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Task-driven imaging in cone-beam computed tomography

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Abstract

Purpose—Conventional workflow in interventional imaging often ignores a wealth of prior information of the patient anatomy and the imaging task. This work introduces a task-driven imaging framework that utilizes such information to prospectively design acquisition and reconstruction techniques for cone-beam CT (CBCT) in a manner that maximizes task-based performance in subsequent imaging procedures.

Methods—The framework is employed in jointly optimizing tube current modulation, orbital tilt, and reconstruction parameters in filtered backprojection reconstruction for interventional imaging. Theoretical predictors of noise and resolution relates acquisition and reconstruction parameters to task-based detectability. Given a patient-specific prior image and specification of the imaging task, an optimization algorithm prospectively identifies the combination of imaging parameters that maximizes task-based detectability. Initial investigations were performed for a variety of imaging tasks in an elliptical phantom and an anthropomorphic head phantom.

Results—Optimization of tube current modulation and view-dependent reconstruction kernel was shown to have greatest benefits for a directional task (e.g., identification of device or tissue orientation). The task-driven approach yielded techniques in which the dose and sharp kernels were concentrated in views contributing the most to the signal power associated with the imaging task. For example, detectability of a line pair detection task was improved by at least three fold compared to conventional approaches. For radially symmetric tasks, the task-driven strategy yielded results similar to a minimum variance strategy in the absence of kernel modulation. Optimization of the orbital tilt successfully avoided highly attenuating structures that can confound the imaging task by introducing noise correlations masquerading at spatial frequencies of interest.

Conclusions—This work demonstrated the potential of a task-driven imaging framework to improve image quality and reduce dose beyond that achievable with conventional imaging approaches.

1. INTRODUCTION

Advances in image guidance technologies have played a considerable role in reducing invasiveness, enhancing precision in target localization, and improving patient outcome in a number of clinical fields.^{1–3} Cone-beam computed tomography (CBCT) guided procedures, in particular, have become prevalent in a wide range of clinical applications including surgery, interventional radiology, and radiotherapy.^{4–7} In such procedures, images from pre-operative planning CT and/or previous intraoperative scans are often available and can

provide valuable information on the patient-specific anatomy and the nature of the imaging task. In addition, modern image guidance systems such as robotic C-arms can leverage a combination of advanced acquisition and reconstruction techniques that are well suited to deliver patient- and task-specific imaging protocols. Conventional imaging approaches are often heuristic and use the prior information in a qualitative sense – e.g., specification of a “large” body habitus and “bone” or “soft tissue” reconstruction protocols. In comparison, an imaging paradigm that jointly optimizes imaging techniques with explicit consideration of the patient anatomy and the imaging task could improve performance and reduce dose.

In this work, we introduce a task-driven imaging framework that incorporates a patient-specific anatomical model, a mathematical specification of the imaging task, and noise and resolution characteristics of the imaging system to prospectively design acquisition and reconstruction techniques that maximizes task-based imaging performance for subsequent procedures. The framework is demonstrated in a joint optimization of tube current modulation and view-dependent reconstruction kernel in filtered-backprojection (FBP). It is also compatible with reconstruction by model-based reconstruction methods such as penalized likelihood (PL) estimation. The task-driven framework is compared with conventional approaches for imaging tasks with distinct spatial frequency characteristics in anthropomorphic phantoms.

2. THEORETICAL AND EXPERIMENTAL METHODS

2.1 Framework for Task-Driven Imaging

The proposed imaging workflow is illustrated in Fig.1. Task-based image quality is described in terms of the detectability index (d') and incorporated as the objective function in an optimization process that identifies a combination of acquisition and reconstruction parameters (denoted Ω_A and Ω_R , respectively) to drive subsequent imaging procedures. Detectability index is defined according to statistical decision theory in a manner that accounts for the imaging task via the hypothesis-testing task function, W_{Task} , as well as noise and resolution characteristics of the reconstructed image in terms of the noise-power spectrum (NPS, denoted S) and modulation transfer function (MTF, denoted T), respectively. For a non-prewhitening matched filter (NPW) observer model, the detectability is:

$$d'_{NPW}^2(\Omega_A, \Omega_R) = \frac{\left[\int \int \int T^2(\Omega_A, \Omega_R) W_{Task}^2 df_x df_y df_z \right]^2}{\int \int \int S(\Omega_A, \Omega_R) T^2(\Omega_A, \Omega_R) W_{Task}^2 df_x df_y df_z} \quad (1)$$

