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Task-Driven Tube Current Modulation and Regularization Design in Computed Tomography with Penalized-Likelihood Reconstruction

G. J. Gang, J. H. Siewerdsen, and J. W. Stayman

Department of Biomedical Engineering, Johns Hopkins University, Baltimore MD, USA 21205

Abstract

Purpose—This work applies task-driven optimization to design CT tube current modulation and directional regularization in penalized-likelihood (PL) reconstruction. The relative performance of modulation schemes commonly adopted for filtered-backprojection (FBP) reconstruction were also evaluated for PL in comparison.

Methods—We adopt a task-driven imaging framework that utilizes a patient-specific anatomical model and information of the imaging task to optimize imaging performance in terms of detectability index (d'). This framework leverages a theoretical model based on implicit function theorem and Fourier approximations to predict local spatial resolution and noise characteristics of PL reconstruction as a function of the imaging parameters to be optimized. Tube current modulation was parameterized as a linear combination of Gaussian basis functions, and regularization was based on the design of (directional) pairwise penalty weights for the 8 in-plane neighboring voxels. Detectability was optimized using a covariance matrix adaptation evolutionary strategy algorithm. Task-driven designs were compared to conventional tube current modulation strategies for a Gaussian detection task in an abdomen phantom.

Results—The task-driven design yielded the best performance, improving d' by ~20% over an unmodulated acquisition. Contrary to FBP, PL reconstruction using automatic exposure control and modulation based on minimum variance (in FBP) performed worse than the unmodulated case, decreasing d' by 16% and 9%, respectively.

Conclusions—This work shows that conventional tube current modulation schemes suitable for FBP can be suboptimal for PL reconstruction. Thus, the proposed task-driven optimization provides additional opportunities for improved imaging performance and dose reduction beyond that achievable with conventional acquisition and reconstruction.

I. INTRODUCTION

Recent years have seen rapid development and adoption of model-based iterative reconstruction (MBIR) algorithms which have shown promise in reducing CT radiation exposures and improving image quality compared to filtered-backprojection (FBP) reconstructions. Such algorithms are typically nonlinear and present distinct noise and resolution tradeoffs from FBP, posing significant challenges to their assessment and optimization. In particular, it is unclear whether conventional acquisition strategies (e.g., tube current modulation) developed with FBP in mind are optimal for MBIR methods.

Task-based optimization has found applications in the design of various imaging systems¹ to find the hardware configurations and software strategies that maximize imaging performance. Task-driven imaging has also been proposed where imaging parameters are prospectively selected based on prior knowledge of the imaging task and patient anatomy. Prior work has considered prospective design of tube current modulation and view-dependent reconstruction kernel in FBP reconstruction,² as well as orbital trajectories in robotic C-arm-based cone-beam CT for interventional imaging.³ This work investigates the utility of task-driven optimization in diagnostic CT using MBIR presuming anatomical information is available (e.g. through a very low exposure 3D scout). Specifically, we investigate a joint optimization of tube current modulation and MBIR regularization design. The significance of such investigation is twofold: 1) to assess whether acquisition schemes commonly adopted for FBP (e.g., automatic exposure control, AEC) are optimal for MBIR; and 2) to present a general methodology for MBIR algorithm optimization that is consistent with task-based definition of image quality.

II. THEORETICAL AND EXPERIMENTAL METHODS

A. Task-Driven Imaging for Model Based Iterative Reconstruction

An overview of the task-driven framework is presented in Figure 1. The framework relies on the definition of a patient-specific anatomical model as well as the specification of the location, contrast, and spatial frequencies of the imaging task. For investigations in this work, we presume a patient-specific anatomical model is available and we choose a specific task function. We identify a set of acquisition parameters (Ω_A) and reconstruction parameters (Ω_R) of interest to be optimized and use detectability index as the objective function. We adopt a specific form for detectability index based on a non-prewhitening observer model, given by:

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

where the imaging task is represented by the task function, W_{Task} . For detection tasks considered in this work, W_{Task} corresponds to the Fourier transform of the stimulus to be detected. The functional relationship between d' and (Ω_A, Ω_R) is established through the noise (in terms of the noise power spectrum or NPS, denoted S) and resolution (in terms of the modulation transfer function or MTF, denoted T) characteristics of the reconstructed image which can be accurately predicted by a system model.

