Reconstruction of attosecond X-ray temporal fields with machine learning

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Introduction

New attosecond soft x-ray modes are being developed at X-ray free-electron lasers, such as the Linac Coherent Light Source (LCLS) at SLAC National Accelerator Lab [1].

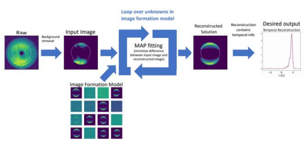
These sub-femtosecond modes must be characterized; however, they are too short to be resolved using standard beamline measurements at LCLS. Instead, an angular streaking technique is used to experimentally determine the temporal properties of the X-ray [2,3]. This technique encodes single-shot X-ray field information into a 2D photoelectron momentum spectrum.

We want to reconstruct the temporal field of the ionizing X-ray pulse from the measured photoelectron momentum spectrum.

Motivation and Related Work

Current reconstruction procedure is relatively slow compared to the data acquisition rate at LCLS

- Maximum-a-posteriori procedure with ADAM optimizer
- Requires optimizations within loops to account for unknown variables in the image formation model [2]
- Requires solving for multiple random seeds to determine solution convergence

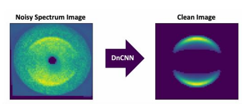


Noisy data

- Signal independent background that we do not have a model for
- Extensive signal processing required prior to reconstruction; prohibits on-line reconstruction of X-ray fields

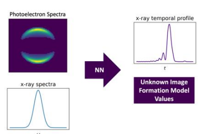
Method / Work-Flow

(1) Denoise/identify experimental background with modified DnCNN [4]



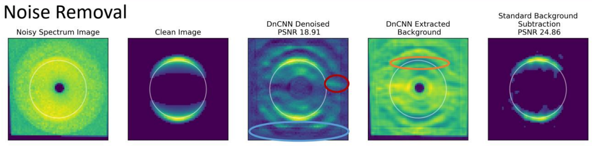
(2) Implement NN for reconstructing X-ray temporal fields

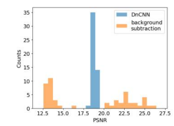
- *Simulate training and test set with image formation model [2]*



Results and Discussion

Noise Removal

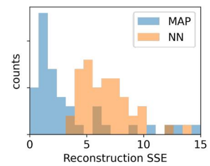




- Misidentifies some noise as signal, edge artifacts
- Difficultly only removing background when signal and noise on the same pixel
- Background subtraction outperforms DnCNN when there is sufficient signal on the detector

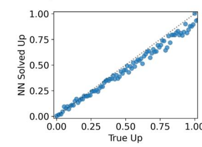
Reconstruction with NN

- Idea: NN will be fast and accurate reconstruction method
- NN does not accurately predict the X-ray temporal profile



*Proof of principle: NN for solving unknown image formation model values (see Future Work *)*

- NN accurately predicts unknown variable Up
- Reducing scanning over 10 values of Up -> 3 values: 10 minutes per shot -> 3 minutes



Up predictions by NN for an entirely different test set than the training set (different inputs and continuous Ups)

Future Work

- Improve NN prediction of simulated X-ray temporal profiles by increasing NN depth, increasing the size of the simulated training set, and tuning the hyperparameters
- Combine machine learning with the MAP pipeline
  - Add machine learning denoising steps before MAP solving
  - Implement machine learning step to determine unknown image formation model values before MAP solving (*)
- Further investigate the two populations of data found in noise removal study, particularly that which has higher PSNR with standard background subtraction than the DnCNN result . Use this to pick a more specific training set for DnCNN

References

[1] J. Duris et al., “Tunable isolated attosecond X-ray pulses with gigawatt peak power from a free-electron laser,” Nat. Photonics, vol. 14, no. 1, pp. 30–36, (2020).

[2] S. Li et al., “Characterizing isolated attosecond pulses with angular streaking,” Optics Express (2018).

[3] Hartmann, N. et al. ”Attosecond time–energy structure of x-ray free-electron laser pulses,” Nat. Photonic, vol. 12, 215–220 (2018)

[4] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, “Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising,” IEEE transactions on image processing, vol. 26, no. 7, pp. 3142–3155, 2017.