Instantaneous Spectral Imaging with Learned Reconstruction

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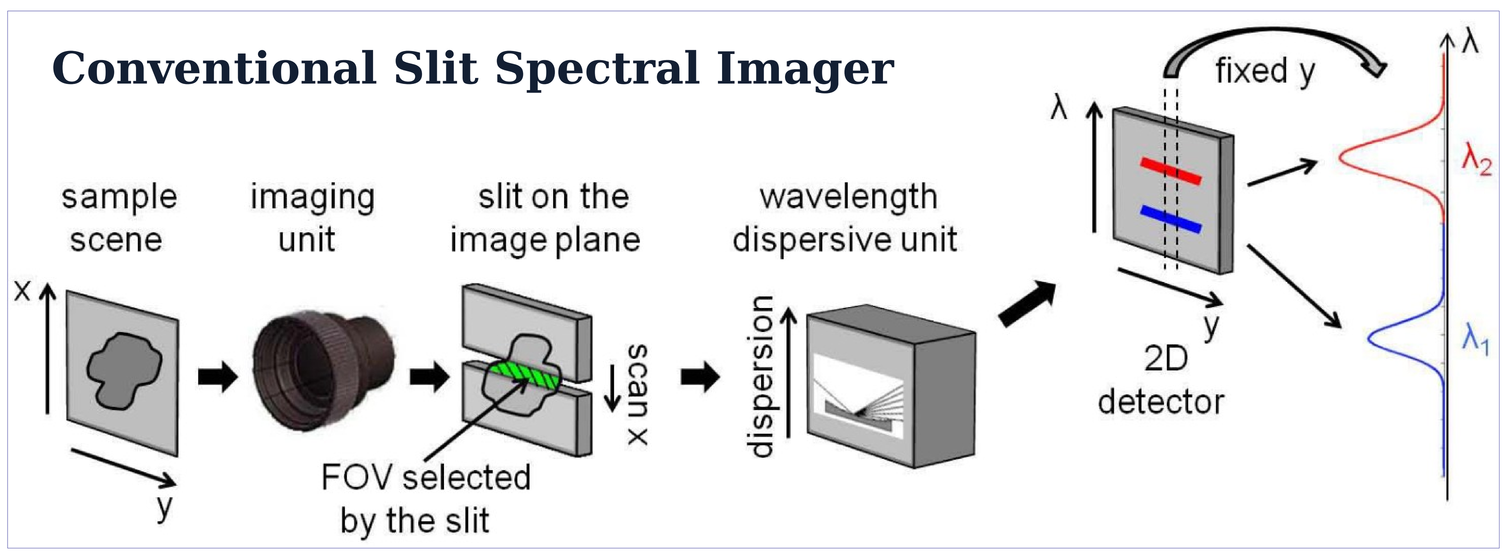
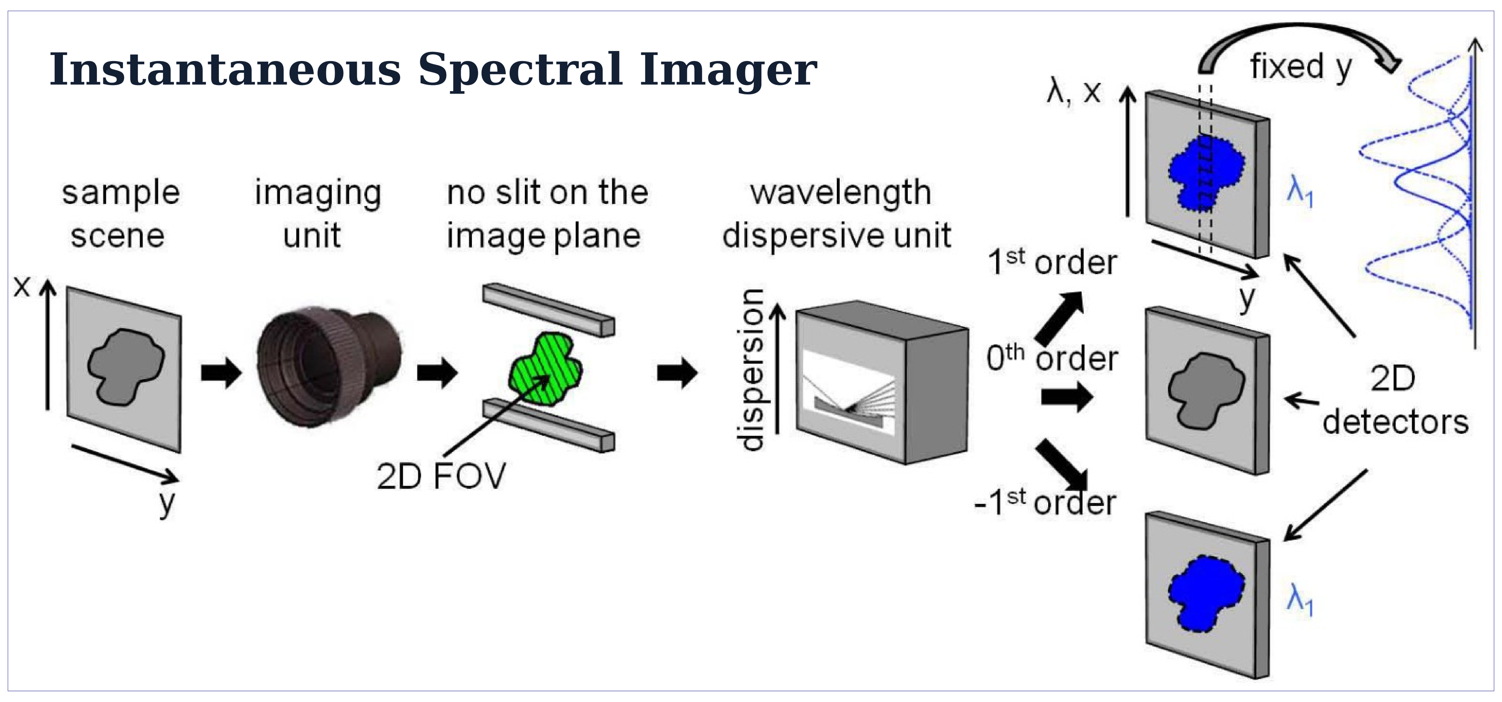
INTRODUCTION