The theoretical predictor of noise and resolution establishes the mathematical relationship between d' and (Ω_A, Ω_R) under basic assumptions of local noise stationarity as well as linearity and shift-invariance.⁸ Such a predictor is capable of accurate prediction of local MTF and NPS for a broad range acquisition techniques (e.g., tube current and voltage), detector configurations (e.g., scintillator material and thickness), system geometry, reconstruction parameters (e.g., apodization kernel or regularization), and the spatial dependencies induced by patient anatomy.

2.2 Imaging Parameters

2.2.1. Tube current modulation—Conventional current modulation employs some form of automatic exposure control (AEC) to provide a constant signal level in a given region(s) of the detector (e.g., the center) or a heuristic sinusoidal modulation pattern associated with an oblate patient cross-section. Gies et al.⁹ introduced a scalar parameterization of the current modulation profile, α , which scales the mean fluence according to attenuation:

$$\frac{\bar{q}_0^i}{\bar{q}_0^j} = \frac{e^{\alpha l_i}}{e^{\alpha l_j}} \quad (2a)$$

where i and j denote projection indices, $\bar{q}_0^i$ is the mean fluence in the bare beam, and l_i is the line integral through the location of interest. Rewriting Eq. 2(a) in relation to the total bare beam fluence, $\bar{q}_0^{tot}$, the fluence of each projection is given by:

$$\bar{q}_0^i = \frac{e^{\alpha l_i}}{\sum_{j=1}^{N_{proj}} e^{\alpha l_j}} \sum_{j=1}^{N_{proj}} \bar{q}_0^j = \frac{e^{\alpha l_i}}{\sum_{j=1}^{N_{proj}} e^{\alpha l_j}} \bar{q}_0^{tot} \quad (2b)$$

Such parameterization yields the following exemplary current modulation strategies:

Strategy 1: Unmodulated Tube Current: The tube current is constant in all projection, corresponding to $\alpha = 0$.

Strategy 2: Conventional AEC: Enforcing constant fluence at the center of the detector is referred to here as “conventional AEC” (denoted AEC). In this work, the central ray was assumed to coincide with the center of the detector. The line integral is therefore computed for the isocenter and $\alpha = 1$.

Strategy 3: Location-Dependent AEC: If the location of the stimulus is known, a “location-dependent” AEC (denoted LocAEC) can be formulated by setting α to 1 and computing l through the specified location. Fluence is therefore constant along the ray that traverses the stimulus, reducing to conventional AEC if the stimulus is at isocenter. Such modulation could potentially be achieved using a variety of spatially varying collimators under development^{10–12}.

Strategy 4: Location-Dependent Minimum Variance: The tube current modulation corresponding to $\alpha = 0.5$ minimizes variance at the location through which l is calculated⁹. Similar to strategy 3 and denoted minVar, this case considers a location of interest but results in a minimum variance in the reconstruction.

The AEC, LocAEC, and minVar strategies summarized above yield modulation patterns that consider the patient attenuation and, for the latter two, the location of interest, but none consider the effect of spatial resolution or noise correlation with respect to the imaging task. Asymmetric tasks especially, may benefit from differential smoothing at each view. The following case thus considers all three factors from above:

Strategy 5: Task-Driven Current Modulation: As derived in Ref. 13, the tube current modulation that maximizes d' for a NPW observer model [Eq.(1)] is given by:

$$\frac{K_Q^i}{\left(\frac{-i}{q_0}\right)^2 e^{-l_i}} - \frac{K_Q^j}{\left(\frac{-j}{q_0}\right)^2 e^{-l_j}} + \frac{2K_E^i}{\left(\frac{-i}{q_0}\right)^3 e^{-2l_i}} - \frac{2K_E^j}{\left(\frac{-j}{q_0}\right)^3 e^{-2l_j}} = 0 \quad (3a)$$

