Deep Learning Techniques of Foreground Removal in 21-cm Cosmology

Eeshan Beohar*[1], Abhirup Datta[1], and Anshuman Tripathi[1]

[1]Department of Astronomy, Astrophysics and Space Engineering, Indian Institute of Technology Indore, Indore 452020, India

Background

One of the most formidable tasks in modern 21-cm cosmology is foreground removal. Astrophysical foregrounds such as Galactic synchrotron emission overwhelm the EoR signal by 4 to 5 orders of magnitude. They are expected to be spectrally smooth in frequency and reside only in the lower $k_{\|}$ modes. This has allowed us to use various 'blind subtraction' methods like polynomial fitting and Principal Component Analysis (PCA). In addition, the problem of 'mode mixing' and other instrumental effects may lead to ambiguous constraints on kernel parameters in techniques like Gaussian Process Regression (GPR). Therefore, to tackle these issues, we explore an alternative philosophy of 'de-noising' the HI signal of foregrounds, using deep learning methods on the SDC-3a data challenge.

SDC-3a Band-5

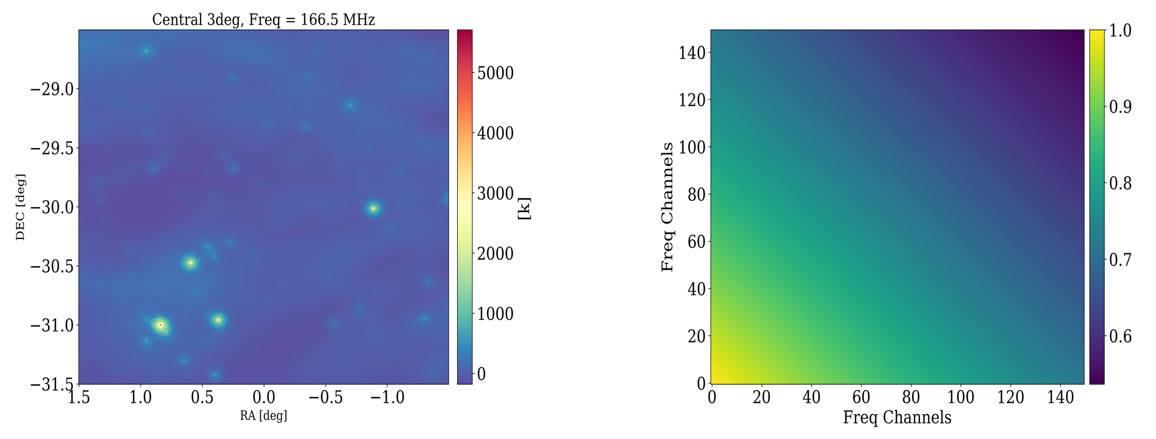


Figure 1: [Left] Beam Corrected and JY/beam to K converted image, [Right] frequency-frequency covariance matrix.

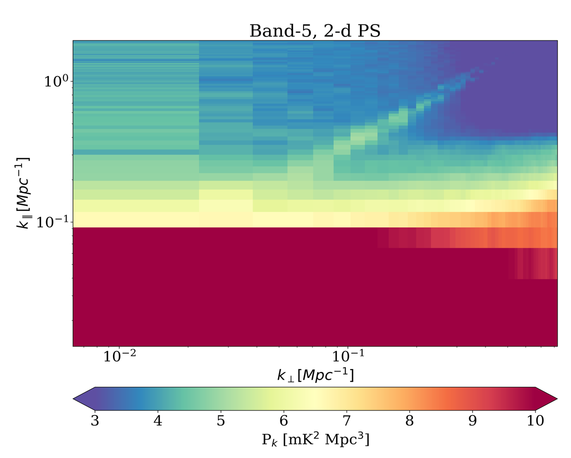


Figure 2: Cylindrical Power Spectrum for the raw data with maximum and minimum baseline of 30 m and 2000 m respectively.

