Response to Reviewers and Associate Editor

This paper was submitted earlier, and out of the three reviewers, two of them had pronounced this as "publish unaltered" and one reviewer (R1) did not recommend resubmission. The handling Editor has encouraged a resubmission of this paper taking into account the comments of R1. We thank all reviewers for their remarks and in this document, we explain the steps we have taken to address the reviews received in our previous submission to TCI. R1 makes the following comments, and we quote excerpts in blue here:

> The authors have spent considerable effort in revising the manuscript and addressing the concerns of the reviewers. I would like to thank the authors for their effort. I believe the manuscript has improved because of these revisions, especially in the structure of the paper and the discussion of related work. Unfortunately, some of my main concerns with regards to the experiments, the accuracy of the proposed method, and the presentation of the findings remain present in the revised manuscript. In some cases the revisions have even increased my concerns about certain aspects. Mainly, the included experiments still do not clearly show that the proposed method improves upon existing 'simple' prior-based methods

The simpler method is based on the well-known "Total Variation". In particular, we address the following main concern of the reviewer

> Note that the total variation minimization results are much better than the l1-ls results that the authors show in the paper

by rewriting the paper considerably. We believe the paper addresses this (correct) stinging criticism of R1. In fact R1 has taken pains in showing how the Total-Variation method (and sometimes FDK) is better than our earlier Compressed Sensing plus spatially-varying prior-based reconstruction, and we gratefully acknowledge the same.

Again, this is correct for the dataset shown, and we accept this to be true.

We re-wrote our code and upon further analysis observed that TV is indeed better suited as a baseline reconstruction method for our datasets and our subsampling choices. Hence, our current paper presents all results using TV regularization coupled with spatially-varying technique, and demonstrates benefits over TV-only and backprojection-only methods. *We have eliminated our previous implicit claim that the CS based scheme is optimal for the dataset provided.*

As far as FDK is concerned, the current results indeed show the superiority of the TV-based scheme (as also noted by the reviewer).

That said, the goal of our previous and current work is to provide a technique that can improve upon a chosen baseline reconstruction when measurements are extremely sparse. One may choose any baseline reconstruction (including an inferior – for this dataset – Compressed sensing prior) for pedagogical, historical, or commercial reasons, and given that, our key question is – is there a way to improve? The spatially-varying method of moderating the prior settles this question.

We also take this opportunity to address other comments given by R1 and the handling editor.

1. ...the paper should at least include a (short) discussion about the possibility of using deep learning for this, and its disadvantages.

   We accept this point, and have now discussed the difficulties in using deep-learning techniques for the current problem in Section. 7B of our paper.

2. There are no added comparisons with popular existing methods for reconstruction with a small number of projections (TV, algebraic techniques, etcetera)

   Among the family of algebraic techniques, we have compared our method with Algebraic Reconstruction Technique (ART) [1] and Simultaneous Algebraic Reconstruction Technique (SART) [2]. In order to use the Discrete Algebraic Reconstruction Technique (DART) [3], one must assume the imaged object to be made of only a few fixed number of known attenuation coefficients. Since we do not make any such assumption about our datasets, we have not used DART. Among other iterative techniques, we have used Simultaneous Iterative Reconstruction Technique (SIRT) [4], Total Variation (TV) [5], [6] and Compressed Sensing (CS) [7] with Haar wavelet and DCT as sparsity basis. The details of solvers used for these algorithms and their reconstructions are in Page. 8 (Section 6B) of the paper. For CS reconstruction, we observed that Haar wavelet and DCT were best suited for our dataset among various other possible sparsity basis.

3. Why did the authors not choose the standard settings for SSIM?...I don't understand the reason given for not including RMSE: the values don't have to be optimized again – you could just optimize for SSIM but at least still report RMSE comparisons.

   We accept the criticism, and have now presented both RMSE and SSIM values for all reconstructions in Tables 1-5 of the main paper.

4. A discussion about computational costs (time, memory) should be included in the paper.

   We accept this point, and present details in Section. 7A of our paper. We also provide the code to reproduce the compute time claimed.

References

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[7] R. Tibshirani, "Regression shrinkage and selection via the Lasso," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 58, no. 1, pp. 267–288, 1996.