Spectral imaging, simultaneous spectroscopy and photography of a scene, is a fundamental diagnostic technique in physical sciences. Conventional spectral imagers require a scanning process to capture the inherently 3D spatio-spectral scene, which renders them inefficient.



Conventional slit spectrometers require a scanning process by sweeping the slit across the scene, which restricts the field of view to a narrow line, enabling the perpendicular dimension to be used for capturing the spectrum on the detector via dispersion.

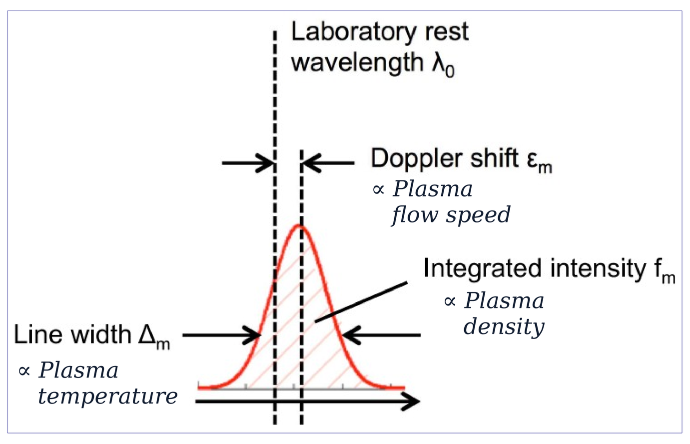


The instantaneous spectral imager removes the slit and does not require a scanning process. This comes with the cost of superposed spectra of the scene along the dispersion direction, to be deconvolved with processing. Multiple diffraction orders can be measured to decrease the ill-posedness of the inverse problem.

