantom are proprietary information and were unknown to the authors. However, to understand their x-ray properties, a dual-energy CT scan (Gemstone Spectral Imaging, GE Healthcare, Waukesha, WI) of the phantom was performed and material decomposition images were reconstructed with iodine and water as the material bases. The measured iodine concentration in the lesion and the liver was 0 and 1.2 mg/ml, respectively, and the water concentration in both locations was 1.0 g/ml. As shown in Fig. 2(c), the absolute value of the contrast between the lesion and the liver increased with decreasing kV. Task B was defined as detecting a hyperattenuating zone in the liver [Fig. 2(d)]. Compared with the lesion in Task A, the diameter of the lesion in Task B is smaller (8 mm). The measured iodine and water concentrations in this lesion were 1.3 mg/ml and 1.1 g/ml, respectively. Although the CT number of the lesion decreased with increasing kV, its contrast relative to the liver background remained constant (44 HU) across the four different kV levels [Fig. 2(d)].

The phantom was scanned using a 64-slice diagnostic CT system (Discovery CT750 HD, GE Healthcare, Waukesha,

FIG. 1. To solve for constrained minimization problem in Eq. (1), exhaustive measurements of detectability index d' and dose values at different kV–mA combinations were performed to generate the isodetectability and isodose contour maps. The two maps are overlaid so that for the prescribed detectability level, d'_R , the dose levels along the corresponding isodetectability contour $d' = d'_R$ can be queried, and the optimal kV–mA pair is the one that minimizes dose.

FIG. 2. (a) CIRS 3D abdomen phantom used in this study. CT images of phantom in (b) and (d) show the two liver lesions used in detection Tasks A and B, respectively. The dashed and solid squares encompass the lesion present and absent ROIs, respectively. (c) Measured CT contrast values of the two lesions as different kV levels.

WI) equipped with both FBP and MBIR (Veo™, GE Healthcare, Waukesha, WI) reconstruction engines. Except kV and mA, all scan parameters were adopted from a clinical abdominal CT protocol used at our institution (helical pitch = 0.516, detector collimation = 40 mm, scan field of view (SFOV) = “Medium Body”). The tube rotation time was fixed at 0.5 s. The display field of view (DFOV) was 26 cm.

The study covered all four tube potentials (80, 100, 120, and 140 kV) provided by the scanner and fifteen different mA levels ranging from 25 to 700 with a sampling interval of 50 mA from 50 to 700 mAs. At each of the 60 kV–mA combinations, 50 sequential scans were performed and reconstructed using both MBIR and FBP. The Standard Kernel was used for both reconstruction methods, as it is the only kernel available for the version of Veo currently available at the authors’ institution. For a few kV–mA combinations (labeled N/A in Table I), a long system cooling period (approximately 6 min) is automatically enforced by the CT system between consecutive scans. This restricted us from performing the 50 repeated scans at each of those specific kV–mA combinations. Based on the technical reference manual of the scanner, the tube automatically switches between x-ray focal spots sizes at these kV–mA combinations; to protect the tube, the system automatically enforces a low tube rating to restrict the prescription of consecutive CT scans. For the other 54 kV–mA combinations in Table I, there was no such cooling period enforced by the system, which enabled the 50 consecutive scans to be finished within 10 min.

2.E. Detectability index measurement method

The detectability index was calculated in the Fourier domain using the NPWEi method described in Eq. (2).

TABLE I. Dose(kV, mA) quantified by the CTDI_{vol} with the unit of mGy. Those marked by N/A (not available) were skipped due to limitations in tube load ratings for consecutive exposures.

mA	kV			
	80	100	120	140
25	0.6	1.1	1.8	2.5
50	1.2	2.2	3.6	5.1
100	2.5	4.7	7.5	10.7
150	3.8	7.1	11.3	16.1
200	5.1	9.5	15.0	21.4
250	6.3	11.9	18.8	26.8
300	7.6	14.2	22.6	32.2
350	8.9	16.6	26.3	37.5
400	10.1	19.0	30.1	42.9
450	11.4	21.3	33.9	N/A
500	12.7	23.7	N/A	53.2
550	13.9	26.1	N/A	58.5
600	15.2	28.4	44.7	63.8
650	16.3	N/A	48.5	N/A
700	17.5	32.9	52.2	N/A

Since the concept of the NPS implicitly requires the noise to meet the wide-sense stationarity condition, the NPS and the detectability index measurement were restricted to two $30 \times 30 \text{ mm}^2$ local regions of interest (ROIs) for each task: ROI₁ contains the liver lesion to represent Hypothesis I (lesion present), and ROI₂ is in the uniform liver region adjacent to the lesion to represent Hypothesis II (lesion absent). At each kV–mA combination, the detection task function S was measured as follows:

$$S(f_x, f_y) = \text{FT}_{2D}[\langle \text{ROI}_2 \rangle - \langle \text{ROI}_1 \rangle], \quad (9)$$

where FT_{2D} denotes a 2D Fourier transform, and $\langle \bullet \rangle$ denotes ensemble averaging across the 50 repeated scans. Similarly, the NPS was measured from the same dataset as

$$\text{NPS}(f_x, f_y) = \frac{\Delta x \Delta y}{N_x N_y} \langle |\text{FT}_{2D}[\text{ROI}_1 - \langle \text{ROI}_1 \rangle]|^2 \rangle. \quad (10)$$

