

Advanced characterization of spatial aspects of image system blur

NLV-004-19, Year 3 of 3

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With contributions from Matti Morzfeld (UCSD), Matthew Kupinski (University of Arizona), Kevin Joyce (LLNL)

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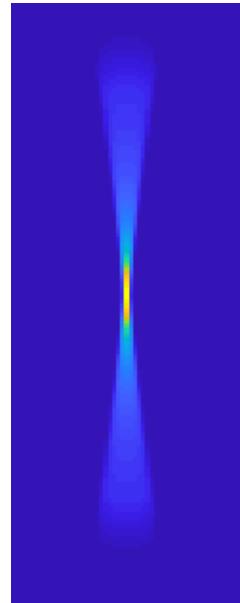
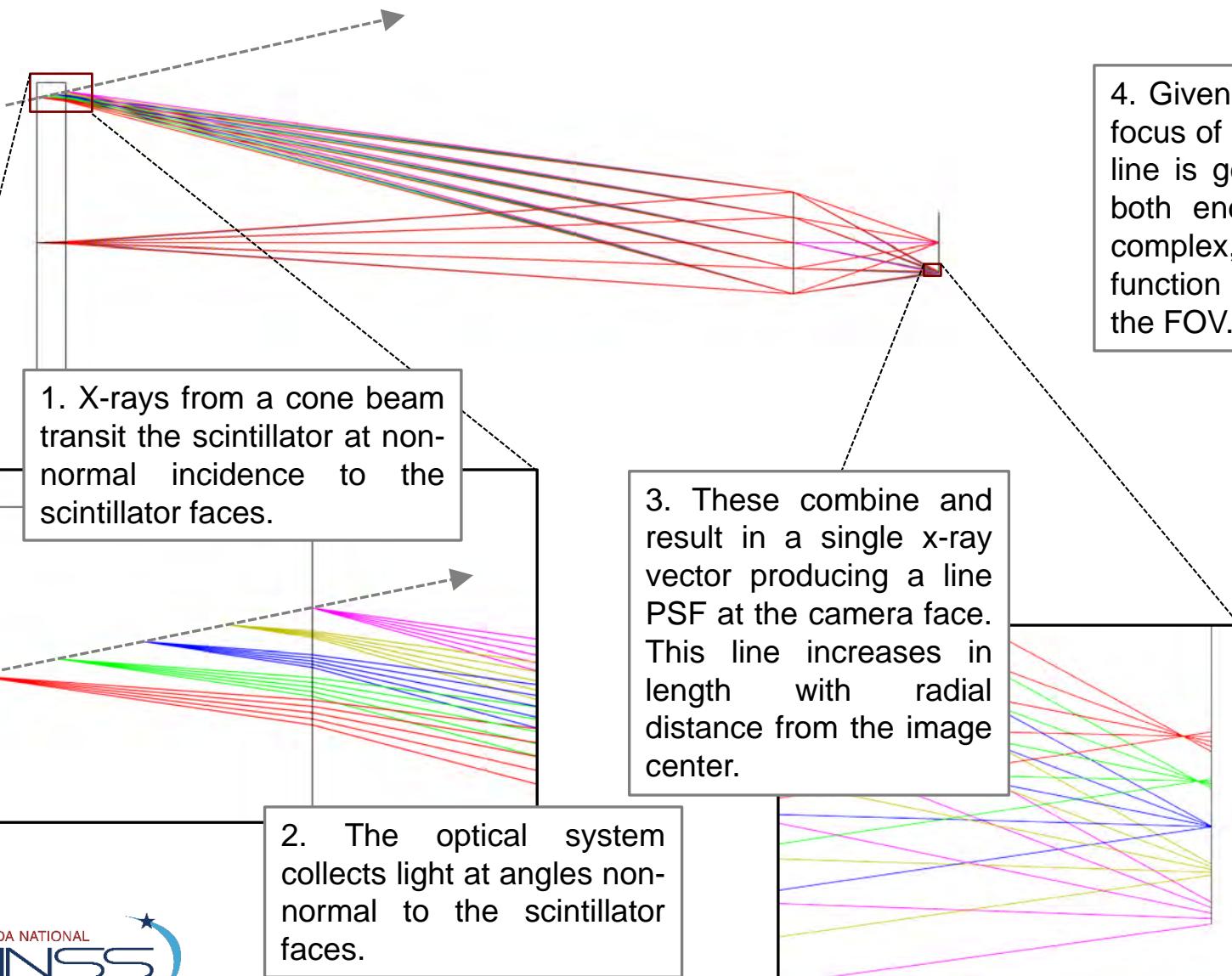


