Published in final edited form as:

Proc SPIE Int Soc Opt Eng. 2018 February ; 10573: . doi:10.1117/12.2294950.

Joint Optimization of Fluence Field Modulation and Regularization for Multi-Task Objectives

Grace J. Gang and J. Webster Stayman

Department of Biomedical Engineering, Johns Hopkins University, Baltimore, Maryland, U.S.A

Abstract

This work investigates task-driven optimization of fluence field modulation (FFM) and regularization for model-based iterative reconstruction (MBIR) when different imaging tasks are presented by different organs. Example applications of the design framework were demonstrated in an abdomen phantom where the task of interest in the liver is a low-contrast, low-frequency detection task while that in the kidney is a high-contrast, high-frequency discrimination task. The global performance objective is based on maximizing local detectability index (d') at a discrete set of locations. Two objective functions were formulated based on different imaging needs: 1) a maxi-min objective where all tasks are equally important, and 2) a region-of-interest (ROI) objective to maximize imaging performance in an ROI while maintaining a minimum level of performance elsewhere. The FFM pattern for the maxi-min objective is determined by the most challenging task in the liver where both angular and spatial modulation resulted in a ~35% improvement in d' compared to an unmodulated case. The FFM for the ROI objective prescribes the most fluence to the organs of interest, boosting d' by ~59%, but manages to achieve the minimum d' target elsewhere. A spatially varying regularization was found to be important when tasks of different frequency content are present in different parts of the image - the optimal regularization strength for the two studied tasks differed by two orders of magnitude. Initial investigations in this work demonstrated that a multi-task objective is potentially important in shaping the optimal FFM and MBIR regularization, and that these tools may help to generalize task-based acquisition and reconstruction design for more complex diagnostic scenarios.

1. INTRODUCTION

Dynamic FFM has garnered significant research interest due to its ability to accommodate different patient habitus and robustness against patient mis-centering. Various hardware solutions¹⁻³ have demonstrated potential for achieving FFM on diagnostic CT scanners. What FFM patterns should be delivered, however, remains an open question. Options include strategies that minimize the mean variance⁴ or peak variance⁵ in filtered-backprojection reconstructions. However, CT image quality assessment has been moving toward more sophisticated metrics that use human observer models to quantify task-based performance. Similarly, MBIR methods are increasingly being adopted for clinical scanners. Previous work⁶ investigated FFM designs and MBIR data processing driven by task-based image quality metrics and found that the FFM optimal for MBIR can be significantly different from those proposed for FBP reconstruction, suggesting an important coupling between the optimization of acquisition and reconstruction. Moreover, the flexibility of MBIR regularization (e.g. in a space-variant fashion) provides a potentially large space of

reconstruction parameters that can be simultaneously optimized with the FFM pattern to achieve the best performance.

A major limitation of the previous work is the assumption of a single imaging task throughout the image. It is more clinically realistic that there are multiple tasks of interest and different organs may present different imaging tasks. Depending on the clinical need, the different task functions may also impact task-driven designs of FFM in different ways. Thus, this work presents an initial investigation of the incorporation of multi-task objectives in the design framework and studies the effect on FFM and regularization design.

2. METHODS

2.1 Multi-Task Multi-Location Objective Function

For a single binary decision task, performance can be quantified by its detectability index (d'), which is, in turn, related to the area-under-curve (AUC) of the receiver-operator characteristics (ROC) curve. For a general clinical scenario, there may be an unknown number of lesions of different types appearing at multiple locations in the image. While existing analysis methods (e.g., the alternative free response ROC) may be extended to describe such cases, computing such a figure of merit is computationally intensive and poorly suited for optimization purposes. In this work, we optimize the local imaging performance in a number of locations (j), which can be quantified by a convenient analytical form of d' , given by:

$$d_j^2(\Omega_A, \Omega_R) = \frac{[\int \int \int W_{Task_j}^2 T_j^2(\Omega_A, \Omega_R) df_x df_y df_z]^2}{\int \int \int S_j(\Omega_A, \Omega_R) T_j^2(\Omega_A, \Omega_R) W_{Task_j}^2 df_x df_y df_z}. \quad (1)$$

The local modulation transfer function (MTF) and local noise power spectrum (NPS) are denoted by T_j and S_j , respectively, with the subscript j indicating location dependence. The task function is represented by W_{Task_j} , which may also vary from location to location. The global imaging performance can thus be formulated according to the imaging needs. Example scenarios integrating this performance measure into multi-task and multi-location designs are detailed and investigated below.