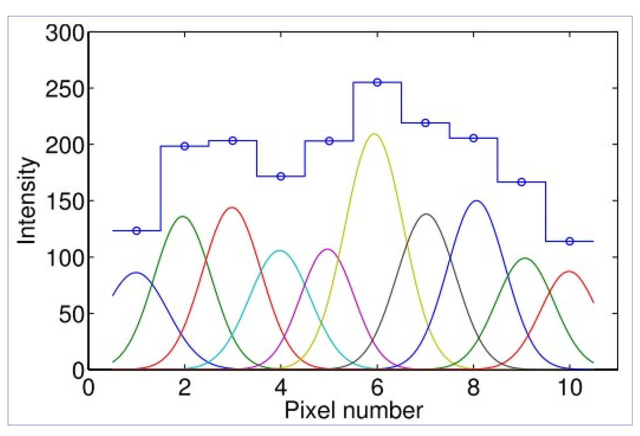
PARAMETRIC FORWARD MODEL

Gaussian Spectrum Assumption

- Spectrum consists of Gaussian spectral lines due to thermal broadening, with known central wavelength λ_0.



Column Measurements



Contribution of the spectral line at position m’ to pixel m:

$$c_{m'} = \int_{m-1/2}^{m+1/2} \frac{f_{m'}}{\sqrt{2\pi}|a|\Delta_{m'}} e^{-\frac{(x'-m'-a\epsilon_{m'})^2}{2(a\Delta_{m'})^2}} dx'$$

Nonlinear dependence on $\Delta_{m'}$ and $\epsilon_{m'}$

a: diffraction order

$$\begin{bmatrix} y_1^{(a)} \\ y_2^{(a)} \\ y_3^{(a)} \\ \vdots \\ y_M^{(a)} \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2\pi}|a|\Delta_1} e^{-\frac{(a\epsilon_1)^2}{2(a\Delta_1)^2}} & \frac{1}{\sqrt{2\pi}|a|\Delta_2} e^{-\frac{(-1-a\epsilon_2)^2}{2(a\Delta_2)^2}} & \cdots & \frac{1}{\sqrt{2\pi}|a|\Delta_M} e^{-\frac{(1-M-a\epsilon_M)^2}{2(a\Delta_M)^2}} \\ \frac{1}{\sqrt{2\pi}|a|\Delta_1} e^{-\frac{(1-a\epsilon_1)^2}{2(a\Delta_1)^2}} & \frac{1}{\sqrt{2\pi}|a|\Delta_2} e^{-\frac{(a\epsilon_2)^2}{2(a\Delta_2)^2}} & \cdots & \frac{1}{\sqrt{2\pi}|a|\Delta_M} e^{-\frac{(2-M-a\epsilon_M)^2}{2(a\Delta_M)^2}} \\ \frac{1}{\sqrt{2\pi}|a|\Delta_1} e^{-\frac{(2-a\epsilon_1)^2}{2(a\Delta_1)^2}} & \frac{1}{\sqrt{2\pi}|a|\Delta_2} e^{-\frac{(1-a\epsilon_2)^2}{2(a\Delta_2)^2}} & \cdots & \frac{1}{\sqrt{2\pi}|a|\Delta_M} e^{-\frac{(3-M-a\epsilon_M)^2}{2(a\Delta_M)^2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{\sqrt{2\pi}|a|\Delta_1} e^{-\frac{(M-1-a\epsilon_1)^2}{2(a\Delta_1)^2}} & \frac{1}{\sqrt{2\pi}|a|\Delta_2} e^{-\frac{(M-2-a\epsilon_2)^2}{2(a\Delta_2)^2}} & \cdots & \frac{1}{\sqrt{2\pi}|a|\Delta_M} e^{-\frac{(a\epsilon_M)^2}{2(a\Delta_M)^2}} \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ \vdots \\ f_M \end{bmatrix}$$

Forward model given in matrix-vector form for a single column of measurements.