Challenge

- ▶ Radiographic applications incorporating scintillators and imaging optics have an inherent trade-off.
 - Systems are nearly always light starved, driving design towards faster optics and thicker scintillators.
 - Both options increase the optical blur, and the inherent geometries of such systems cause the blur to vary across the FOV.
 - This blur cannot be fixed through deconvolution or any other existing method. It can be reduced in telecentric or pericentric lenses, but these are generally impractical.
 - Radiographic systems designed conservatively to minimize constant and variable blur are not able to take full advantage of available options.
- ▶ Future radiographic systems will have increasing performance requirements, and yet no current technology or method will allow them to beat this trade-off.
- ▶ *A new technique is required to allow higher resolution and contrast in the data products of radiographic imaging.*

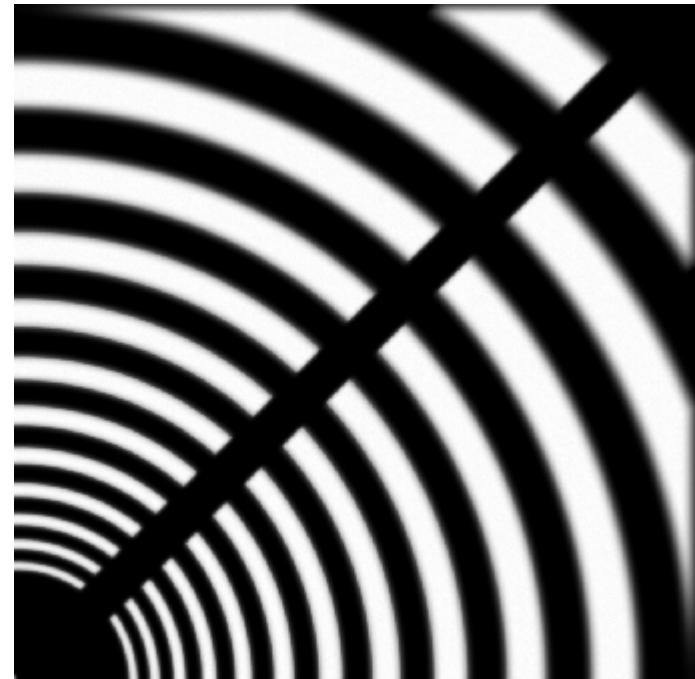
Challenge (Illustrated)

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Challenge (Illustrated)

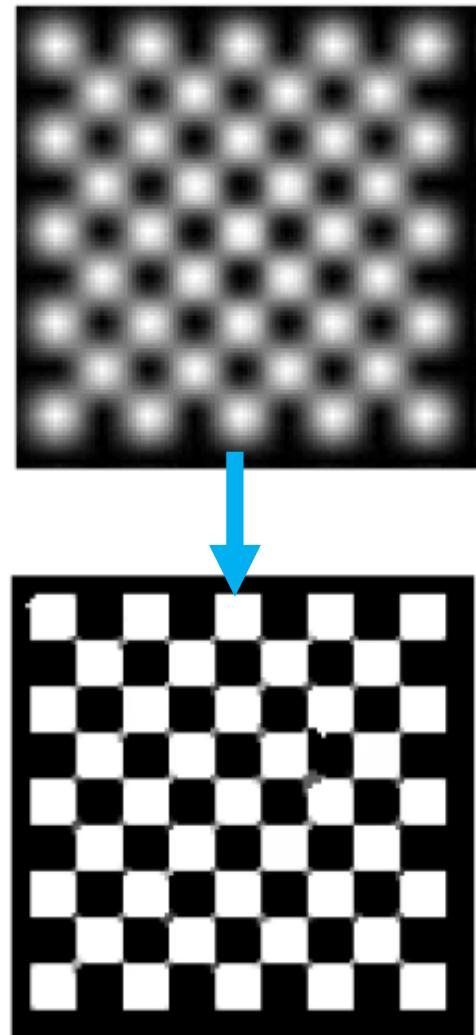
As a result, radiographs that we expect to look like the image on the left end up looking like that on the right – blurred everywhere, but much worse towards the edges and anisotropically (note that straight edges stay crisp, while the arcs get progressively blurrier). Note that the center of the FOV is in the lower left of each image.



