Point Source Detection with Fully-Convolutional Networks: Performance in Realistic Microwave Sky Simulations

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Brief Summary

In this work we develop a method based on Fully Convolutional Networks to detect point sources in realistic simulations and compare its performance against one of the most used point source detection method in this context, the Mexican Hat wavelet 2 (MHW2). The frequencies for our analysis are the 143, 217 and 353 GHz *Planck* channels.

Context

- Point Sources are one of the **main contaminants** to the recovery of Cosmic Microwave Background signal at small scales and can be relevant even for Polarization

- Their careful detection will be important for the next generation of Cosmic Microwave Background experiments like LiteBird.

- For this reason, it is quite important to develop highly performing methods for Point Source detection.

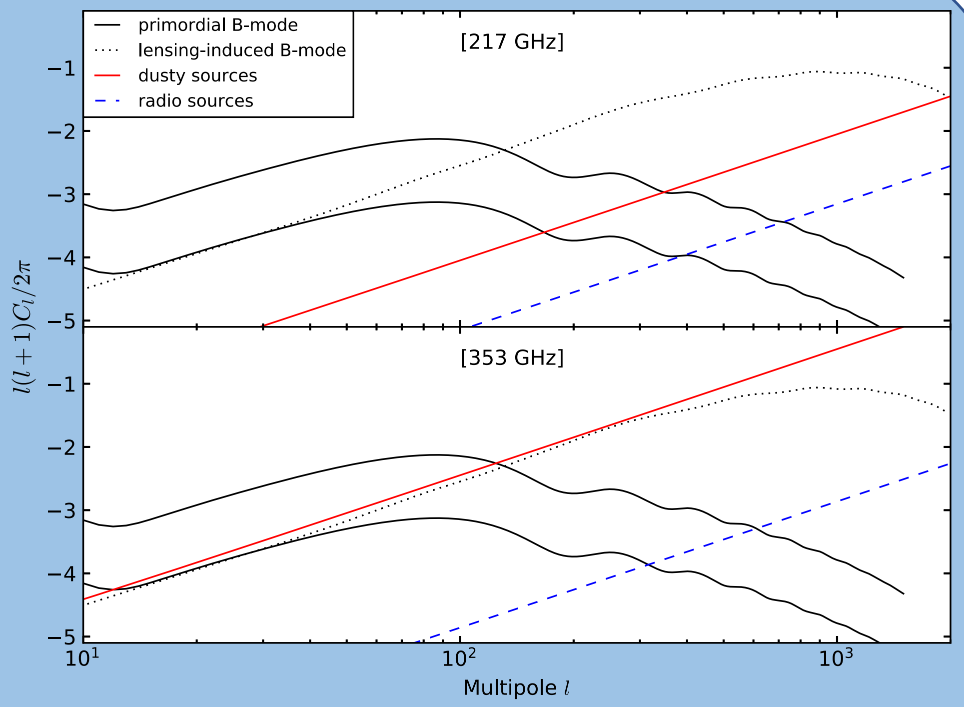

Figure 7. Power spectrum contribution from the dusty (red solid line) and radio (blue dashed line) sources to the power spectrum, compared with the primordial B-mode for $r = 0.1, 0.01$, from top to bottom (black solid line) and the lensing-induced B-mode (black dotted line).

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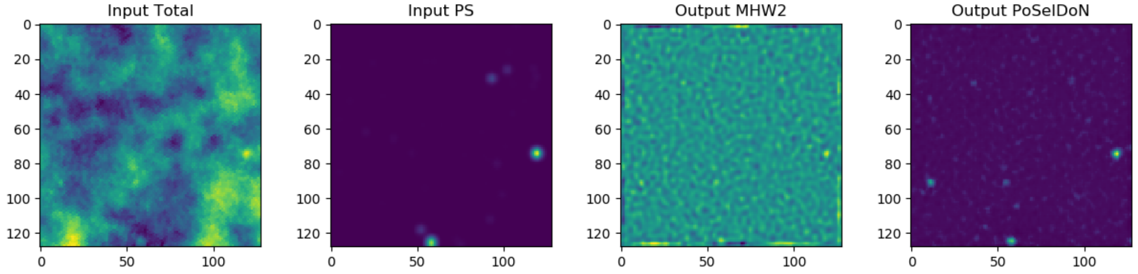
Methodology

Realistic simulations



CMB, CIB, Galactic Thermal emission, thermal SZ, point sources and instrumental noise.