where K is a view-dependent, but tube-current-independent constant that accounts for the imaging task as well as gains and blurs in the image formation processes (detection and reconstruction). Subscripts Q and E denote quantum and electronic noise, respectively. Equation 3(a) can be rewritten as a cubic equation relative to a fixed projection and fluence, e.g., the 1st projection ($i=1$) at the nominal fluence level, as the following cubic equation:

$$\left[\left(\frac{K_Q^1}{\left(\frac{-1}{q_0}\right)^2 e^{-l_1}} + \frac{2K_E^1}{\left(\frac{-1}{q_0}\right)^3 e^{-2l_1}} \right) e^{-2l_j} \right] \left(\frac{-j}{q_0} \right)^3 - \left(K_Q^j e^{-l_j} \right) \frac{-j}{q_0} - 2K_E^j = 0. \quad (3b)$$

The fluence for each projection can thus be obtained by solving Eq. 3(b). The total fluence can then be normalized to that given as the dose constraint. The cubic equation is solved by the `fminsearch` function in Matlab (2014a)

2.2.2. Orbital tilt—Many modern diagnostic CT scanners and interventional CBCT systems are capable of scanning with an orbital tilt (at an orbital tilt angle, φ) relative to the axial plane of the patient. For example, in head CT applications, scans are often performed along the canthomeatal line (corresponding to $\varphi \sim 10^\circ$ - 15°) to avoid the highly attenuating temporal/petrous bones and reduce exposure to the ocular lenses. In this work, the cranial-caudal tilt was optimized via the task-driven imaging framework in combination with tube current and reconstruction kernel modulation. Following the convention from Sec. 2.2.1., Strategies 1-4 correspond to a conventional orbit with $\varphi = 0^\circ$, while Strategy 5 adopts an orbital tilt from the task-driven optimization. Extension to non-circular source-detector orbits for model-based reconstruction methods has also been reported¹⁴ and is the subject of ongoing work.

2.2.3. View-dependent reconstruction kernel—The FBP algorithm commonly employs a constant reconstruction kernel for each view. However, the level of quantum noise varies in each view due to attenuation through the patient anatomy, and may be even more non-uniform after tube current modulation. For noisier views and/or views that have little contribution to the spatial frequencies associated with the imaging task, application of a smoother reconstruction kernel could reduce noise and benefit detectability. The task-driven framework presents a means by which a view-dependent reconstruction kernel can be identified that can result in improved task performance.

In this work, reconstruction kernel was varied through the ratio of the cutoff to the Nyquist frequency (denoted as f_0) in the apodization filter, T_{win} :

$$T_{win} = \begin{cases} h_{win} + (1 - h_{win}) \cos\left(\frac{2\pi \Delta u f_u}{f_0}\right) & f_u / f_{Nyq} \leq f_0 \\ 0 & f_u / f_{Nyq} > f_0 \end{cases}, \quad (4)$$

where u is the pixel size along the u -direction, f_u is the corresponding frequency axis, and f_{Nyq} denotes the Nyquist frequency. The parameter, h_{win} , is also frequently employed to vary the smoothness of the filter but was fixed to 0.5 in this work. Following the convention from Sec. 2.2.1., Strategies 1-4 correspond to reconstructions with constant kernel, while Strategy 5 adopts view-dependent kernel according to the task-driven optimization.

2.3. Joint optimization algorithm

The algorithm for joint optimization of tube current modulation, orbital tilt, and view-dependent reconstruction kernel is provided in Fig. 2. Tube current and kernel modulation profiles are denoted as $mAs(\theta)$ and $f_0(\theta)$, respectively, where θ denotes projection angle. The total number of projections was set to 360 for all experiments below. Both orbital tilt and reconstruction kernel were optimized at discrete levels: orbital tilt from -30° to $+30^\circ$ in 10° increments, and reconstruction kernel from 0.1 to 1.0 in 0.1 increments. Tube current was continuous as calculated from Eq. 3(b) and discretized to the nearest mAs station available on the x-ray tube ranging from 0.1 (generator limit) to 1.25 mAs (detector saturation).

A constraint on the imaging dose was specified in terms of the total mAs over all projections – in this work, a total of 90 mAs distributed over 360 projections, corresponding to 0.25 mAs per projection in an unmodulated scan. More sophisticated dose constraints, e.g., the total energy imparted or local dose deposition to sensitive organs, will be investigated in future work.