The mathematical formula for the eye filter is given as follows:³⁷

$$E(f) = f \exp(-cf), \quad (11)$$

where $f = \sqrt{f_x^2 + f_y^2}$ is the radial frequency, and the numerical factor c was selected to be 3.1 mm so that the maximum response of E occurred at 4 cycles/degree³⁷ at a viewing distance of 70 cm. The internal noise (N_{in}) was assumed to be static (independent of dose level); its magnitude was selected as follows:^{37,38}

$$N_{in} = 0.02 N_0 L^2, \quad (12)$$

where $L = 0.70$ is the viewing distance in meters, and N_0 is the amplitude of the white noise-equivalent NPS of the background, which is given by³⁷

$$N_0 = \frac{\iint N(f_x, f_y) df_x df_y}{\iint df_x df_y}. \quad (13)$$

In our data analysis, it was found that the contribution of N_0 to the detectability index was negligible. The integration ($\iint \bullet df_x df_y$) was implemented as discrete summations of ($\Delta f_x \Delta f_y \sum \sum \bullet$) within the $\pm$ Nyquist frequency with $\Delta f_x = \Delta f_y = 0.04$ cycles/mm.

2.F. Generation of dose and detectability contour maps

The dose function, $Dose(kV, mA)$, and the detectability function, $d'(kV, mA)$, measured at different kV–mA combinations were used to generate the isodose and isodetectability contours, respectively. These operations were performed using the MATLAB function *contourf* (The MathWorks, Inc., Natick, MA). The kV–mA optimization was performed from these contour lines using methods described in Sec. 2.C.

2.G. Feasibility study using an *in vivo* animal model

An *in vivo* animal model was used to demonstrate how the developed optimization framework can be used in animal studies. Under an Institutional Animal Care and Use Committee (IACUC) approved protocol, a four month-old female swine with a weight of 54 kg was scanned using the same CT system and scanning protocol as the phantom experiment. An intravenous (IV) contrast injection was performed with a 50 ml bolus of Iovue-370 (Bracco Diagnostics, Inc., Princeton, NJ) and an injection rate of 3 ml/s. CT scans were performed 40 min after the contrast injection so that most of the iodine was washed out from the liver. This allowed the x-ray attenuation properties of the gall bladder and the liver of the swine to match those in Task A of the phantom, which was confirmed through a dual-energy CT scan with iodine/water material decomposition: the iodine concentration in the gall bladder and the liver of the swine was measured to be 0 and 2 mg/ml, respectively, and the water concentration was 1.0 g/ml in both the gall bladder and liver. With a fixed radiation dose (CTDI_{vol}) of 3.8 mGy and a fixed tube rotation time of 0.5 s, four consecutive scans were performed at the following kV–mA combinations: (80 kV, 140 mA); (100 kV,

75 mA); (120 kV, 55 mA); and (140 kV, 35 mA). Both FBP and MBIR reconstructions were performed, and the detectability of the gall bladder relative to the liver at each of these kV–mAs combinations was subjectively evaluated.

2.H. Feasibility study using a human subject

A HIPPA compliant and IRB approved human subject study was performed. A 67 yr-old female subject with a CT exam ordered for the surveillance of non-Hodgkin's lymphoma was recruited in this study with signed informed consent obtained. The patient size measured in the abdomen as 38 cm (lateral), or 29 cm (anterior–posterior). Immediately following a routine-dose contrast-enhanced (portal venous phase) abdomen–pelvis CT scan, an ultralow-dose scan with 87% dose reduction was obtained. The total dose from the routine and ultralow-dose scans were kept the same as those from standard clinical scans. The IV contrast injection was performed with a 126 ml bolus of Omnipaque-300 (GE Healthcare, Inc., Princeton, NJ) and an injection rate of 3 ml/s, followed by 40 ml of saline flush at a rate of 3 ml/s. The tube potentials used for the routine and ultralow-dose series were 120 and 80 kV, respectively. The mA levels for the two scans were controlled indirectly by adjusting the noise index; the actual mA values for the two series were 650 and 275, respectively. The CTDI_{vol} values for the two series were 19.4 and 2.4 mGy, respectively. Other scan parameters were matched between the two scans: rotation time = 0.4 s, pitch = 0.984, detector collimation = 40 mm, SFOV = “Large Body,” and DFOV = 44 cm. Standard kernels were used for both the FBP and MBIR reconstructions. The contrast values between the hepatic portal vein and liver and between the liver and gall bladder were measured.