We choose to focus on a specific class of MBIR methods based on a penalized-likelihood (PL) objective with a quadratic penalty. The PL reconstruction seeks a reconstruction, $\hat{\mu}$, such that:

$$\hat{\mu} = \underset{\mu}{\operatorname{argmax}} [\log L(\mu; y) - \beta R(\mu)] \quad (2)$$

where $L(\mu, y)$ denotes a likelihood term and $R(\mu)$ is a quadratic roughness penalty whose strength is controlled by the regularization parameter, β . We presume the measurements, y ,

to be Poisson distributed and independent, and have means given by the following forward model:

$$\bar{y} = I_0 e^{-\mathbf{A}\mu} \quad (3)$$

where I_0 is the number of unattenuated photons per detector pixel and $\mathbf{A}$ is the forward projection operator. The quadratic regularization term, $R(\mu)$, penalizes pairwise differences between neighboring voxels such that

$$R(\mu) = \sum_j \frac{1}{2} \sum_k w_{jk} \frac{(\mu_j - \mu_k)^2}{2} \quad (4)$$

where w_{jk} denotes a weighting term associated with a specific voxel pair. Quadratically penalized PL reconstruction is an excellent choice for task-driven MBIR since predictors for spatial resolution and noise prediction were derived in Refs ⁴ and ⁵ using the implicit function theorem and Fourier approximation for fast computation:

$$T_j \approx \frac{\mathcal{F} \left\{ \mathbf{A}^T D \{ \bar{y}(\mu) \} \mathbf{A} e_j \right\}}{\mathcal{F} \left\{ \mathbf{A}^T D \{ \bar{y}(\mu) \} \mathbf{A} e_j + \beta \mathbf{R} e_j \right\}} \quad (5a)$$

$$S_j \approx \frac{\mathcal{F} \left\{ \mathbf{A}^T D \{ \bar{y}(\mu) \} \mathbf{A} e_j \right\}}{|\mathcal{F} \left\{ \mathbf{A}^T D \{ \bar{y}(\mu) \} \mathbf{A} e_j + \beta \mathbf{R} e_j \right\}|^2} \quad (5b)$$

where T_j and S_j are the local MTF and NPS at voxel location j . The e_j term denotes the j th unit vector, $D\{\cdot\}$ is an operator that puts its vector argument on a diagonal matrix, and $\mathbf{R}$ represents the Hessian of the quadratic penalty. Note that both of these expressions are related to important design parameters - tube current modulation through the forward model in the diagonal weighting, $D\{\bar{y}(\mu)\}$, and regularization design through the Hessian term, $\mathbf{R}$.

B. Imaging Parameters and Optimization Algorithm

For optimization we sought a relatively low-dimensional parameterization of the acquisition. Specifically, tube current modulation was parameterized as a linear combination of Gaussian basis function illustrated in Fig.2. Under an assumption of circular trajectory and parallel beams, views 180° apart are redundant and assigned the same fluence to further reduce the dimensionality of the optimization. This constraint will be relaxed in future work to allow for divergent beam and helical geometries. The total barebeam fluence is constrained to 9.0×10^5 photons per detector pixel (10^3 photons per pixel per mAs with a nominal constant mAs of 0.25).

We also chose to optimize the regularization design through a modification of the directional weights, w_{jk} , in Eq.(4). For conventional in-plane regularization involving 8 neighboring voxels, w_{jk} is 1 for horizontal and vertical neighbors and $\frac{1}{\sqrt{2}}$ for diagonal neighbors as illustrated in Fig 3. The four neighboring pixels (seemingly without penalties) are penalized with symmetric weights. The kernel in Fig. 3 is applied to all image locations.

For a directionally optimized penalty we allow each w_{jk} to vary freely, permitting control of anisotropy in local spatial resolution and noise. Note that the regularization strength β affects spatial resolution and noise characteristics as well but is kept constant in this work. Task-based optimization of β has been investigated in previous work⁶ and will be integrated with w_{jk} design in the future. More general design with a location dependent kernel⁵ will be investigated as well.

The coefficients for tube current modulation and the regularization weights were optimized using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES)⁷ algorithm which is suitable for nonlinear, nonconvex problems.

C. Experimental Methods

The optimization results were demonstrated in simulation studies involving a cadaver abdomen illustrated in Fig.4. The anatomical model was obtained from a diagnostic CT scan acquired at 120kV and reconstructed at $\sim 0.87 \times 0.87 \times 3$ mm voxel size. The CT image was interpolated linearly to have isotropic voxel size $\sim 0.87 \times 0.87 \times 0.87$ mm. The system geometry was set to SAD=80.0 cm and SDD=120.0 cm. The pixel pitch was simulated at 1.3×1.3 mm. The imaging task was the detection of a Gaussian stimulus of 3.0 mm width at 0.025 mm^{-1} contrast relative to the soft tissue background. Penalized-likelihood reconstruction was performed using paraboloidal surrogate updates and ordered-subset subiterations.

Based on the imaging parameters in Sec.II.B., four imaging strategies were applied to PL reconstruction and evaluated in this work. For all strategies, dose is constrained by the total bare beam fluence.

Strategy 1: Unmodulated—Tube current is constant for all projections. Regularization follows the conventional weighting scheme shown in Fig.3.

Strategy 2: Automatic exposure control (denoted as AEC)—Conventional tube current modulation commonly employs AEC circuitry to achieve uniform fluence at the center of the detector. Following parameterization by Gies et al,⁸ the AEC tube current modulation profile is given by:

$$\bar{I}_0^i = \frac{e^{\alpha I_i}}{\sum_{j=1}^{N_{proj}} e^{\alpha I_j}} \sum_{j=1}^{N_{proj}} \bar{I}_0^j = \frac{e^{\alpha I_i}}{\sum_{j=1}^{N_{proj}} e^{\alpha I_j}} \bar{I}_0^{tot} \quad (6)$$

with $\alpha = 1$ and I_i corresponding to the line integral through the isocenter for the i -th projection. Regularization follows conventional weighting scheme.