Optimal orbital tilt (φ^*) was identified through an exhaustive search that forms the outer loop of the algorithm. For each value of φ , an alternating optimization was employed for tube current and reconstruction kernel. Using an initial value of constant $mAs(\theta)$, an exhaustive search first identified the optimal kernel, $f_0^*(\theta)$, independently for each projection using d'_{proj} as the objective function [i.e., d' for the NPW model (Eq. 1) with MTF and NPS corresponding to a single backprojected projection]. Note that this differs from a multivariate optimization of the complete kernel profile in which d' is maximized for the 3D reconstruction. This technique was adopted as a computationally tractable approach that reduces the dimensionality of the problem. Next, using the $f_0^*(\theta)$ obtained from the previous step, $mAs^*(\theta)$ was calculated following Eq. (3b) as described in Sec. 2.B.1. Detectability index (Eq. 1) was then calculated using $mAs^*(\theta)$ and $f_0^*(\theta)$ for the current iteration. The algorithm iterates with the updated $mAs^*(\theta)$ until d'_{NPW} improves by less than 2% compared to the previous iteration. Finally, the optimal combination of $[\varphi^*, f_0^*(\theta), mAs^*(\theta)]$ was identified from the outer loop.

2.4. Experimental Methods

Images were acquired on an experimental CBCT imaging bench [Fig. 3(a)] with a PaxScan 4343CB flat-panel detector (Varian Medical Systems, Palo Alto CA) with a CsI:Tl scintillator, and 3052×3052 pixels at 0.194 mm pixel pitch operating in 2×2 binning mode.

System geometry was set to a source-to-detector distance (SDD) of ~120 cm and source-to-axis distance (SAD) of ~80 cm, approximating the geometry of a Zeego interventional C-arm (Siemens Healthcare, Forchheim Germany).

Investigation of tube current and kernel was performed for phantoms and imaging tasks illustrated in Fig. 3. The water-filled elliptical cylinder (major axis 24 cm, minor axis 16 cm) contained a 7.75 cm diameter acetal cylinder mimicking bone (~287 HU) and a 7.75 cm diameter polypropylene cylinder mimicking soft tissue (~122 HU). A variety of objects representing different stimuli or imaging tasks (spheres and line-pair patterns described below) were placed within the elliptical cylinder at 5 locations shown in Fig. 3(b). Imaging tasks investigated include: (1) A sphere detection task was based on a 3.2 mm diameter Teflon sphere, with the imaging task modeled simply as the Fourier transform of the sphere against a uniform background with contrast $\sim 0.164 \text{ mm}^{-1}$. The resulting task function primarily consists of low and middle spatial frequencies. (2) A line-pair detection task involved an idealized representation of a directional, mid-high frequency task, such as the visualization of fractures, surgical devices, etc. The imaging task was modeled as discrimination of the line-pair pattern from a uniform block with attenuation equal to the average of the two materials. The task function is therefore the Fourier transform of the difference between the line-pair square wave pattern and a constant, with the majority of signal power concentrated along the axis orthogonal to the line-pairs. The line-pair pattern was oriented along the lateral (the major axis) and AP (the minor axis) directions as shown in Fig. 3(b). The line pair stimulus in the ellipse phantom was based on a custom $10 \times 5 \times 10 \text{ mm}^3$, ~ 1 line pair/mm block of alternating 0.5 mm thick sheets of acetal and polypropylene as illustrated in Fig. 3(b).

Orbital tilt optimization was investigated in a simulation study based on a CT scan of an anthropomorphic head phantom [Fig. 3(c)] acquired at 120 kV, 350 mAs and reconstructed at isotropic voxel size 0.465 mm with a medium smooth U30u kernel (Siemens Healthcare, Forchheim Germany). A metal sphere (9.2 mm in diameter, $\mu = 0.33 \text{ mm}^{-1}$) simulating an embolization coil was digitally inserted posterior to the skull base. The imaging task was a spherical lesion detection task involving a 4 mm diameter sphere with contrast 0.0084 mm^{-1} to background (simulating an intracranial hemorrhage) inserted posterior to the coil. A monoenergetic 60 keV beam was simulated with a bare-beam fluence of 4.9×10^5 photons/ mm^2 at 1 mAs (approximating a 100 kV beam with 4 mm Al and 0.2 mm Cu added filtration). System geometry was the same as above. Projections were generated using a linear forward projector. Gantry tilt ranging from -30° to 30° about the lateral axis was achieved by an image transform specified with respect to the bench reference frame.