3. RESULTS

3.A. Isodose, isodetectability, and iso-CNR contours

Figure 3 shows the isodose contours as a function of kV and mA. As expected, the measured radiation dose level (in terms

FIG. 3. Isodose contour map (left) and representative line profiles through the map (right). The dose is quantified in terms of CTDI_{vol} with the unit of mGy. As expected, dose is linearly proportional to mA for a given kV and is approximately proportional to the third power of kV for a given mA.

FIG. 4. Isodetectability contours of FBP (a) and MBIR (b) and iso-CNR contours of FBP (c) and MBIR (d) for Task A.

of CTDI_{vol}) was linearly proportional to mA at a given kV. When the mA was fixed, radiation dose was related to kV through a power law of $\text{dose} \propto (\text{kV})^{2.6}$. Note that for at a given kV–mA combination, the dose level is independent of the reconstruction method.

Figures 4(a) and 4(b) show the isodetectability contours for Task A (detection of the hypoattenuating liver lesion). For a given kV–mA pair, the d' of MBIR was consistently higher than that of FBP. Compared with MBIR, the d' of FBP featured a stronger kV dependence: to match the detectability of a 140 kV scan, an 80 kV scan required much higher mA for FBP. For certain high detectability levels, the required mA at 80 kV was so large that it exceeded the maximum mA of the tube. For example, the isodetectability contour of $d' = 18$ extended only to the point of 110 kV and 700 mA; to achieve this detectability level with FBP, the CT exam could not be prescribed at 80 kV. In contrast, the d' of MBIR demonstrated a relatively relaxed dependence on kV: the iso- d' lines are almost in parallel with the kV axis, and most of these isolines extended all the way to the kV = 80 vertical line without exceeding the tube power limit. This would potentially enable more CT exams to be prescribed at low kV for additional dose savings.

Figures 4(c) and 4(d) show the iso-CNR contours for Task A. The topography of the iso-CNR contours of FBP was almost identical to that of the isodetectability contours. This is consistent with the theoretical predictions given in Eqs. (6)–(8). In comparison, the topographies of the iso-CNR

map and the isodetectability map were fundamentally different in MBIR: all of the iso-CNR contours featured “anomalous” positive slopes, which means that smaller mA is needed at lower kV to reach the same CNR when compared to high kV scans. This is because in MBIR, the noise magnitude is less sensitive to mA;²⁹ since lower kV generates higher contrast, noisier images can be tolerated at lower kV to match the CNR high kV images. Due to the discrepancy between the isodetectability and iso-CNR contours, the use of these two methods led to fundamentally different kV/mA optimization results in MBIR. An example can be found in Sec. 3.B.

The isodetectability contours of Task B (detection of the hyperattenuating liver lesion) are shown in Figs. 5(a) and 5(b). Again, the detectability (d') of MBIR was consistently higher than that of FBP for a given kV–mA pair. Unlike Task A, the isodetectability contours of MBIR for Task B are no longer in parallel with the kV axis. This is due to the fact that the contrast of the lesion in this task is nearly independent of kV. As a result, the benefits of contrast enhancement at low kV diminished, and higher mA is needed at lower kV to compensate for the reduction in photon fluence rate.

Figures 5(c) and 5(d) show the iso-CNR contours of Task B. For FBP, the topography of the iso-CNR map was almost identical to that of the isodetectability contours. For MBIR, the topographies of the two types of maps were still different. Unlike Task A, however, the iso-CNR contours of MBIR for Task B demonstrated negative slopes. In other words, higher

FIG. 5. Isodetectability contours of FBP (a) and MBIR (b) and iso-CNR contours of FBP (c) and MBIR (d) for Task B.

mA was needed at lower kV to maintain the prescribed d' or CNR level when compared with that of high kV scans. This result is primarily due to the fact that the contrast of the positive lesion in Task B remains relatively constant across different kV levels.

3.B. Optimal kV/mA selection: Task A

This section presents an example of how to use the proposed framework to optimize kV and mA selection for Task A. We assumed the radiologists prescribed a detectability level of 16 for the hypoattenuating hepatic lesion detection task. As shown in Fig. 6(a), the contour line of $d'_R = 16$ extracted from Fig. 4 was overlaid on top of the isodose contour map. Along this contour line, all kV–mA pairs were inspected to search for the one that minimized dose. As a result, the optimal kV and mA were found to be 100 (kV) and 500 (mA) for FBP, and 80 (kV) and 150 (mA) for MBIR. The corresponding dose levels were 23.7 and 3.8 mGy, respectively (Table II). Representative images acquired at the optimized settings are shown in Fig. 7. The 80 kV–150 mA MBIR image demonstrated improved contrast between the liver and the lesion, and the MBIR algorithm successfully reduced image noise so that the desired detectability level was achieved with a much lower dose. Compared with unoptimized 120 kV scan with FBP reconstructions (30.1 mGy), the combined use of MBIR and kV/mA optimization led to a dose reduction of 84%.