2.1.1 Imaging Task and Phantom—Example applications of multi-task optimization is demonstrated in an abdomen phantom shown in Fig.1. From an anatomical model (e.g., derived from a low-dose 3D scout image⁷), we extract two organ masks - one for the liver and spleen, and one for the left and right kidneys. We investigate a simplified case where the imaging task of interest in the liver and spleen is the detection of a low-contrast, hypo-dense spherical lesion, and the imaging task in the kidney is a high-contrast discrimination task to differentiate a cluster of kidney stones from a larger monolithic stone. The orientation of the cluster is allowed to vary, i.e., the local performance metric may account for signal variability. Rather than performing d' calculations over every point in the two regions, evaluations were performed at a subset of discrete locations as illustrated by the uniform placement of stimuli within each mask in the phantom image in Fig.1.

2.1.2 Maximizing minimum d' (Maxi-min Objective)—One possible formulation of the image quality objective is for all tasks to seek a acquisition and reconstruction solution where all tasks are performed at a minimum level performance. Or alternatively, under a fixed dose budget, find a solution that maximizes the minimum performance for all tasks in the image. The objective function thus follows the following maxi-min form:

$$\arg \max_{\Omega} \min_{\vec{v}} d'_j(\vec{v}; \Omega) \quad (2)$$

where $\vec{v}$ denotes the set of discrete sample locations, and Ω denotes the imaging parameters to be optimized.

2.1.3 Maximizing d' in an organ of interest while maintaining min d' elsewhere (ROI Objective)—Consider the following alternate design objective: If there is a particular organ of interest, one may want to maximize performance in that organ while maintaining a minimum level of image quality elsewhere. Towards this end, we formulate an objective function that follows the maxi-min formulation in the region of interest (region 1 – the region of interest, ROI), and impose a penalty when the d' in region 2 (elsewhere) is less than a minimum level. Furthermore, to maximize d' in the region of interest, we encourage the d' in region 2 to be at by imposing another penalty with a smaller weight. The ROI objective function is therefore:

$$\arg \max_{\Omega} \left\{ \min_{\vec{v}_1} d'^2(\vec{v}_1; \Omega) - w_m * \sum [d'_{< d'_{min}}(\vec{v}_2; \Omega) - d'_{min}]^2 - w_f * \sum [d'_{> d'_{min}}(\vec{v}_2; \Omega) - d'_{min}]^2 \right\} \quad (3)$$

where w_m is the penalty weight for d' less than the minimum level (d_{min}) and is set to 1, w_f is the weight for flatness and is set to 0.15. In this work, we maximize d' in the kidneys while assigning a minimum level of d' in the liver that is equivalent to the minimum d' under a constant/unmodulated fluence pattern.

2.2 Task-Driven Optimization of Acquisition and Reconstruction

The MBIR method investigated in this work is quadratic penalized-likelihood reconstruction, which is written:

$$\hat{\mu} = \arg \max_{\mu} [\log L(\mu, y) - \frac{1}{2} \mu^T \mathbf{C}^T \mathbf{D} \{\beta\} \mathbf{C} \mu] \quad (4)$$

where the volume μ is reconstructed from measurements y , and L denotes the likelihood function and C is a pairwise voxel difference operator. Regularization strength is given by a vector β , whose element β_j are allowed to vary as a function of location and constitute the reconstruction parameters to be jointly optimized with FFM. The local MTF and NPS for