2.5. Image quality and dose

Image noise was computed as the standard deviation in voxel values in ROIs surrounding the stimulus. The measured noise was compared with theoretical predictions given by the square root of the integral under the predicted 3D NPS from the cascaded systems model. For purposes of comparing measured and predicted NPS, we limited analysis to the 2D NPS in axial slices, assuming noise to be stationary within the fairly small ($99 \times 99 \times 50$ voxels, $18 \times 18 \times 9 \text{ mm}^3$) volume of interest local to the stimulus. Detrended 2D ROIs [denoted

$ROI(x,y)]$ were computed from difference images between two axial slices sufficiently far apart (~ 1.8 mm) to assume uncorrelated noise. The 2D NPS was then calculated as the sample average of the square of the Fourier transform:

$$NPS(f_x, f_y) = \frac{1}{2} \frac{a_x a_y}{n_x n_y} \left\langle |FT\{\Delta ROI(x, y)\}|^2 \right\rangle \quad (5)$$

where n is the number of voxels along each direction of the ROI and a is the voxel size. The factor of two accounts for noise amplification from the subtraction. For comparison, the theoretical 2D slice NPS was calculated by integrating the 3D NPS from the cascaded systems model along the direction orthogonal to the slice (f_z for axial slices).

In addition to the 3D NPW observer, detectability index was calculated for a 2D non-prewhitening observer model with eye filter and internal noise (NPWEi), which has demonstrated reasonable agreement with human observers for simple imaging tasks^{17,18}:

$$d'_{NPWEI}^2 = \frac{\left[\iint E^2 (fT \cdot W_{Task} df_z)^2 df_x df_y \right]^2}{\iint \left(E^4 \int S df_z + N_i \right) \cdot (fT \cdot W_{Task} df_z)^2 df_x df_y} \quad (6a)$$

The eye filter, E , and internal noise, N_i , were based on previous work¹⁹: $E(f) = f \exp(-cf)$ and $N_i = \xi \left(\frac{D}{100} \right)^2 S_{eq}(0)$ where c was 2.2 mm^{-1} , the viewing distance, D was 50 cm, and the internal noise was modeled as a fraction of S_{eq} , a white noise NPS equivalent in total power to the NPS of the ROI in the reconstruction. The scaling factor, ξ , was set to 40.

Dose maps for the five imaging strategies were calculated by a Monte Carlo simulation with details presented in previous work^{20,21}.

III. RESULTS AND BREAKTHROUGH WORK

Figure 4 shows tube current (top row) and kernel (bottom row) modulation profiles for four example tasks and locations in the elliptical phantom. Each plot includes the five acquisition strategies introduced in Sec. 2.2.1. For Strategies 1-4, the kernel plot shows the c_0 value maximizing d'_{NPW} when the kernel is held constant from view to view. For Strategy 5, results shown were obtained from the alternating optimization (Fig. 2) with the orbital tilt fixed at 0° . The algorithm typically converges after 2~3 iterations.

For the rotationally symmetric sphere detection task [Fig. 4(a-b)], the task-driven tube current modulation was similar to the minVar Strategy, and the task-driven kernel profile was constant due to all views contributing equally to the task power [numerator in Eq. (1)]. Such results were also observed for other rotationally symmetric tasks (not shown). For the asymmetric tasks, both tube current and kernel solutions from the task-driven approach exhibited stronger view dependence. For example, the AP line-pair task [Fig. 4(c-d)] yielded a tube current modulation profile in which mAs increases sharply in views that better contribute signal power associated with the imaging task – in this case, along the AP and PA views. The optimal kernel modulation followed a similar trend, as did results for the same

task at a different location [Fig. 4(e-f)]. For the laterally oriented line-pair task [Fig. 4(g-h)], both the mAs and kernel modulation profiles were shifted by 90° , reflecting a corresponding shift in spatial frequencies of interest.