PCA Residual

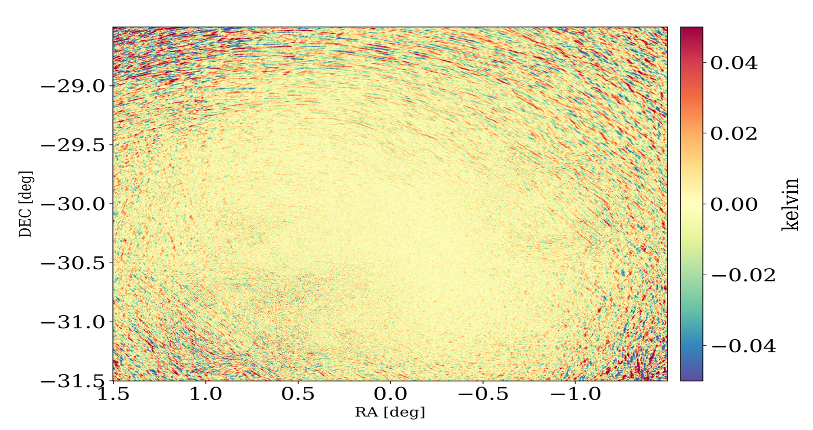


Figure 4: PCA reduction by SVD for n=3 components

Research Highlights

- **Less Training data!** limited sky region within the beam area (26 times less data than the full sky)
- **Spectral Resolution**: [1] simulated data had $\Delta\nu$=1MHz while SDC-3a data has $\Delta\nu$=0.1MHz. Might have to regulate the frequency dimension ([2],[3])
- **More Simulations** We can tackle the above issues with a higher frequency resolution, longer bandwidth and instrument-affected simulated data.

References

1. Makinen et al., 2021, JCAP, 10.1088/1475-7516/2021/04/081
2. Shi et al., 2024, arXiv:2310.06518v2
3. Chen et al., 2023, MNRAS, arXiv:2311.00493v1

Contact Information

Eeshan Beohar
mail: eeshan.beohar@gmail.com
github: eebeohar

Proposed SDC-3a Pipeline

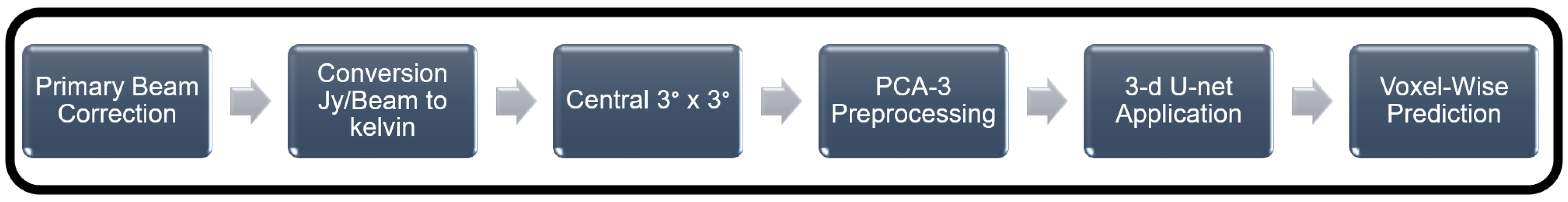


Figure 3: This pipeline currently only allows for voxel-wise predictions and not the full 2-d power-spectrum.