In comparison, the CNR-based kV/mA optimization process for Task A was shown in Fig. 6(b). For FBP, based on the similarity in topography between its isodetectability and iso-CNR map, a CNR of 2 corresponded to a detectability index of 16, therefore the use of the iso-CNR contour of $\text{CNR}_R = 2$ led to the same kV/mA optimization result as the isodetectability contour of $d'_R = 16$ for FBP. For MBIR, however, there was no $\text{CNR} = 2$ contour; the minimum dose (0.6 mGy at 80 kV 25 mA) still generated a CNR of 4. However, by inspecting the actual image acquired under this condition (Fig. 7), it is obvious that the detectability of the lesion in the $\text{CNR} = 4$ MBIR image is inferior to that of the $\text{CNR} = 2$ FBP image. Therefore, using CNR alone to optimize kV/mA in MBIR resulted in an overly aggressive dose reduction factor and unacceptable image quality.

3.C. Optimal kV/mA selection: Task B

As another example, the proposed detectability-based kV/mA optimization work flow for Task B is shown in Fig. 6(c), and the corresponding results are listed in Table II. Again, the prescribed detectability level for the hyperattenuating hepatic lesion detection task was assumed to be 16. For FBP, the optimal kV and mA were found to be 140 (kV) and 350 (mA), which correspond to a dose level of 37.5 mGy. For MBIR, all three kV–mA combinations on the contour of $d'_R = 16$ correspond to very similar dose values; the 120 kV–250 mA led to

FIG. 6. Two examples of the proposed detectability-based and the classical CNR-based kV/mA optimization methods. The prescribed detectability level was assumed to be $d' = 16$, the corresponding isodetectability lines [(a) for Task A and (c) for Task B] were overlaid on top of the isodose map; along this isodetectability line, the kV–mA pair that led to the lowest dose was deemed optimal. By replacing the isodetectability line with the iso-CNR line [(b) for Task A and (d) for Task B], the kV/mA optimization process was repeated, which generated the same (for FBP) or different (for MBIR) optimization results.

slightly lower dose (18.8 mGy) if an optimal combination has to be selected. Compared with the standard 120 kV scan with FBP reconstructions (41.4 mGy), the combined use of MBIR and kV/mA optimization led to a dose reduction of 55%.

Figure 6(d) shows an example of the CNR-based kV/mA optimization process for Task B. For FBP, based on the similarity in their topographies, the isocontour lines of $CNR = 2$ and $d' = 16$ are equivalent; therefore, the use of $CNR_R = 2$

TABLE II. List of kV, mA, and dose values [mGy] on the isodetectability and iso-CNR lines in Fig. 6 for Tasks A and B.

Task A									Task B							
Detectability-based method					CNR-based method				Detectability-based method				CNR-based method			
		FBP		MBIR			FBP	MBIR			FBP	MBIR			FBP	MBIR
kV	mA	Dose	mA	Dose	mA	Dose	mA	Dose	mA	Dose	mA	Dose	mA	Dose	mA	Dose
80	N/A	N/A	150	3.8	N/A	N/A	25	0.6	N/A	N/A	N/A	N/A	N/A	N/A	25	0.6
100	500	23.7	140	6.6	500	23.7	40	1.9	N/A	N/A	400	19.0	N/A	N/A	N/A	N/A
120	400	30.1	150	11.3	400	30.1	75	5.6	550	41.4	250	18.8	550	41.4	N/A	N/A
140	350	37.5	160	17.2	350	37.5	110	11.8	350	37.5	180	19.3	350	37.5	N/A	N/A

FIG. 7. Representative phantom images for Task A acquired at standard 120 kV and optimized kV/mA levels. Both global and close-up (of the hypoattenuating liver lesion) images are included in the figure. The detectability-based method generated much more reasonable kV/mA optimization results than the CNR-based method for MBIR.

and $d_R = 16$ led to the same kV/mA optimization results. For MBIR, there was no contour with $\text{CNR} = 2$: the minimal dose (0.6 mGy at 80 kV and 25 mA) still generated a CNR of 3. However, by inspecting the actual image acquired at this setting (Fig. 8), it can be seen that the detectability of the lesion in the MBIR image with a CNR of 3 was inferior to that of the FBP image with a CNR of 2. Therefore, the CNR-based method led to biased kV/mA optimization results for MBIR.