Figure 5 shows the image reconstructions associated with the mAs and kernel modulation profiles of Fig. 4 along with d' computed from the NPWEI observer. It is worth reiterating that d'_{NPW} was the objective function for optimization in the task-driven imaging strategy, and d'_{NPWEI} is shown simply as a complement to qualitative assessment of the images. For the sphere detection task at location 1, conventional AEC actually reduced detectability since it ignores the location of interest. The other modulation strategies yielded similar performance and showed a slight improvement in comparison to the unmodulated case. For the AP line-pair task at locations 1 and 3, a stronger enhancement in detectability was observed. At location #1, conventional AEC again degraded performance, and the strategies that consider location dependence offered an improvement; moreover, the task-driven imaging strategy gave a strong boost in detectability due to both current and kernel modulation. For the lateral line-pair task, the location-dependent strategies (LocAEC and minVar) again provided an improvement by allocating higher mAs in otherwise noisy views through the high density insert, and the joint optimization of both mAs and kernel in the task-driven approach offered still greater improvement.

Figure 6 further illustrates the effect of current and kernel modulation in terms of the noise and local NPS for the five acquisition strategies for the AP line-pair detection task at location 1. Each case compares measured and theoretical estimates of the local noise and NPS, which demonstrate good agreement consistent with previous work⁸. The unmodulated case exhibits a local noise level of $\sigma \sim 2.1 \times 10^{-3} \text{ mm}^{-1}$ and a local NPS that is governed by the attenuation of the object. For this task, conventional AEC results in a slight increase in local noise and NPS, since it modulates according to the attenuation along the central ray but not necessarily the location of interest, consistent with the reduction in detectability noted in Fig. 5. The LocAEC strategy results in a nearly isotropic local NPS as expected, with small discontinuities observed as a result of mAs discretization. The MinVar strategy minimizes image noise when kernel modulation is not present but does not consider the spatial frequency characteristics of the imaging task. The task-driven strategy reduces the local noise to $\sim 0.85 \times 10^{-3} \text{ mm}^{-1}$ by increasing tube current along the AP and PA views and applying smoother kernels to other views, thereby preserving task power [numerator in Eq. (1)] and decreasing overall noise – especially noise that masquerades as signal at spatial frequencies of interest. The results are confirmed in the more complex anthropomorphic context in the head phantom in Fig. 7. The oblique line-pair stimulus inserted posterior to the skull base results in analogous mAs and kernel modulation profiles as Figs. 4(c)-(h), with the task-driven imaging strategy allocating dose and modulating frequency response in a manner optimal to the imaging task.

Figure 7 shows the dose distribution for example tasks at various locations in the ellipse phantom. For the unmodulated strategy (the left column), dose maps in units of mGy are presented, whereas for the other 4 strategies, the dose ratio relative to the unmodulated case is presented to better illustrate fractional change in dose. The total energy deposited in the central slice of the phantom is indicated in μJ along with the total mAs after discretizing to

experimentally available levels (~ 90 mAs). The trend in d'_{NPWEI} across the five strategies corresponds fairly closely with the amount of dose deposited locally in each case. For example, the small sphere detection task in the ellipse phantom exhibits the lowest dose at location 1 for the AEC case, consistent with a d'_{NPWEI} value that is the lowest among the five strategies. The task-driven strategy for the PA line-pair detection tasks exhibit the highest local dose at the location of the stimulus among all five strategies (and correspondingly highest d' , but only a $\sim 4.9\%$ increase in total deposited energy). Interestingly, the task-driven case for the lateral line-pair detection task has approximately the same local dose as the other four strategies due to a slightly lower total mAs, but nonetheless exhibits strong improvement in d' .

Results from the joint optimization of orbital tilt, tube current and reconstruction kernel are shown in Fig. 8. The task-driven optimization identified an optimal orbital tilt at $\varphi = -20^\circ$, successfully avoiding the highly attenuating metal coil as well as maxillofacial anatomy. Detectability improves in each case for gantry tilts of $\sim -20^\circ$ (the canthomeatal line) and an opposing tilt at $+15^\circ$ (which appears to minimize attenuation from maxillofacial anatomy). Detectability suffers from increased attenuation for more extreme tilt angles. The associated tube current and kernel modulation profiles are similar to the sphere detection case in Fig. 4(a) but are not shown for brevity.

