Deep Learning Approach for Identification of HII regions during Reionization in 21-cm Observations

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Tomographic imaging of the 21cm signal

Probe reionization process by observing the redshifted 21cm signal

$$\delta T_{b}(z) \sim (1+z)^{1/2} n_{\text{HI}}(z)$$

Square Kilometre Array (SKA1-Low):
21-cm images of redshifted 21cm signal

Sequence of 21-cm images from different redshifts (observed frequency)

3D tomographic dataset
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Tomographic imaging of the 21cm signal

**SKA1-Low:** tomographic images of redshifted 21cm signal

- Foreground emission (signal ~ 1 - 1000 K)
- Instrumental noise (signal ~ 5 K)
- Long integration time
- Radio frequency interference
- And more ...
Image Segmentation with Convolutional Neural Networks

Modern Computer Vision technology based on AI and deep learning methods

learn visual patterns to predict object classes that make up in image
Segmentation with U-Net
(Bianco+ 2021)

- Convolutional layers extract features from 2D data
- Encoder (contraction path) and decoder (expand path)
Mock Data for 21cm Observations

EoR semi-numerical simulations:

- 10k 21cmFAST coeval simulations
- Astrophysical params (Greig+ 2015)
- Redshift range: 7 – 9
- Heating approximation: $\delta T_b \sim n_{\text{HI}}(z)$

Noise:

- SKA1-Low simulated instrumental noise model (Ghara+ 2017, Giri+ 2018b)
- $t_{\text{obs}} = 1000h$ of integration time

Interferometric Smoothing scale:

- Gaussian kernel, $B=2\text{km}$ (SKA1-Low)
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Simulated Systematic Noise

System noise SKA1-Low **Gaussian noise** (Ghara+ 2017, Giri+ 2018b):

- Noise centred at 0 K with standard-deviation:

\[
\sigma = \frac{\sqrt{2k_B T_{\text{sys}}}}{\epsilon A_D \sqrt{\Delta \nu t_{\text{int}}}}
\]

- Network trained on system noise for \( t_{\text{obs}} = 1000 \text{ hrs} \) of observation
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Interferometric Smoothing scale
- Gaussian kernel, $B_{\text{max}} = 2$km
Interferometric Smoothing Scale

Interferometric smoothing scale: $\Delta \theta_{\text{FWHM}} = \lambda_0 (1 + z)/B$

- Gaussian kernel for maximum baseline: $B = 2$ km
- Smoothing done in the angular and frequency directions

![Image showing two 2D maps with x and y axes in cMpc, with color gradients indicating the distribution or intensity of smoothing results.](image-url)
Interferometric Smoothing Scale

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Segmentation with U-Net: Pipelines

Training SegUnet with 10k 3D dataset and different:
- ICs for density field
- Astrophysical parameters ($\zeta$, $R_{\text{mfp}}$, $T_{\text{min\ vir}}$)

21cm tomography dataset

$(z, \nu_{\text{obs}})$
21cm signal = image
$x_{\text{HI}}$ field = mask

SegUnet (2.5M trainable params.)

Compare Prediction/True mask

$L(y, \hat{y})$
Calculate Score

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Seg-Unet: Correlation Coefficient $r_\Phi$

- Average accuracy: 87%
- Low redshift perform better due to the redshift dependency of the instrumental noise model
  - $z > 8.5$: accuracy 85%
  - $z < 7.5$: accuracy 88%

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Seg-Unet: Reionisation History Recovery

- Recovered Reionisation history from the network binary field
- Accuracy within \( \sim 0.5 \sigma \)
- Learns independent pattern of the simulation ionized regions in mock observations
Visual Evaluation and Network per Pixel-Uncertainty

- Network HII binary field recovers with “confidence” large regions
- Inaccuracy at Bottleneck and on a pixel-pixel scale

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SegU-Net: HI Region Size Distribution

- Estimations consistent at the early ($x_{HI} = 0.8$), middle ($x_{HI} = 0.5$) and late ($x_{HI} = 0.2$) stage of reionisation

- Relative difference within $\sim 5\%$
SegU-Net response to Different Noises

Test on different instrumental noise level: under- or over-estimate

- Predictions on un-trained data with $t_{\text{obs}} = 500 - 2000$ hrs
- $t_{\text{obs}} > 500$ hrs (SNR>3) same level of accuracy as in the testing data
Conclusions & Future Work

Summary:
● Fast, reliable and stable on systematic noise variations
● Learns independent pattern of the regions based on intensity gradient between neutral/ionized regions

Paper available: arXiv2102.06713
Code available: github.com/micbia/SegU-Net

Future work:
● Extragalactic & galactic foreground contaminations and ionosphereric refraction effects
● Improve SegU-Net to not only recover binary maps (e.g. ConvLSTM2D layers, Bayesian U-Net)