3.D. Results of the *in vivo* animal study

Figure 9 shows CT images of the swine acquired at four different kV–mAs combinations. The contrast values between the gall bladder and the liver at different kV levels were measured to be 44 HU (80 kV), 38 HU (100 kV), 34 HU (120 kV), and 31 HU (140 kV). Although there was certain contrast enhancement at lower kV, there was no noticeable improvement in the detectability of the gall bladder in the 80 kV FBP image due to its noisier appearance: the noise standard deviation (σ) values measured in a 1 cm² uniform region in the liver of the swine were 77, 69, 64, and 63 HU for the 80, 100, 120, and 140 kV FBP images, respectively. In comparison, the noise magnitude remained relatively constant across the four kV levels in the MBIR images: the σ values measured in the 80, 100, 120, and 140 kV MBIR images

were the same (13 HU). This feature of MBIR allowed the 80 kV scan technique to demonstrate its advantage (contrast enhancement) at low dose level (3.8 mGy).

3.E. Results of the *in vivo* human subject study

Figure 10 shows results of the human subject study. Compared with the 120 kV image in Fig. 10(a), the 80 kV images in Figs. 10(b) and 10(c) demonstrated noticeable contrast enhancement: the contrast between the liver and the gall bladder is 95 HU in the 120 kV image and is 129 HU in the 80 kV images; the contrast between the portal vein and liver is 107 HU in the 120 kV image and is 136 in the 80 kV images. However, the 80 kV FBP image in Fig. 10(b) demonstrated significantly increased noise that offset the contrast enhancement. In comparison, the 80 kV MBIR image in Fig. 10(c) enjoyed both improved contrast and reduced noise. The impact of this low kV scan + MBIR reconstruction technique on clinical diagnostic performance will be systematically studied in the future after more subjects are enrolled.

4. DISCUSSION

The detectability improvement by MBIR demonstrated in this work is consistent with results of several clinical

FIG. 8. Representative phantom images for Task B acquired at standard 120 kV and optimized kV/mA levels. Both global and close-up (of the hypoattenuating liver lesion) images are included in the figure.

FIG. 9. CT images of the swine acquired along the isodose line of 3.8 mGy at the following kV–mA combinations: (80 kV, 140 mA); (100 kV, 75 mA); (120 kV, 55 mA); (140 kV, 35 mA). The tube rotation time was 0.5 s. Close-up images of the gall bladder (indicated in the 140 kV MBIR image) are included. The image display window and level are 300 and 0 HU, respectively.

studies.^{39–42} For Task A, MBIR resulted in a relaxed dependence of the detectability on kV: most of the isodetectability contours of MBIR run semiparallel with the kV axis in Fig. 4(b). This is because for a given mA, the slightly increased noise of MBIR images at lower kV is compensated by the significant contrast enhancement. Without MBIR, the contrast improvement at low kV is offset by significant increase in noise unless much higher mA is used. For FBP, quite often the isodetectability contours were cut off by the maximum mA before intercepting with the line of kV = 80. In those cases, the optimal kV is chosen to be 100 kV because of the infeasibility of 80 kV scans. This mA cutoff is less pronounced in MBIR, which potentially allows more CT scans to be prescribed at lower kV without saturating the tube current limit. For Task B whose contrast is nearly independent of kV values, the detectability index of MBIR is still consistently higher than that of FBP at any kV/mA combination. For this task, the topography of the isodetectability map of MBIR is similar to that of the isodose map; therefore, low kV does not offer a substantial dose benefit. For FBP, it is actually

more desirable to use 140 kV for this task. The differences in the kV/mA optimization results between the two imaging tasks demonstrate the importance of the task-driven rationale in kV/mAs selection.

There are three major differences between the proposed kV/mAs optimization method and the traditional methods. First, frequency-dependent metrics such as NPS and MTF are incorporated into the optimization framework. This is particularly important for kV/mAs selections in MBIR, which causes kV and mAs to be correlated with noise texture and spatial resolution. Second, the imaging task is incorporated so that the optimal kV/mAs selection is directly driven by a specific clinical need. For example, the detection of calcium depositions in the aorta and the detection of hepatic tumors can be modeled as two independent task functions to generate two different kV–mAs pairs. Third, traditional zero-frequency methods usually require only a few measurements due to system linearity, whereas the proposed method relies on repeated measurements, local analysis, and the creation of isodose/isodetectability maps. This means

FIG. 10. CT images of human subject. (a) FBP image of the routine dose scan (120 kV, 650 mA, 19.4 mGy). (b) FBP image of the ultralow-dose scan (80 kV, 275 mA, 2.4 mGy). (c) MBIR image of the ultralow-dose series. The tube rotation time was fixed at 0.4 s. The image display window and level are 400 and 50 HU, respectively.

optimizing kV/mAs selection is much more challenging for MBIR.