- ▶ Commonly, blurred images are deblurred by the use of deconvolution (which does not work for varying blur) or other simple techniques (which may not be quantitatively rigorous), or more sophisticated approaches that employ prior knowledge and require user guidance, thereby leaving room for variability and uncertainty.
- ▶ This effort took inspiration from recent developments in Integrated Depth of Field (IDOF) and astronomical imaging. We develop a new method using a Bayesian framework with spatially varying hyper-parameters to deblur radiographic images that are affected by spatially varying blur while decreasing variability in the outcome. The result is rigorous, while applicable as simply as deconvolution.

Technical Approach

- Two approaches were employed in this spatially varying blur SDRD project, resulting in method for removing spatially varying blur:
 1. Develop a methodology that allows for a spatially varying blur kernel (field of kernels) in the formulation for deconvolution.
 - 1D method was developed in-house with support from LLNL.
 - 2D method was developed in collaboration with PNNL.
 2. Develop a Markov Chain Monte Carlo method that allows the spatial variation of regularization parameters, along with the ability to spatially partition between regularization types.
 - This was developed through a University of Arizona collaboration.

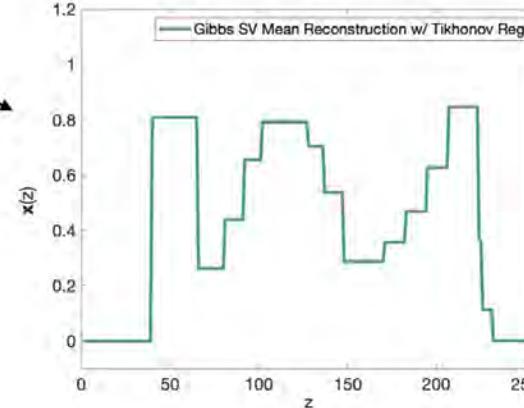
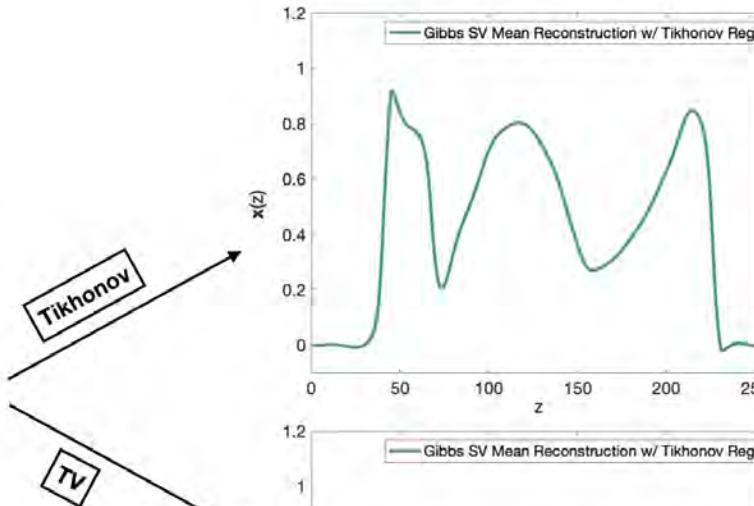
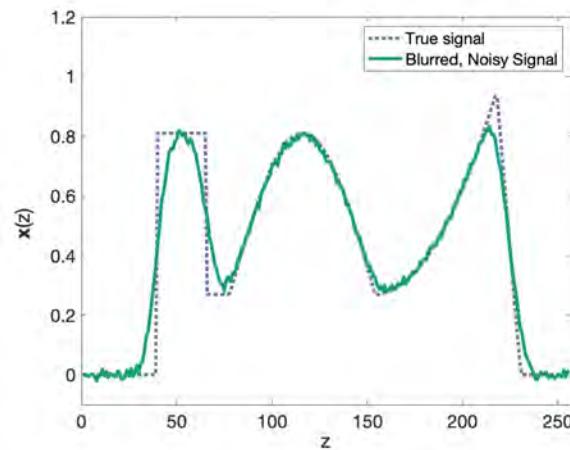


Technical Approach: University of Arizona

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Spatially Varying Parameters and Multi-regularization

- The method of regularization allows us to reconstruct a signal or image while imposing a priori knowledge about the data.
- What if different regions of an image require different types of regularization?