Training and Testing Data Assembly

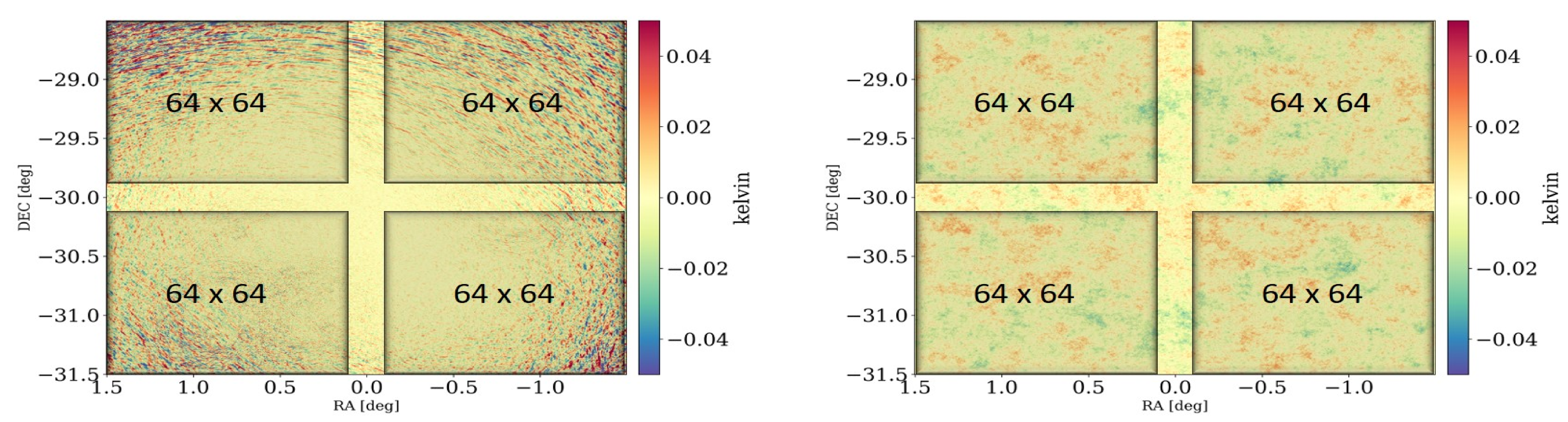
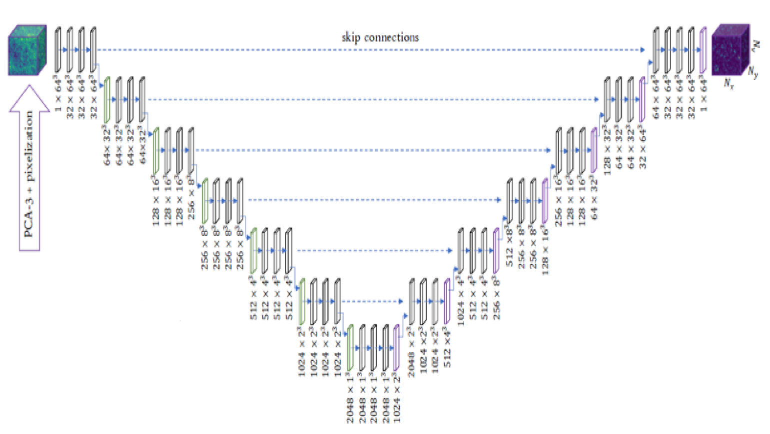
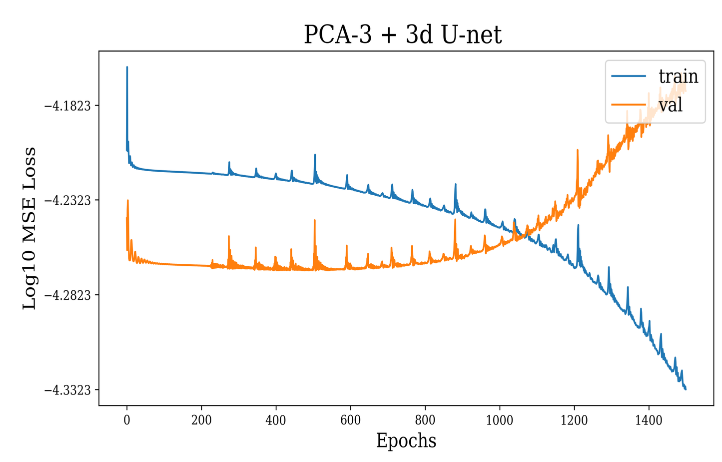


Figure 5: Each sky per frequency was gridded into (64x64) sky patches and 64 frequencies were uniformly sampled from the entire bandwidth giving us training, validation and testing 3-d voxels of dimensions (64x64x64)