There are several earlier publications from other groups on combining the low kV scan technique with iterative reconstruction algorithms to achieve radiation dose reduction:^{14,40,43} Martin *et al.* applied the adaptive statistical iterative reconstruction (ASiR) algorithm to contrast-enhanced abdominal CT to enable more abdominal CT scans to be performed at 80 kV. Due to the limited noise reduction capability of ASiR, however, the low kV scans were prescribed with much higher tube currents.⁴³ Hur *et al.* found that the image quality and diagnostic performance of 100 kV MBIR images for hepatic vessel evaluations were preserved at reduced radiation dose levels when compared with 120 kV scans.⁴⁰ Samei *et al.* compared the performances of iterative reconstruction in image space (IRIS) and FBP in terms of image quality and dose under both noncontrast and contrast-enhanced conditions. They found that the optimal kV strongly depended on the patient size and imaging task.¹⁴ We hope the optimization methods and experimental findings presented in this work could add new insight into the protocol optimization efforts to reduce radiation dose while maintaining the diagnostic performance of CT exams.

This work has several limitations. As the focus of this work is to develop the optimization framework instead of performing clinical evaluations, only one phantom size and two imaging tasks were included. It is expected that the proposed method can help determine the corresponding optimal kV and mAs values for other tasks and body sizes, although this is subject to further validation. The NPWEi observer model which has demonstrated good correlation with human observers for MBIR in another independent study³³ has yet to be validated by the radiologist readers at the authors' institution. The use of the frequency-domain metrics such as NPS during the calculation of NPWEi detectability index also deserves further validation due to the possible violation of wide-sense stationarity in MBIR (and even in FBP). Other image domain-based detectability measurement methods can also be used in the proposed optimization framework,^{35,44} although they may require many more repeated scans.⁴⁵ The current work used 50 repeated scans at each kV–mA combination, which took approximately 10 min. Methods that can reduce the size of image ensemble required for accurate estimation of detectability index need to be explored in the future to further improve the practicality of the proposed framework. Finally, the *in vivo* studies are still preliminary and were only used to demonstrate the feasibility of the presented framework. A thorough *in vivo* validation study with more subjects is needed in the future to provide a sample size sufficient to allow any statistically significant conclusions to be drawn.

5. CONCLUSION

A task-based kV and mAs optimization framework has been developed in this work. This method is a generalization of the classical zero-frequency kV/mAs optimization methods

developed for linear CT systems and is applicable to both linear and nonlinear CT systems such as those equipped with MBIR. It has been demonstrated that the optimal kV and mAs determined from this method are task-specific rather than task-generic. The maximal dose reduction can be potentially achieved by combining the optimal kV/mAs selection with the MBIR CT reconstruction method.

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¹D. J. Brenner and E. J. Hall, "Computed tomography—An increasing source of radiation exposure," *N. Engl. J. Med.* **357**, 2277–2284 (2007).

²W. Huda, E. M. Scalzetti, and G. Levin, "Technique factors and image quality as functions of patient weight at abdominal CT," *Radiology* **217**, 430–435 (2000).

³J. M. Boone, E. M. Geraghty, J. A. Seibert, and S. L. Wootton-Gorges, "Dose reduction in pediatric CT: A rational approach," *Radiology* **228**, 352–360 (2003).

⁴M. J. Siegel, B. Schmidt, D. Bradley, C. Suess, and C. Hildebolt, "Radiation dose and image quality in pediatric CT: Effect of technical factors and phantom size and shape," *Radiology* **233**, 515–522 (2004).

⁵A. B. Sigal-Cinqualbre, R. Hennequin, H. T. Abada, X. Chen, and J.-F. Paul, "Low-kilovoltage multi-detector row chest CT in adults: Feasibility and effect on image quality and iodine dose," *Radiology* **231**, 169–174 (2004).

⁶Y. Funama, K. Awai, Y. Nakayama, K. Kakei, N. Nagasue, M. Shimamura, N. Sato, S. Sultana, S. Morishita, and Y. Yamashita, "Radiation dose reduction without degradation of low-contrast detectability at abdominal multi-section CT with a low-tube voltage technique: Phantom study," *Radiology* **237**, 905–910 (2005).

⁷B. Wintersperger, T. Jakobs, P. Herzog, S. Schaller, K. Nikolaou, C. Suess, C. Weber, M. Reiser, and C. Becker, "Aorto-iliac multidetector-row CT angiography with low kV settings: Improved vessel enhancement and simultaneous reduction of radiation dose," *Eur. Radiol.* **15**, 334–341 (2005).

⁸F. Holmquist and U. Nyman, "Eighty-peak kilovoltage 16-channel multidetector computed tomography and reduced contrast-medium doses tailored to body weight to diagnose pulmonary embolism in azotaemic patients," *Eur. Radiol.* **16**, 1165–1176 (2006).

⁹A. Waaijer, M. Prokop, B. K. Velthuis, C. J. G. Bakker, G. A. P. de Kort, and M. S. van Leeuwen, "Circle of Willis at CT angiography: Dose reduction and image quality—Reducing tube voltage and increasing tube current settings," *Radiology* **242**, 832–839 (2007).