INVERSE PROBLEM

- The goal in the inversion is to estimate the parameters of the Gaussian spectral lines at all spatial positions within the 2D FOV. (field of view)

$$\hat{\mathbf{f}}, \hat{\Delta}, \hat{\epsilon} = \arg\min_{\mathbf{f},\Delta,\epsilon} \{ \underbrace{\|\mathbf{y} - \mathbf{H}(\Delta,\epsilon)\mathbf{f}\|_2^2}_{\textit{Data Fidelity}} + \underbrace{\mathcal{R}(\mathbf{f},\Delta,\epsilon)}_{\textit{Regularization / Prior}} \}$$

- An ill-posed multi-frame semi-blind deblurring problem, which is
  - *Nonlinear* (in Δ, ϵ) and *nonconvex*; hence, hard to optimize.
- How to choose the regularization / prior term?

LEARNED RECONSTRUCTION

✔Forward model is known
✔Previous observational data exists

Supervised Learning

1) Take the data, simulate measurements
2) Train a model with (input, output) pairs

$$x = \begin{bmatrix} f \\ \Delta \\ \epsilon \end{bmatrix}$$

$\mathcal{A}(\cdot)$: Forward model (nonlinear)

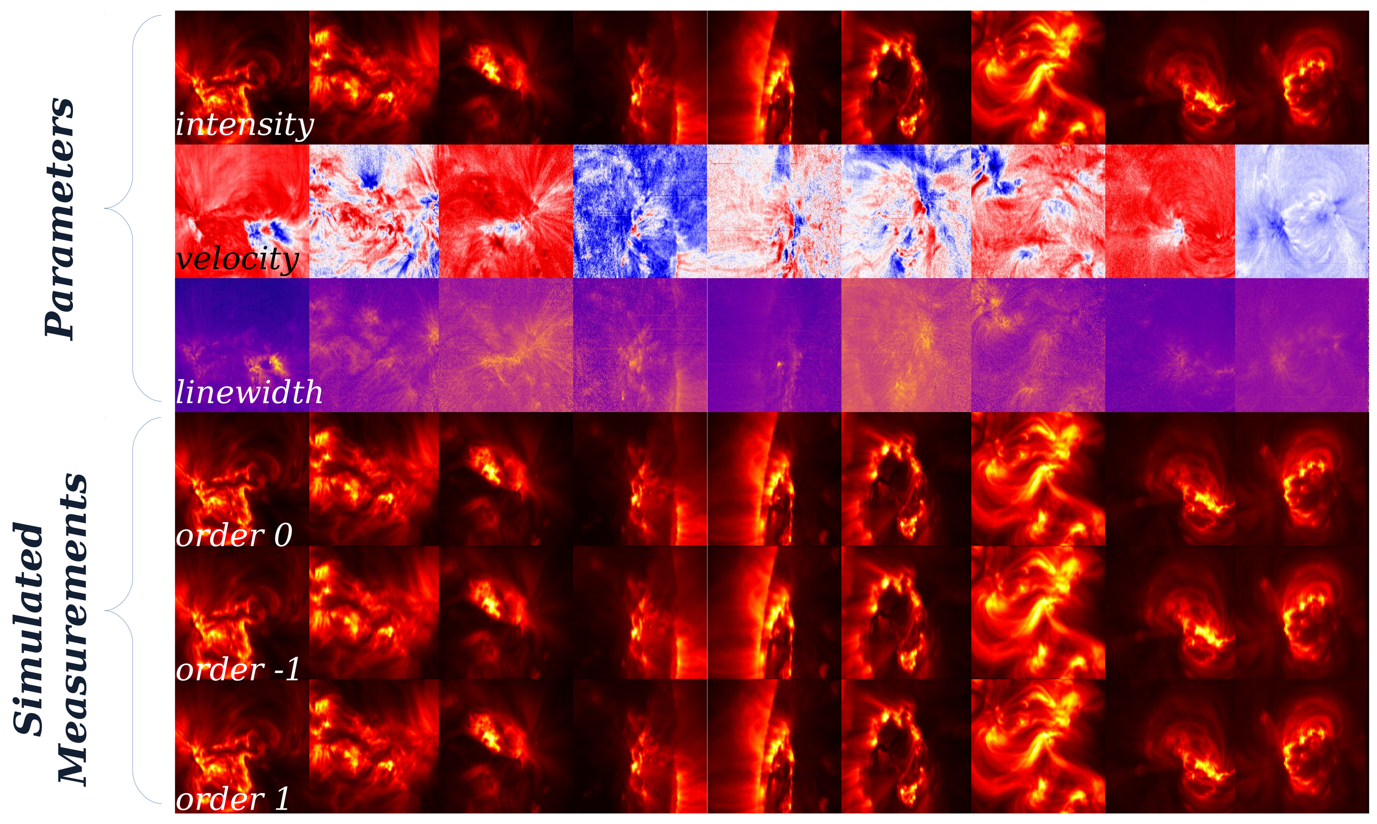
n : Additive Gaussian noise

$$y = \mathcal{A}(x) + n \qquad \hat{\theta} = \arg\min_{\theta} \sum_i \|x_i - f_\theta(y_i)\|_2^2$$

$f_\theta(\cdot)$: reconstruction network

Dataset

1088 scans of Fe XII 195 Å emission from the Extreme Ultraviolet Imager (EIS) aboard Hinode observatory were selected.



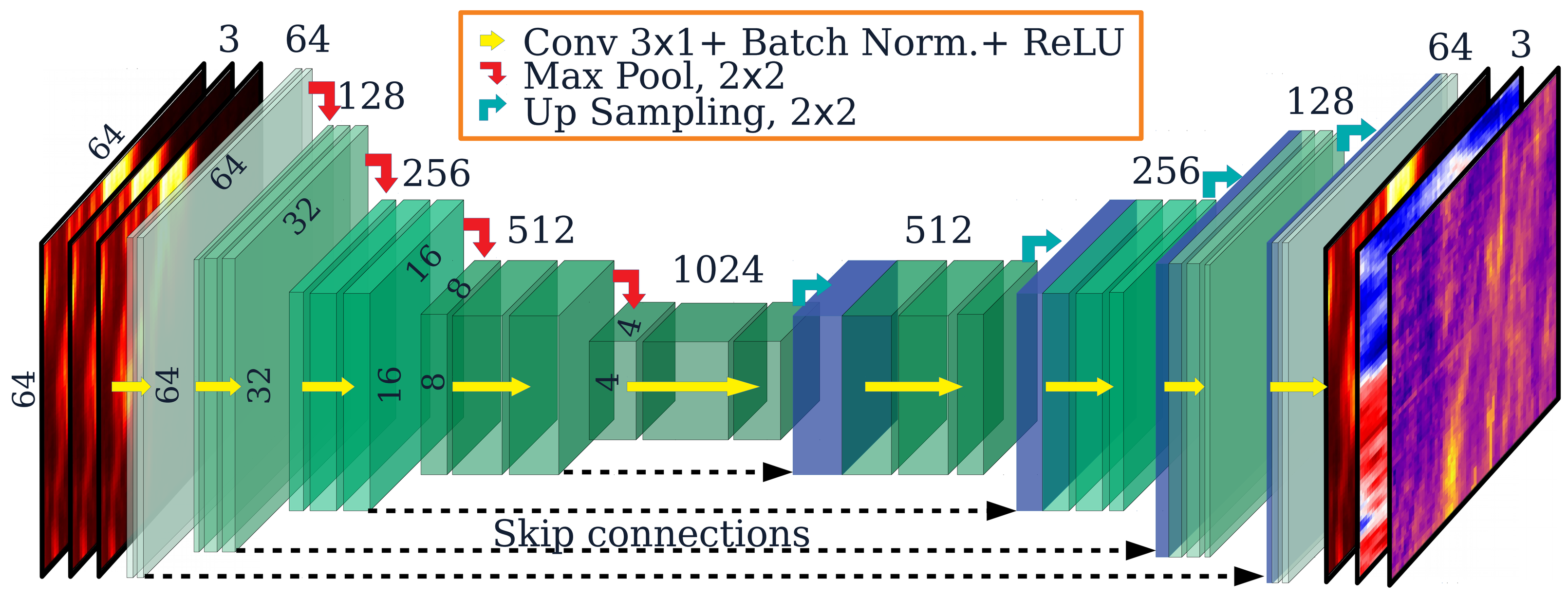
1088 scans
- 888 train.
- 100 val.
- 100 test