PoSeIDoN structure

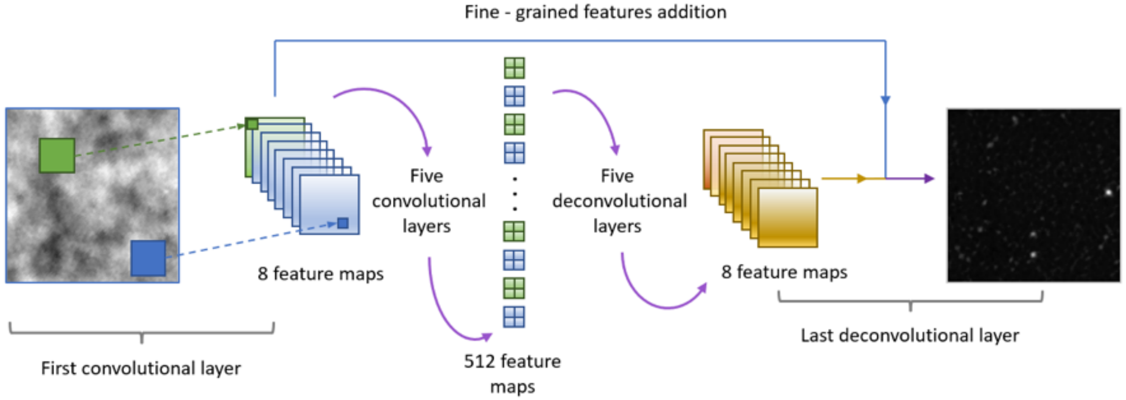
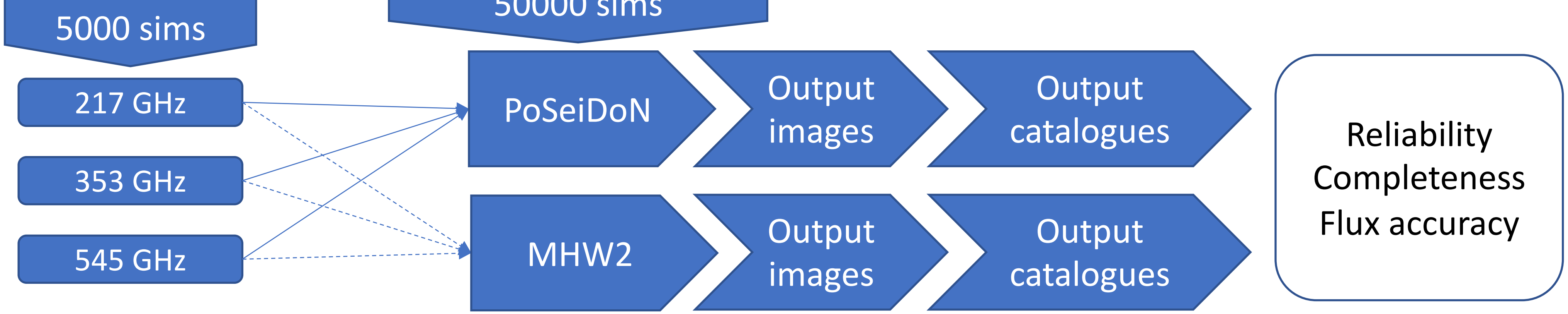
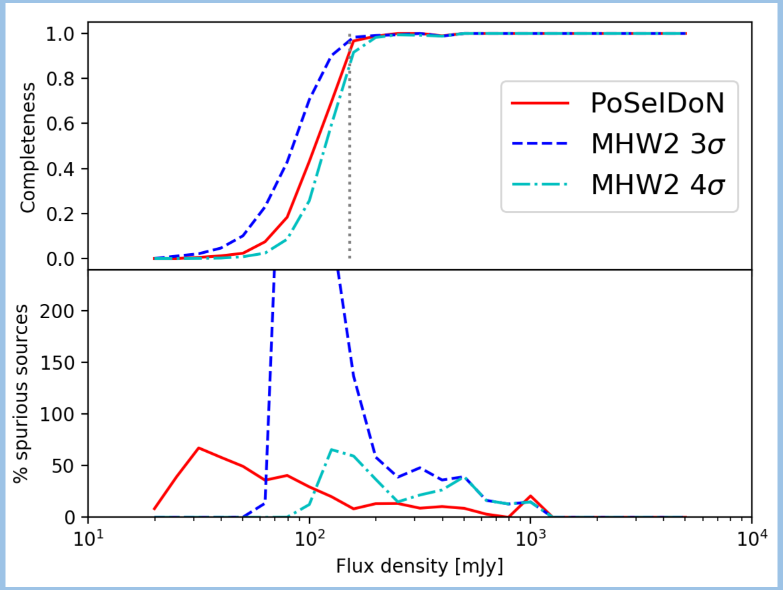