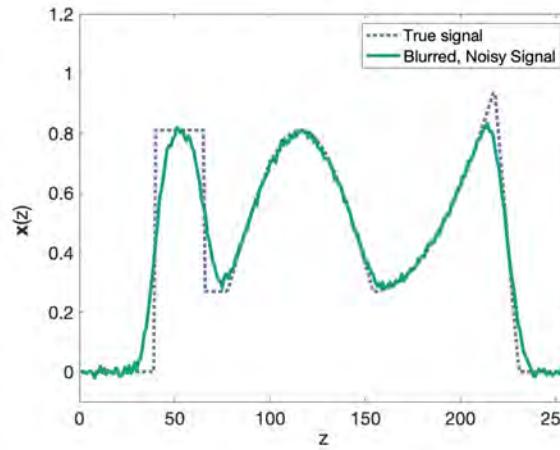


Here, neither regularization method is satisfactory for the entire signal

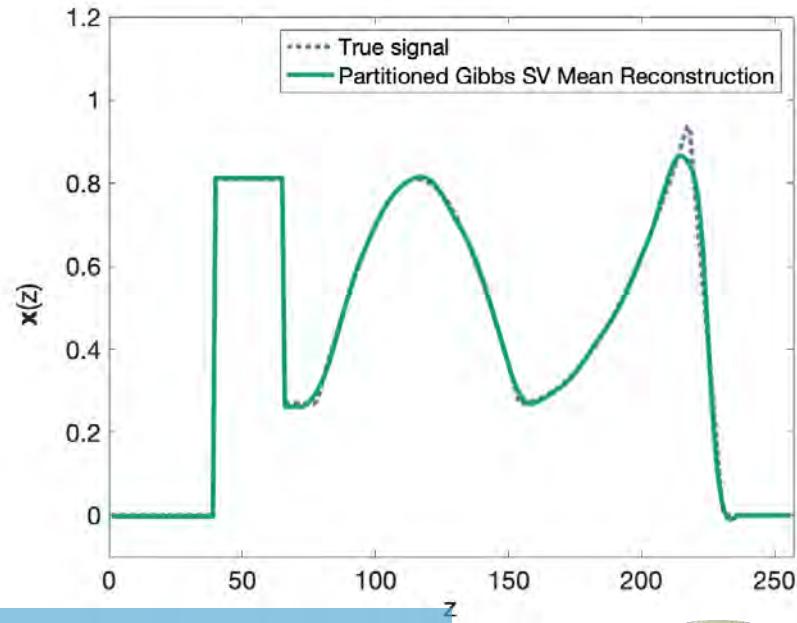
Technical Approach: University of Arizona