IV. DISCUSSION and CONCLUSION

This work presents a task-driven imaging framework that utilizes prior information of patient anatomy and the imaging task to prospectively design image acquisition and reconstruction processes that maximize task-based detectability. The framework was demonstrated in prescribing a combination of tube current modulation, source-detector orbital tilt, and view-dependent reconstruction kernel for specific tasks in interventional imaging. The task-driven approach yielded improvement in image quality compared to conventional techniques, especially for directional tasks.

Future work involves incorporating uncertainties in the input prior information. For example, deformation in patient anatomy from the prior scan will be resolved through an additional non-rigid registration step. Uncertainties in the imaging task (e.g., location, orientation) can potentially be incorporated in the objective function in terms of a signal-known statistically (SKS) or signal-known exactly but variable (SKEV) paradigm in statistical decision theory.²² In addition, the design of noncircular orbits and model-based reconstruction can be combined with optimization of view-dependent tube current and spatially varying image regularization.

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Figure. 1.

Task-driven imaging workflow that incorporates patient-specific prior image information and specification of the imaging task to prospectively design image acquisition and reconstruction techniques.

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Initialize  $mAs(\theta)$  with constant, nominal value;
FOR each orbital tilt angle  $\phi$ 
    % Alternating optimization of tube current and kernel
    WHILE  $d'_{NPW}[\phi, f_0^*(\theta), mAs^*(\theta)]$  improves by 2% compared to previous iteration
        % Exhaustive search of kernel for each projection
        FOR each projection,  $\theta$ 
            FOR each  $f_0$ 
                compute  $d'_{proj}(f_0, \theta)$  for current  $mAs(\theta)$ 
            ENDFOR
        ENDFOR
        update  $f_0^*(\theta) = \underset{f_0}{\operatorname{argmax}} d'_{proj}(f_0, \theta)$ 
        update  $mAs^*(\theta)$  for current  $f_0^*(\theta)$  according to Eq.(3b) and normalize to dose constraint
        compute  $d'_{NPW}[\phi, f_0^*(\theta), mAs^*(\theta)]$  for current iteration
    ENDWHILE
ENDFOR
RETURN  $[\phi^*, f_0^*(\theta), mAs^*(\theta)] = \underset{\phi, f_0, mAs}{\operatorname{argmax}} d'_{NPW}[\phi, f_0^*(\theta), mAs^*(\theta)]$ 

```

Figure 2.

Pseudo-code representation of the task-driven joint optimization of orbital tilt (outer loop), view-dependent reconstruction kernel, and tube current modulation.

Figure 3.

Experimental methods. (a) Imaging bench for CBCT. (b) Elliptical phantom and five locations at which stimuli (sphere or line-pair patterns) were placed. (c) Digital head phantom for investigation of orbital tilt.

Figure 4.

Tube current and reconstruction kernel modulation profiles for four example imaging tasks. Results for all five acquisition strategies are superimposed as described by the legend. The top row shows tube current modulation profiles computed from Eqs. (2) and (3), with tick marks on the vertical axis corresponding to the twelve discrete mAs levels available in the physical experiments.

Figure 5.

Reconstruction of example tasks in the ellipse phantom under the five strategies in Fig.4.

The task-driven strategy outperforms the other four in all cases, with the greatest improvement observed for the line pair tasks.

Figure 6.

Local noise and NPS for the five modulation strategies. Examples are shown for the AP line-pair detection task in Location 1 of Fig. 3. The task-driven imaging strategy reduces the local noise and concentrates the local noise-power spectral density in a manner that mismatches noise correlations from the spatial frequencies of interest.

Figure 7.

Dose maps associated with the five modulation strategies and various imaging tasks. The left column shows the dose map (units mGy) for the unmodulated case, whereas the other columns show the ratio of the dose map for each modulation strategy normalized by that of the unmodulated case. The total energy deposited in the central axial slice (units μ J) and the total mAs are also shown.

Figure 8.

Axial and sagittal reconstruction of an unmodulated acquisition at $\varphi=0^\circ$ compared to a task-driven image reconstruction at $\varphi=-20^\circ$.