Crop 64x64 patches

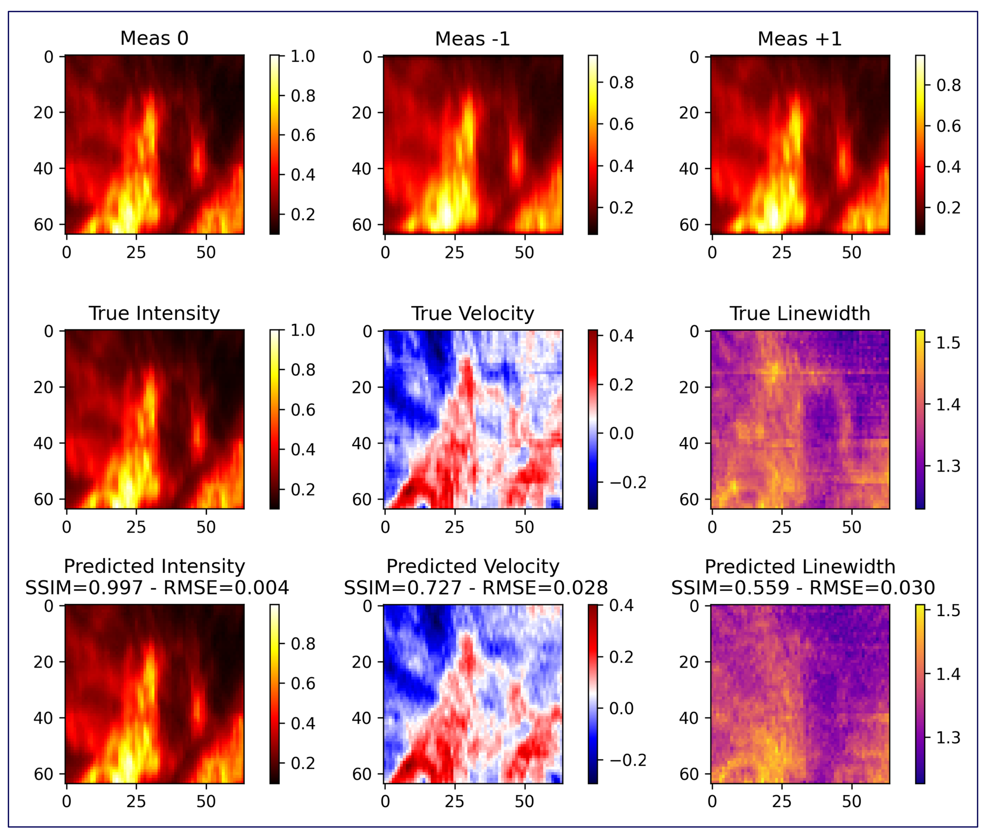
Dataset size:
- 8698 train.
- 1218 val.
- 1256 test

Network Architecture

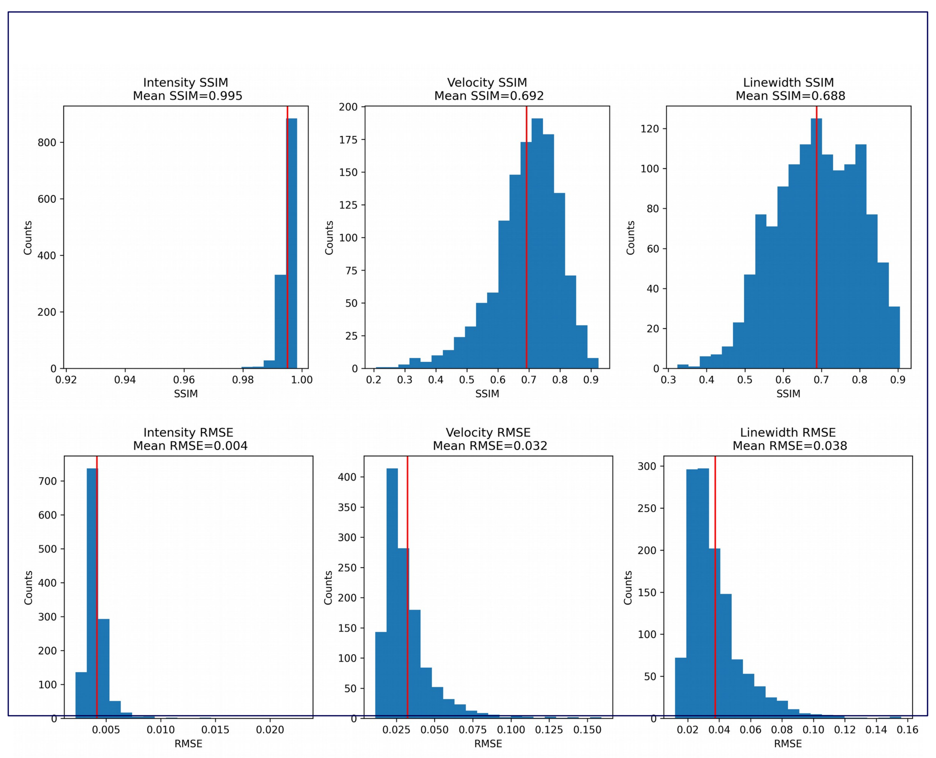
A moderate sized U-net suits for the learning task given the limited dataset size, and the proven success of the U-net on various computational imaging problems.