Spatially Varying Parameters and Multi-regularization

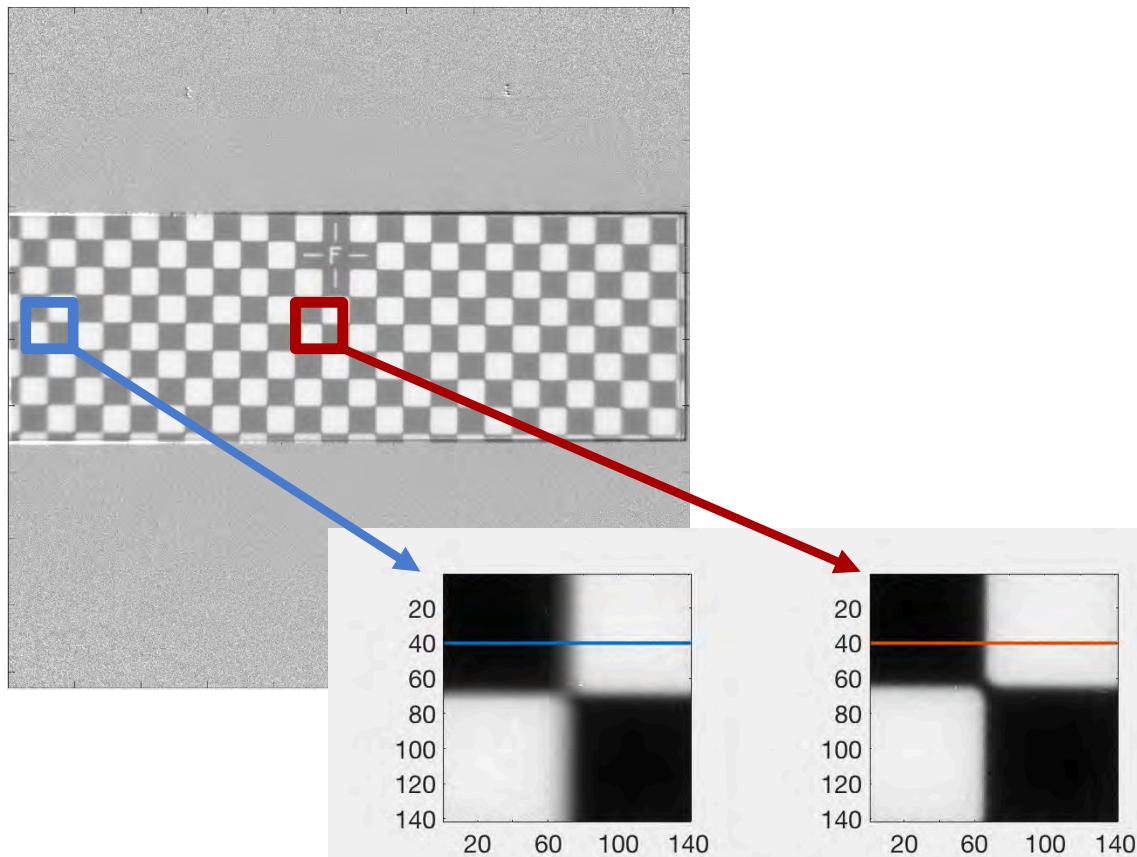
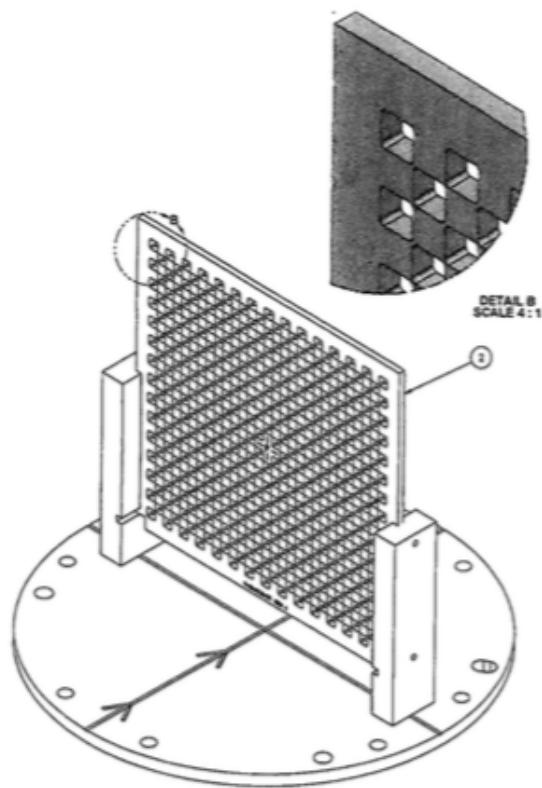
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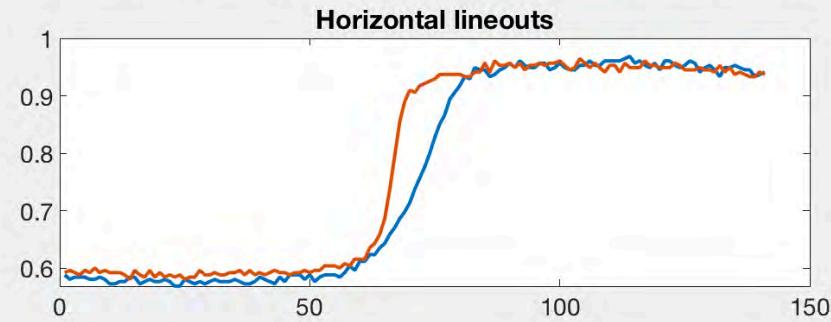
Tikhonov + TV
With spatially varying hyper-parameters in the MCMC reconstruction method