¹⁰S. T. Schindera, R. C. Nelson, S. Mukundan, E. K. Paulson, T. A. Jaffe, C. M. Miller, D. M. DeLong, K. Kawaji, T. T. Yoshizumi, and E. Samei, "Hypervascular liver tumors: Low tube voltage, high tube current multi-detector row CT for enhanced detection: Phantom study," *Radiology* **246**, 125–132 (2008).

¹¹W. A. Kalender, P. Deak, M. Kellermeier, M. van Straten, and S. V. Vollmar, "Application- and patient size-dependent optimization of x-ray spectra for CT," *Med. Phys.* **36**, 993–1007 (2009).

¹²J. Reid, J. Gamberoni, F. Dong, and W. Davros, "Optimization of kVp and mAs for pediatric low-dose simulated abdominal CT: Is it best to base parameter selection on object circumference?," *Am. J. Roentgenol.* **195**, 1015–1020 (2010).

¹³L. Yu, H. Li, J. G. Fletcher, and C. H. McCollough, "Automatic selection of tube potential for radiation dose reduction in CT: A general strategy," *Med. Phys.* **37**, 234–243 (2010).

¹⁴E. Samei, S. Richard, and L. Lurwitz, "Model-based CT performance assessment and optimization for iodinated and noniodinated imaging tasks as a function of kVp and body size," *Med. Phys.* **41**, 081910 (8pp.) (2014).

¹⁵J. Thibault, K. Sauer, C. Bouman, and J. Hsieh, "A three-dimensional statistical approach to improved image quality for multislice helical CT," *Med. Phys.* **34**, 4526–4544 (2007).