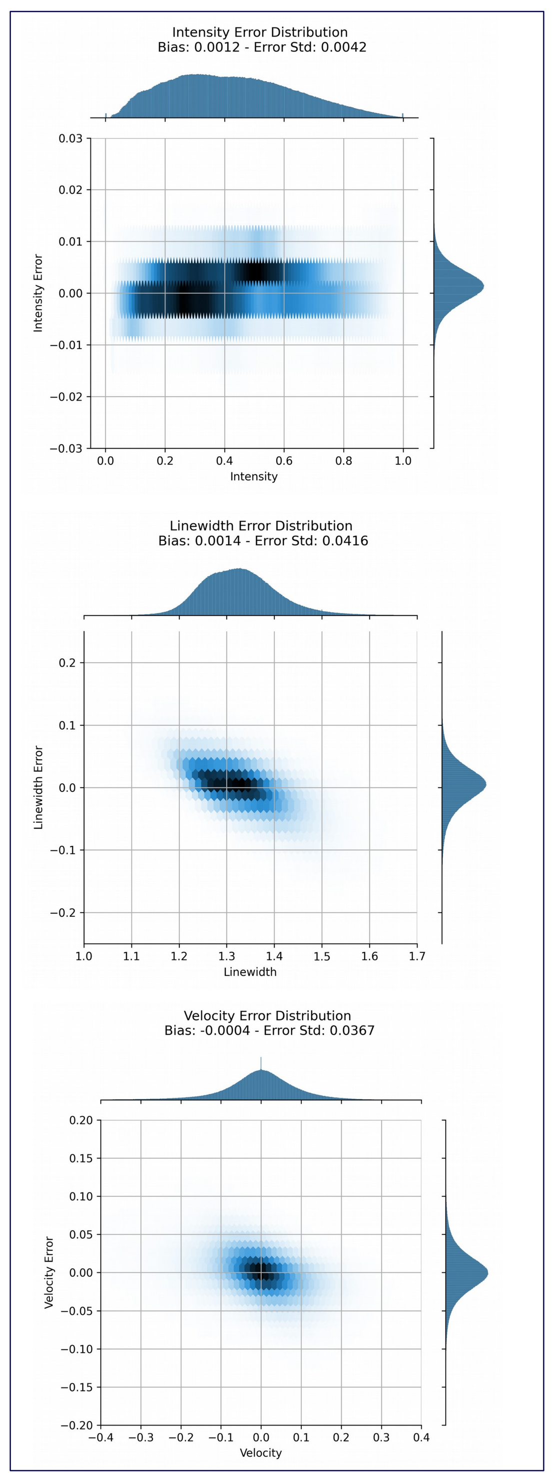
RESULTS



An example reconstruction by the U-Net.



Histograms of the RMSE and SSIM values of the reconstructed parameters by the U-Net on the testing dataset.



2D histograms of the parameters in the testing set and their reconstruction errors by the U-Net. The predictions have negligible bias and Gaussian shaped error distribution.