images reconstructed with (4) can be efficiently predicted using Fourier and analytical approximations in Refs.^{8,9} which follows:

$$T_j \approx \frac{|\mathcal{F}\{\mathbf{A}^T \mathbf{W} \mathbf{A} e_j\}|}{|\mathcal{F}\{\mathbf{A}^T \mathbf{W} \mathbf{A} e_j\} + \mathcal{F}\{\mathbf{C}^T \mathbf{D}\{\beta\} \mathbf{C} e_j\}|} \text{ and } S_j \approx \frac{|\mathcal{F}\{\mathbf{A}^T \mathbf{W} \mathbf{A} e_j\}|}{|\mathcal{F}\{\mathbf{A}^T \mathbf{W} \mathbf{A} e_j\} + \mathcal{F}\{\mathbf{C}^T \mathbf{D}\{\beta\} \mathbf{C} e_j\}|^2} \quad (5)$$

The diagonal weighting matrix $\mathbf{W} = \mathbf{D}\{y\}$ models the variance of fluence modulated data.

Allowable FFM patterns spans the sinogram domain, (u, θ) , where u denotes horizontal detector elements, and θ denotes projection angles. To reduce the dimensionality of the optimization, we parameterized FFM as a linear combination of local 2D Gaussian basis functions (Fig.2) capable of producing a versatile class of modulation patterns. In addition, a constant plane (not shown) is also added in order to include a "no modulation" case in the search space. A dose constraint is imposed such that the total barebeam fluence incident on the phantom sums up to a fixed value. Thus the design space (Ω) for acquisition and reconstruction parameters includes the coefficients of these bases and the vector of regularization parameters, β .

To jointly optimize FFM and regularization, we adopted an alternating optimization approach. The fluence of each ray affects image quality in multiple locations, while β_j only affects performance locally. Thus, the coefficient vector for FFM is optimized using a covariance matrix adaptation evolution strategy (CMA-ES) optimizer following the objective function in 2.1, while each local β_j is identified through an exhaustive search to maximize local d' . One may also use such methods to optimize regularization alone for any given FFM pattern.

3. RESULTS

As a reference, the d' map, $d'(x, y)$, for a constant fluence (unmodulated) is shown in Fig. 3(a). A constant β was chosen to maximize the minimum d' in the liver (minimum at yellow cross). The magnitude of d' decreases from the edge to the center. The d' from a β only optimization is shown in Fig.3(b) together with the optimal β map. The d' is much higher in the kidney due to lower local β_j values suited for the high frequency task.

Optimization results using the maxi-min objective function are shown in Fig.4. The FFM pattern is driven by performance requirements of the more challenging task in the liver (where the lower d' is always found), and the angular modulation pattern prescribes higher fluence to the less attenuating anteroposterior views, consistent with findings in previous work.^{6, 10} The d' in the liver is flatter compared to the unmodulated case and the minimum d' is improved by ~35%. The β map reflects similar trends as Fig.3 where the optimal values in the kidney is much lower compared to those in the liver.

Results for the ROI objective are shown in Fig.5. The angular fluence modulation pattern still mirrors that of the maxi-min objective, but the fluence distribution along detector elements are bi-modal and closely follow the sinogram locations of two kidneys (overlaid as

a magenta mask). As a result, the d' values in the kidneys are significantly increased. The minimum d' is kept the same as that in the unmodulated case in Fig.3. The difference in β between the kidney and liver is even greater than in the maxi-min example.

4. DISCUSSION AND CONCLUSION

This work explored two example multi-task objectives that drive FFM and regularization designs based on different clinical needs. For the maxi-min objective, we found that FFM designs were dictated by the more difficult task (that with lower d' values). Alternately, the ROI objective permits improvements in regional detectability while maintaining a minimum performance level elsewhere. For future work, we will examine additional multi-task scenarios, and evaluate image quality in simulated reconstructions. While these initial studies have only begun to probe multi-task design for FFM and MBIR regularization, the maxi-min and ROI objectives are potentially important tools in optimizing performance for a wider range of clinical diagnostic tasks.