Results on real data: Checkerboard object



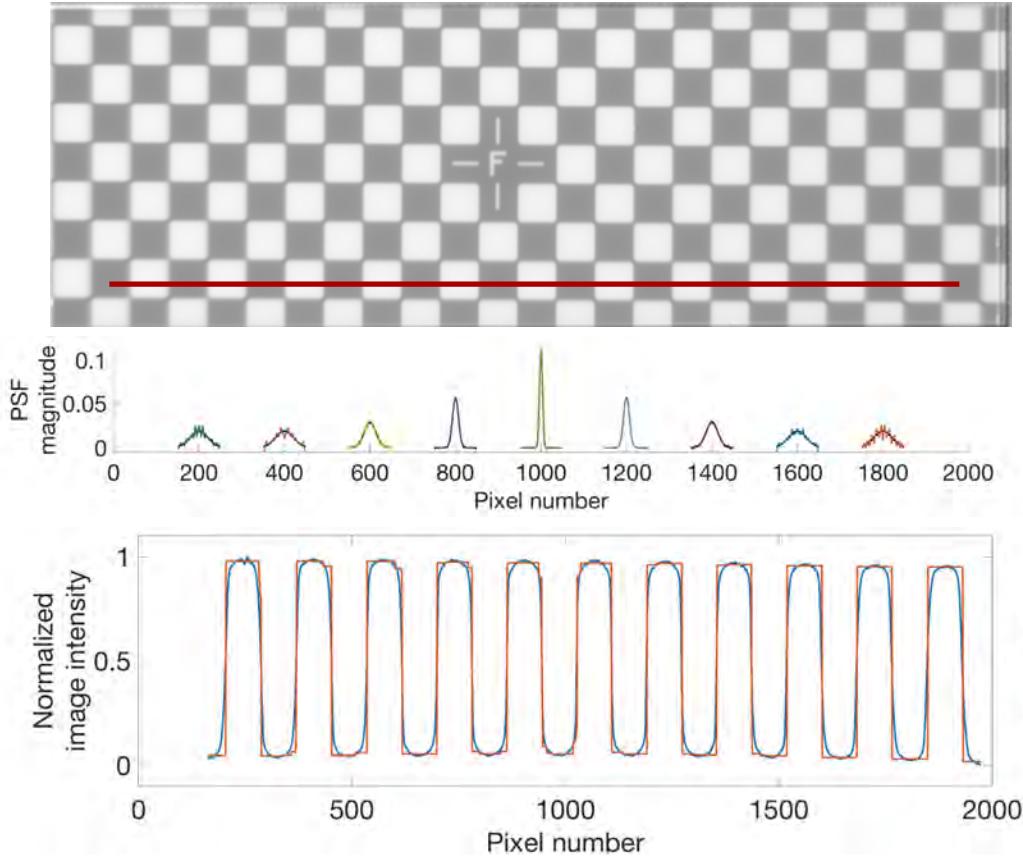
We developed the methodology for deblurring spatially varying blur in 1D and extended it to 2D.



Results on real data: Checkerboard object, 1D

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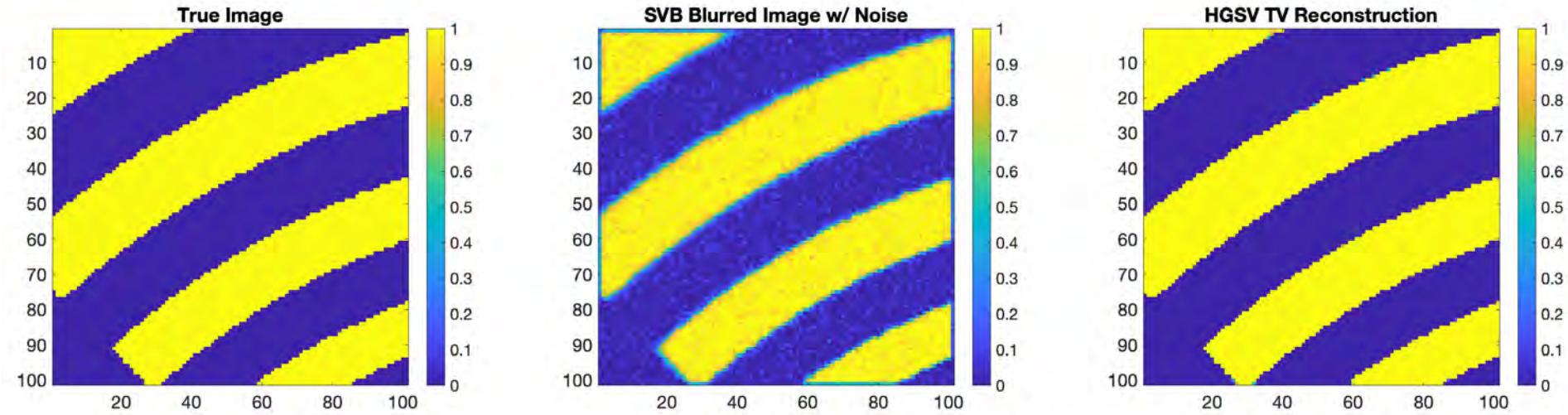
- Deconvolution assumes a single deblurring kernel, which is not the case in spatially varying blur.