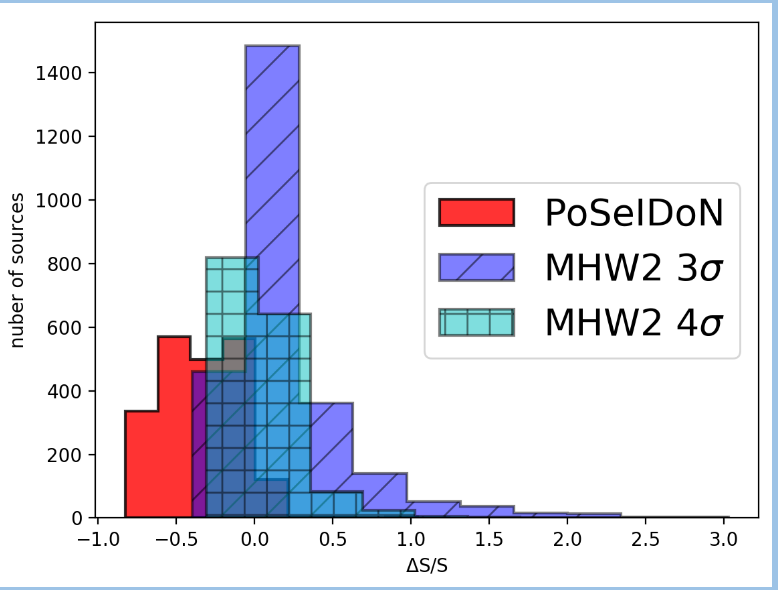
Fig. 2. Details of the FCN used for PS detection in PoSeIDoN. The network has a block of 8 convolutional layers, where the main characteristics are extracted, resulting in 512 feature maps, connected with a deconvolutional block of 8 deconvolutional layers. Fine-grained features are added from each convolution to the corresponding deconvolution.

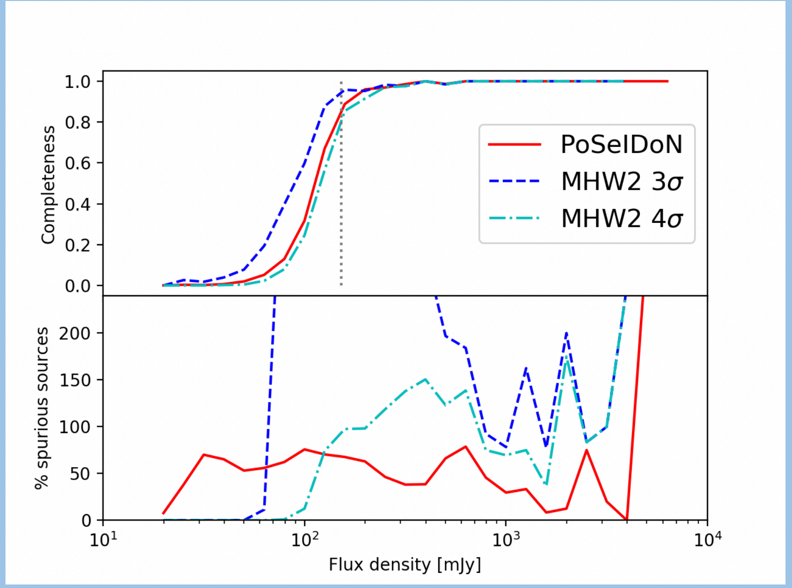
Analysis Pipeline



Results @217 GHz
(the training frequency)