Acknowledgments

This research is supported in part by NIH Grant U01EB018758.

References

1. Hsieh SS, Pelc NJ. The feasibility of a piecewise-linear dynamic bowtie filter. *Medical physics*. 2013; 40(3):31910.
2. Stayman J, Mathews A, Zbijewski W, Gang G, Siewerdsen J, Kawamoto S, Blevis I, Levinson R. Fluence-field modulated x-ray CT using multiple aperture devices. *Proc SPIE*. 2016; 9783
3. Szczykutowicz TP, Mistretta CA. Experimental realization of fluence field modulated CT using digital beam attenuation. *Physics in medicine and biology*. 2014; 59(5):1305. [PubMed: 24556823]
4. Harpen MD. A simple theorem relating noise and patient dose in computed tomography. *Medical Physics*. 1999; 26(11):2231. [PubMed: 10587203]
5. Hsieh SS, Pelc NJ. Algorithms for optimizing CT fluence control. *Proc SPIE*. 2014:90330M–90330M.
6. Gang GJ, Siewerdsen JH, Stayman JW. Joint Optimization of Fluence Field Modulation and Regularization in Task-Driven Computed Tomography. *Proc SPIE*. 2017:101320E–101320E.
7. Gomes J, Gang G, Mathews A, Stayman J. An investigation of low-dose 3D scout scans for computed tomography. *Proc SPIE*. 2017; 10132
8. Fessler J, Rogers W. Spatial resolution properties of penalized-likelihood image reconstruction: space-invariant tomographs. *IEEE Transactions on Image Processing*. 1996; 5(9):1346–1358. [PubMed: 18285223]
9. Schmitt, SM., Fessler, JA. Fast variance computation for quadratically penalized iterative reconstruction of 3D axial CT images; 2012 IEEE Nuclear Science Symposium and Medical Imaging Conference Record (NSS/MIC); 2012. p. 3287–3292.
10. Gang GJ, Siewerdsen JH, Stayman JW. Task-Driven Optimization of Fluence Field and Regularization for Model-Based Iterative Reconstruction in Computed Tomography. *IEEE Transactions on Medical Imaging*. 2017; 36(12):2424–2435. [PubMed: 29035215]

Phantom with Multiple Tasks

Imaging Task in the Liver

Imaging Task in the Kidneys

Figure 1.

Abdomen phantom with an organ mask for the liver and spleen as well as an organ mask for the two kidneys. The imaging task in the liver and spleen is a sphere detection task presenting a low-frequency task function. The imaging task in the kidneys is the discrimination between a cluster of kidney stones of random orientations and a larger monolithic stone, resulting in a mid-to-high spatial frequency task function.

Figure 2.
Local 2D Gaussian basis functions for low dimensional parameterization of FFM.

Figure 3.

(a) The detectability map, $d'(x, y)$, for the unmodulated case with an optimal constant β . The locations of the minimum and maximum d' are indicated by a yellow and a black cross. The value of β was chosen to maximize the minimum d' which occurs in the liver indicated by a yellow cross. The maximum d' (b) The detectability and the optimal spatially varying β map for the unmodulated fluence case. The improvement of d' in the kidneys are attributed the lower β optimal for the higher frequency task.

Maxi-Min Objective **Figure 4.**

Joint optimization of FFM and spatially varying β following the maxi-min objective. The FFM, $I_0(u, \theta)$, is determined by the most challenging task/location, and exhibits angular modulation that prescribes higher fluence to less attenuating views. The liver d' more constant and higher than Fig.3 results.

Figure 5.

Joint optimization of FFM and spatially varying β following the ROI objective. The sinogram locations of the two kidney are overlaid as magenta masks. The d' values in the kidneys are improved compared to both the unmodulated and the maxi-min objectives, while the minimum d' in the liver is the same as the target level.