- Point Spread Functions (PSFs) are approximated at a finite number of points in the image and interpolated to obtain PSF estimates at each pixel in the image.
- The “deconvolved” image shows the reconstruction with sharper edge features and behaves like a step function, as expected.

Results on 2D synthetic data: Radial blur

- ▶ Earlier results were in 1D and were published.
- ▶ In FY21, we extended the method to 2D reconstruction.
- ▶ Given the kernel(s) for a spatially varying radial blur, we have demonstrated successful deblurring of images using a deconvolution-like approach!

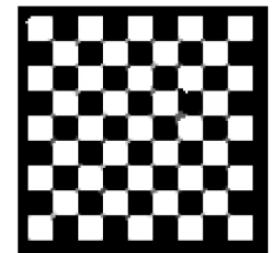
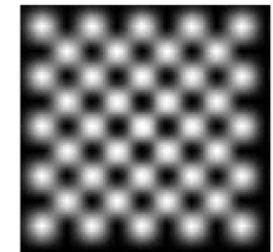


Results

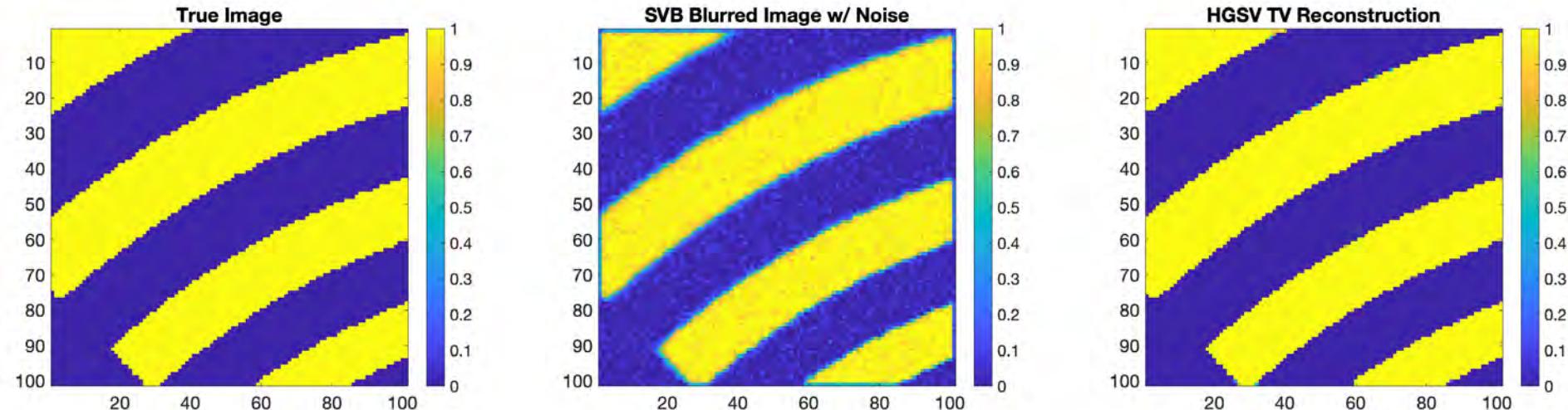
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- Novel method has been successfully demonstrated in both 1D and 2D

- Parallelized version prototyped to work on $4k \times 4k$ images (e.g., Cygnus radiography)
- Any future programmatic follow-on should focus on increased computational efficiencies with matrix-free methods for larger images.