U-net Architecture

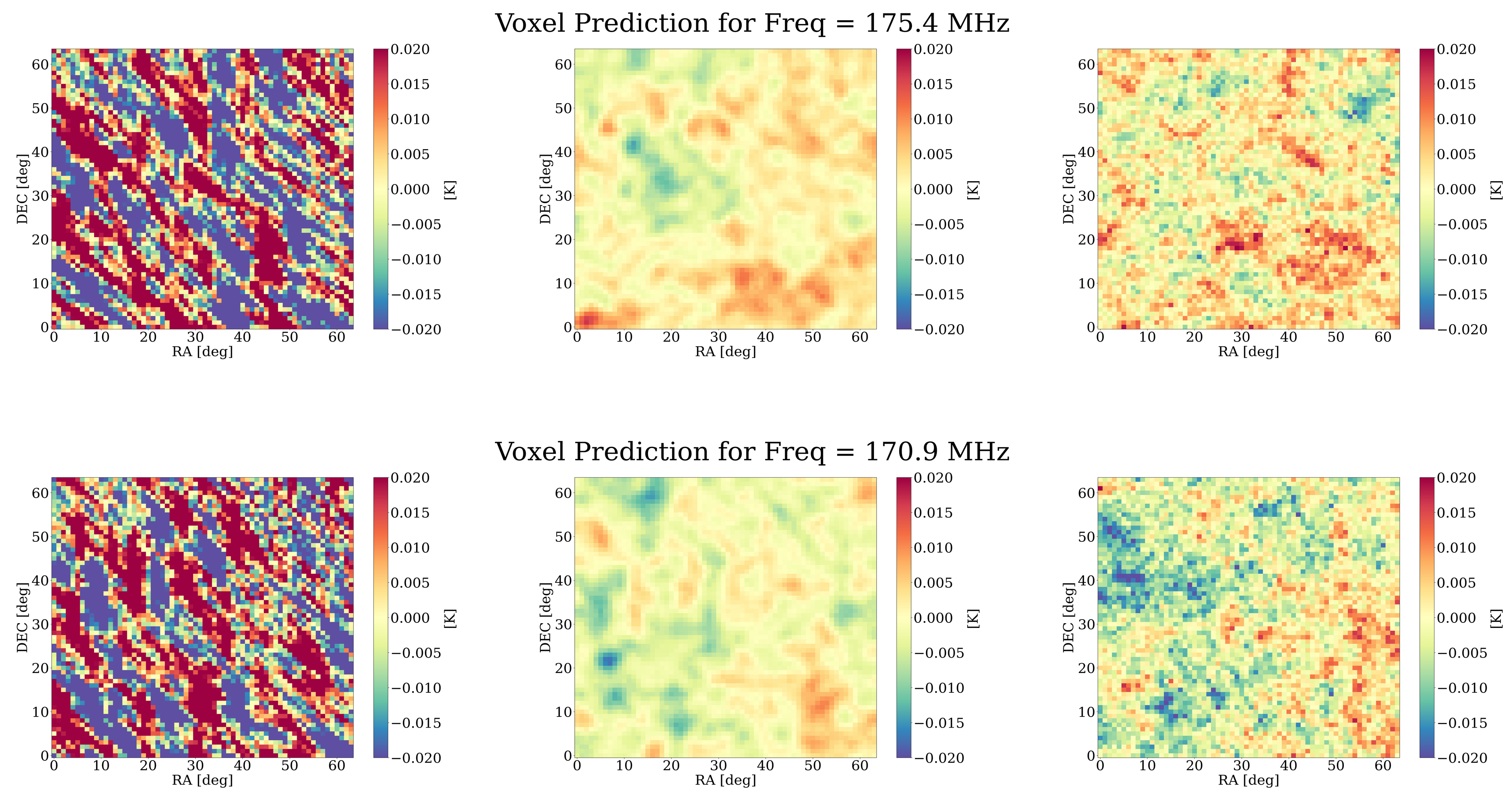




$n_{filters}$	64
Width	1
Depth	3
lr.	0.0003
Dropout	0.05
Loss	MSE
Optimiser	Adam

Table 1: Unet Hyperparameters

Results: PCA vs U-net vs True HI+Noise



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