Strategy 3: Minimum Variance for FBP (denoted as MinVarFBP)—Gies et al. showed that the tube current modulation that yields in minimum variance at a location in FBP reconstruction is given by Eq.(6) when $\alpha = 0.5$ and I_i corresponds to the line integral through the location of interest. Conventional regularization is applied.

Strategy 4: Task-Driven—Tube current modulation profile and directional regularization are obtained from the task-driven optimization described in Sec.II.A and B.

III. RESULTS AND BREAKTHROUGH WORK

Acquisition and reconstruction parameters for the four strategies are shown in Fig. 5. Regularization for strategies 1-3 follows the conventional weighting scheme shown in Fig. 3 and are not shown for brevity. To achieve uniform fluence at the center of the detector, the AEC strategy assigns the highest fluence along the highly attenuating later view across the abdomen ($\sim 90^\circ$ and 270°). The MinVarFBP profile follows a similar trend as AEC but is less aggressive in comparison. Interestingly, the task-driven strategy yields a modulation profile that is the opposite – assigning the highest fluence to the less attenuating anterior-posterior views. The regularization design (presented in base 10 exponents) heavily penalizes the vertical neighbors (higher w_{ij} compared to conventional weighting scheme in Fig. 3), while enhancing other directions (lower w_{ij} compared to conventional weighting scheme in Fig. 3). The local MTF and NPS at the location of the stimulus are shown in Fig 6 for the four strategies. The unmodulated case shows the intrinsic anisotropy in noise and resolution as a result of the different statistical weightings in each view. Noisy data are penalized more heavily in quadratic PL, resulting in the MTF and NPS having almost complementary shapes. The AEC strategy almost equalizes fluence at the detector behind the stimulus in each view, resulting in nearly isotropic MTF and NPS. The trend for the MinVar case can be explained similarly. The task-driven strategy further enhances spatial resolution along the f_x direction through a combination of high fluence and low regularization, thus resulting in more high frequency, low noise content around the f_x axis which boosts d' .

Example reconstructions are shown in Fig.7 as axial and coronal ROIs centered around the Gaussian stimulus. The d' and variance, σ^2 , relative to the unmodulated case, d'_{rel} and σ_{rel}^2 are presented. Both the AEC and MinVar case performed worse compared to the unmodulated cases, demonstrating that tube current modulation designed for FBP reconstruction may be suboptimal for PL reconstruction. It is also interesting to note that the tube current modulation that results in minimum variance in FBP reconstruction does not necessarily minimize variance in PL reconstruction. The stimulus in the task-driven reconstruction is the most conspicuous, with a corresponding $\sim 20\%$ improvement in d' compared to the unmodulated case.

IV. DISCUSSION and CONCLUSION

We presented a task-driven imaging framework that prospectively designs tube current modulation and regularization parameters that maximize detectability index for specific imaging tasks in PL reconstruction. The task-driven approach outperforms tube current modulation schemes commonly adopted for FBP reconstruction. It was found that AEC and the minimum variance approach proposed for FBP in fact performs worse than the unmodulated case for PL reconstruction, calling for the need to further assess such strategies for a wider range of imaging tasks, phantoms, and other model-based reconstruction algorithms. The task-driven approach suggested an optimal tube current modulation pattern that is different from either, which, in combination with directional penalty design, improves

detectability. Future work will extend the local design approach to a global optimization at multiple locations within the object, including additional strategies of fluence field modulation and location-dependent penalty designs.

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Fig.1.

Task-driven imaging framework. A patient specific pre-operative CT provides the anatomical model and information of the imaging task. Detectability index is then used as the objective function to optimize imaging parameters for subsequent procedures.

Fig.2.

Polar plots of the Gaussian basis functions used for tube current modulation. The radial axis represents mAs per frame. Views 180° apart are assigned the same weights in our investigations of a 360° circular scan.

Fig.3.

Conventional regularization weighting scheme with $w_{ij}=1$ for horizontal and vertical pairwise neighbors, and $\frac{1}{\sqrt{2}}$ for diagonal pairwise neighbors

Fig.4.
 (a) Anthropomorphic abdomen phantom and (b) a Gaussian stimulus with (c) the associated task function.

Fig.5.

Tube current modulation profiles and regularization design for the four imaging strategies.

The task-driven approach yields a modulation pattern that is the opposite of conventional approaches designed according to FBP noise and resolution characteristics.

Fig.6.
The MTF and NPS at the location of the stimulus for the four imaging strategies.

Fig.7.

Example image reconstructions and the relative detectability index and variance for the four imaging strategies. The task-driven approach outperforms all other strategies.