Results for |b|>30°:
- Similar completeness
- Better Reliability

PoSeIDoN: Flux underestimation
MHW2 3σ: Severe Eddington Bias

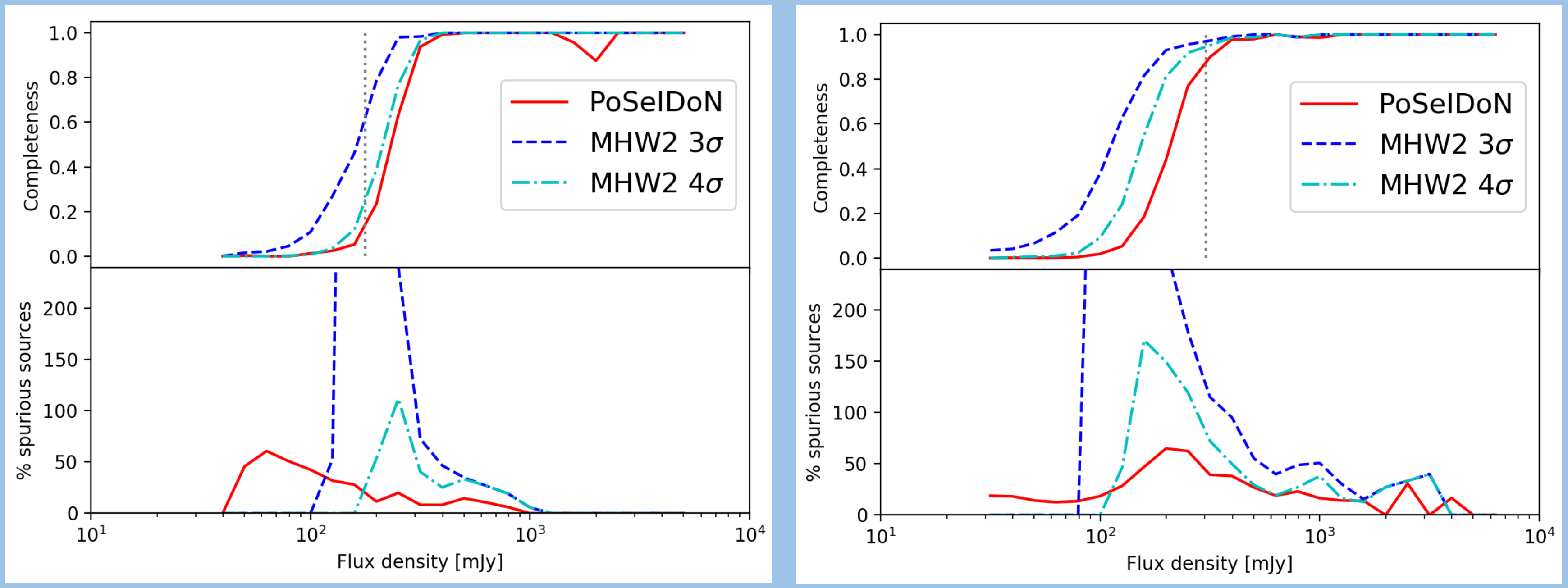
Results for |b|>10 ° :
- Similar completeness
- Better Reliability

Interpretation: PoSeIDoN applies a kind of "Confidence factor" to the flux density depending on how hard is to detect each source. This allows the technique to control the number of spurious sources, but the consequence is that most of the recovered flux densities are under-estimated.

Results @ frequencies different from training

143 GHz

353 GHz



Similar conclusions as for 217 GHz, slightly worse performance

Interpretation: Although only slightly, the performance of PoSeIDoN worsen when applied to images with different statistical properties from the ones used for training.

(Where the MHW2 optimal scale was updated for each channel instead.)

Therefore, these results can be improved by training PoSeIDoN for each particular channel or scientific case.

Impact & Future

- Neural Networks are a very promising approach to detect point sources using data from CMB experiments.
- They provide overall better results with respect to the more usual filtering approaches.
- The results are robust but can be further improved with a tailored training.
- An Additional Neural Network can be trained to correct the flux density estimation.
- Multifrequency improvement: A natural extension is to train PoSeIDoN to deal with multifrequency images.
  - Different frequencies
  - Intensity + Polarization
- This kind of Neural Networks are being studied to detect extended objects (shapes, orientations, ...; Euclid) or to deal with blending (SKA)