- ¹⁶P. J. Pickhardt, M. G. Lubner, D. H. Kim, J. Tang, J. A. Ruma, A. M. del Rio, and G.-H. Chen, "Abdominal CT with model-based iterative reconstruction (MBIR): Initial results of a prospective trial comparing ultralow-dose with standard-dose imaging," *Am. J. Roentgenol.* **199**, 1266–1274 (2012).
- ¹⁷J. Nuyts, B. D. Man, J. A. Fessler, W. Zbijewski, and F. J. Beekman, "Modelling the physics in the iterative reconstruction for transmission computed tomography," *Phys. Med. Biol.* **58**, R63–R96 (2013).
- ¹⁸J. Solomon, A. Mileto, J. C. Ramirez-Giraldo, and E. Samei, "Diagnostic performance of an advanced modeled iterative reconstruction algorithm for low-contrast detectability with a third-generation dual-source multidetector CT scanner: Potential for radiation dose reduction in a multireader study," *Radiology* **275**, 735–745 (2015).
- ¹⁹S. Richard, D. B. Husarik, G. Yadava, S. N. Murphy, and E. Samei, "Towards task-based assessment of CT performance: System and object MTF across different reconstruction algorithms," *Med. Phys.* **39**, 4115–4122 (2012).
- ²⁰B. Chen, O. Christianson, J. M. Wilson, and E. Samei, "Assessment of volumetric noise and resolution performance for linear and nonlinear CT reconstruction methods," *Med. Phys.* **41**, 071909 (12pp.) (2014).
- ²¹B. Chen, J. C. Ramirez Giraldo, J. Solomon, and E. Samei, "Evaluating iterative reconstruction performance in computed tomography," *Med. Phys.* **41**, 121913 (11pp.) (2014).
- ²²K. Li, J. Garrett, Y. Ge, and G.-H. Chen, "Statistical model based iterative reconstruction (MBIR) in clinical CT systems. Part II. Experimental assessment of spatial resolution performance," *Med. Phys.* **41**, 071911 (12pp.) (2014).
- ²³J. G. Ott, F. Becce, P. Monnin, S. Schmidt, F. O. Bochud, and F. R. Verdun, "Update on the non-prewhitening model observer in computed tomography for the assessment of the adaptive statistical and model-based iterative reconstruction algorithms," *Phys. Med. Biol.* **59**, 4047–4064 (2014).
- ²⁴E. Samei and S. Richard, "Assessment of the dose reduction potential of a model-based iterative reconstruction algorithm using a task-based performance metrology," *Med. Phys.* **42**, 314–323 (2015).
- ²⁵B. Chen, S. Richard, and E. Samei, "Relevance of MTF and NPS in quantitative CT: Towards developing a predictable model of quantitative performance," *Proc. SPIE* **8313**, 83132O (2012).
- ²⁶J. B. Solomon, O. Christianson, and E. Samei, "Quantitative comparison of noise texture across CT scanners from different manufacturers," *Med. Phys.* **39**, 6048–6055 (2012).
- ²⁷J. Solomon and E. Samei, "Are uniform phantoms sufficient to characterize the performance of iterative reconstruction in CT?," *Proc. SPIE* **8668**, 86684M (2013).
- ²⁸J. Solomon and E. Samei, "Quantum noise properties of CT images with anatomical textured backgrounds across reconstruction algorithms: FBP and SAFIRE," *Med. Phys.* **41**, 091908 (12pp.) (2014).
- ²⁹K. Li, J. Tang, and G.-H. Chen, "Statistical model based iterative reconstruction (MBIR) in clinical CT systems: Experimental assessment of noise performance," *Med. Phys.* **41**, 041906 (15pp.) (2014).
- ³⁰T. L. Slovits, "Children, computed tomography radiation dose, and the as low as reasonably achievable (ALARA) concept," *Pediatrics* **112**, 971–972 (2003).
- ³¹A. Burgess, R. Wagner, R. Jennings, and H. Barlow, "Efficiency of human visual signal discrimination," *Science* **214**, 93–94 (1981).
- ³²M. Ishida, K. Doi, L. N. Loo, C. E. Metz, and J. L. Lehr, "Digital image processing: Effect on detectability of simulated low-contrast radiographic patterns," *Radiology* **150**, 569–575 (1984).
- ³³O. Christianson, J. J. S. Chen, Z. Yang, G. Saiprasad, A. Dima, J. J. Filliben, A. Peskin, C. Trimble, E. L. Siegel, and E. Samei, "An improved index of image quality for task-based performance of CT iterative reconstruction across three commercial implementations," *Radiology* **275**, 725–734 (2015).
- ³⁴A. E. Burgess, F. L. Jacobson, and P. F. Judy, "Human observer detection experiments with mammograms and power-law noise," *Med. Phys.* **28**, 419–437 (2001).
- ³⁵L. Yu, S. Leng, L. Chen, J. M. Kofler, R. E. Carter, and C. H. McCollough, "Prediction of human observer performance in a 2-alternative forced choice low-contrast detection task using channelized Hotelling observer: Impact of radiation dose and reconstruction algorithms," *Med. Phys.* **40**, 041908 (9pp.) (2013).
- ³⁶K. Li, J. Garrett, and G.-H. Chen, "Correlation between human observer performance and model observer performance in differential phase contrast CT," *Med. Phys.* **40**, 111905 (14pp.) (2013).
- ³⁷A. E. Burgess, X. Li, and C. K. Abbey, "Visual signal detectability with two noise components: Anomalous masking effects," *J. Opt. Soc. Am. A* **14**, 2420–2442 (1997).
- ³⁸P. G. J. Barten, *Contrast Sensitivity of the Human Eye and Its Effects on Image Quality* (SPIE, Bellingham, WA, 1999).
- ³⁹W. P. Shuman, D. E. Green, J. M. Busey, O. Kolokythas, L. M. Mitsumori, K. M. Koprowicz, J.-B. Thibault, J. Hsieh, A. M. Alessio, E. Choi, and P. E. Kinahan, "Model-based iterative reconstruction versus adaptive statistical iterative reconstruction and filtered back projection in liver 64-MDCT: Focal lesion detection, lesion conspicuity, and image noise," *Am. J. Roentgenol.* **200**, 1071–1076 (2013).
- ⁴⁰B. Y. Hur, J. M. Lee, I. Joo, M. H. Yu, J. H. Yoon, J. K. Han, and B. I. Choi, "Liver computed tomography with low tube voltage and model-based iterative reconstruction algorithm for hepatic vessel evaluation in living liver donor candidates," *J. Comput. Assisted Tomogr.* **38**, 367–375 (2014).
- ⁴¹W. P. Shuman, K. T. Chan, J. M. Busey, L. M. Mitsumori, E. Choi, K. M. Koprowicz, and K. M. Kanal, "Standard and reduced radiation dose liver CT images: Adaptive statistical iterative reconstruction versus model-based iterative reconstruction-comparison of findings and image quality," *Radiology* **273**, 793–800 (2014).
- ⁴²D. Husarik, H. Alkadhi, G. Puippe, C. Reiner, N. Chuck, F. Morsbach, Z. Szucs-Farkas, and S. Schindera, "Model-based iterative reconstruction for improvement of low-contrast detectability in liver CT at reduced radiation dose: Ex-vivo experience," *Clin. Radiol.* **70**, 366–372 (2015).
- ⁴³D. Marin, R. C. Nelson, S. T. Schindera, S. Richard, R. S. Youngblood, T. T. Yoshizumi, and E. Samei, "Low-tube-voltage, high-tube-current multidetector abdominal CT: Improved image quality and decreased radiation dose with adaptive statistical iterative reconstruction algorithm-initial clinical experience," *Radiology* **254**, 145–153 (2010).
- ⁴⁴Y. Zhang, S. Leng, L. Yu, R. E. Carter, and C. H. McCollough, "Correlation between human and model observer performance for discrimination task in CT," *Phys. Med. Biol.* **59**, 3389–3404 (2014).
- ⁴⁵I. Reiser and Z. Lu, "SU-E-I-46: Sample-size dependence of model observers for estimating low-contrast detection performance from CT images," *Med. Phys.* **41**, 140 (2014).