Given the kernel(s) for a spatially varying radial blur, we can successfully deblur images with a deconvolution-like approach in both 1D and 2D



Impact

► Papers

- J. Adams, M. Morzfeld, K. Joyce, M. Howard, A. Luttmann, “A Blocking Scheme for Dimension-Robust Gibbs Sampling in Large-Scale Image Deblurring,” *Inverse Problems in Science and Engineering*, 2021. DOI: 10.1080/17415977.2021.1880398.
- J. Adams, J. Pillow, et al., “An Approach to Characterizing Spatial Aspects of System Blur,” *Statistical Analysis and Data Mining*, 2021 (accepted).
- J. A. Pillow, E. Machorro, M. Howard, K. Joyce, D. Frayer. “Methods for Spatially Varying Deconvolution,” 2021. In preparation.
- J. A. Pillow, M. Morzfeld, J. Adams, M. Kupinski, M. Howard. “Bayesian Spatially Varying Multi-Regularization Image Deblurring,” 2021. In preparation.

► Conferences

- Conference on Data Analysis, Santa Fe, February 2020: An Approach to Characterizing Spatial Aspects of Image System Blur
- SIAM CSE 2021: Dimension Robust Gibbs Sampling for Large-scale MCMC in Image Deblurring

Poster from Conference on Data Analysis 2020

An Approach to Characterizing Spatial Aspects of Image System Blur
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¹ Nevada National Security Site, ² Lawrence Livermore National Laboratory, ³ Pacific Northwest National Laboratory, ⁴ Tufts University, ⁵ Massachusetts Institute of Technology, ⁶ University of Arizona, ⁷ Los Alamos National Laboratory, ⁸ Los Alamos National Laboratory

Abstract
In imaging applications, such as X-ray radiography, the experimental system setup and data capture process can produce images with significant blur. The images taken with thick scintillators or spatially varying system blur is observed, requiring a nonstationary deconvolution approach for image reconstruction and removal. We demonstrate an approach to estimation of local point spread functions using a large dataset of images taken at the National Research Laboratory (NRL) and extend that to a map defining the kernel over the camera field of view.

Checkboard Data
A checkboard target can be used as a calibration object for quantifying blur in X-ray radiography. This image was captured with a 20mm thick Lutetium yttrium orthosilicate (LYSO) scintillator at NRL.

Figure 1: Imaging system schematic
In high energy X-ray radiography, X-rays are produced from a source and pass through a scatterer that is not attenuated by objects in the scene are absorbed by a thick scintillator and converted to light. An imaging system then captures the light to produce the output image as depicted in Figure 1.

Figure 2: X-ray path through a thick scintillator
X-rays from the source are emitted as a cone beam. The photons produced via scintillation can occur at any point along the path through the scintillator. The X-ray path has a larger kernel further from the center of the X-ray source as depicted in Figure 2, which results in blur that varies spatially.

Figure 3: On the left, a photograph of a Lucent checkerboard is overlaid with the camera parameters, and on the right, the raw image. Specific portions are marked in red and blue. On the right, these portions are averaged, and the mean vertical and horizontal values are plotted along with their associated PSFs, denoted as in Figure 4.

Figure 4: The set of horizontal and vertical PSFs and approximation for a PSF at any point in the grid can be produced via a partition of unity (POU) between successive PSFs across the image.

Figure 5: 2D PSF contour with vertical and horizontal radius (RM) (Gaussian 2D PSF)

Conclusion
In many dataset treatments, the blurring process is modeled as a convolution between the true image and a spatially invariant PSF.

$$g(x, y) = A(p(x, y)) = \int_{\mathbb{R}^2} \psi(x, y, z) f(z) \, dz$$

The tools under development here seek a higher fidelity, higher precision model that accounts for spatially varying blur that has been found experimentally [6].

Blur or techniques that can model blur (or PSFs) but only in small regions across boundaries of high contrast [1]. The team has developed the tools to model blur in a spatially varying manner. One approach is to use a POU to create a PSF that is piecewise constant and then convolve it with the image. Another approach is to create a PSF that is piecewise constant and then convolve it with the image.

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References
[1] J. A. Pillow, J. Joyce, and M. Howard, “An Approach to Characterizing Spatial Aspects of System Blur,” *Statistical Analysis and Data Mining*, 2021 (accepted).

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- ▶ Collaboration with University of Arizona
 - PhD student graduated and hired on as Postdoc: Dr. Jordan Pillow
- ▶ Programmatic Transfer of Knowledge
 - Radiography is the primary diagnostic for Great Basin SCE
 - Radiographic requirements will require quantifying sources of error (e.g., noise, blur)
 - NNSS has been asked by LLNL to support Great Basin through an analytical approach for radiography analysis, which includes both Abel inversion and removing spatially varying blur using the methods developed in this project
 - **This work WILL be used in upcoming SCEs!**