



# Microwave Radiometer RFI Detection Using Deep Learning

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### Motivation



- Radio frequency interference (RFI) remains a challenge especially with the advent of wideband receivers and spectrometers with interest in spectrum outside the designated bands
- Large amounts of accumulated data necessary for current techniques which require post processing
- Deep learning can be used to detect RFI in data represented as spectrograms, suitable for wideband receivers







### Deep Learning – How Does It Work

- Deep learning is a type of machine learning
  - Machine learning manually extract relevant features in an image
  - Deep learning, feed raw images directly to a deep neural network that learns features automatically
  - Deep learning requires 100s of thousands or millions of images for best results, computationally intensive









- Transfer learning uses an existing network trained on millions of images
- Pre-trained network fine-tuned, learned features transferred to new task using a smaller number of training images





### Experiments



- Used pre-trained networks Alexnet, GoogleNet, ResNet-101
- Training input 2507 images of RFI, 2507 images of no RFI
- No RFI cases taken over Antarctica, the ocean and Australia with the conditions that RFI level < 2 K and number of pixels flagged < 50 %</li>
- RFI cases taken from all parts of the globe, high level, low level, different types, RFI > 5 K or > 50% of spectrogram blanked
- 80 % of data used for training, 20 % validation

 Object is to classify image as RFI or no RFI



No RFI examples



**RFI** examples



### Experiments



- Training performed twice on each network
  - Experiment 1: RFI free images contained coastlines
  - Experiment 2: RFI free images excluded coastlines







Excluding coastlines in training images can result in false alarms along the coasts





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#### **RFI looks like a Coastline**

Including coastlines in training images can result in missed detections



# Training Results and SMAP Agreement



Network	Accuracy 1 (%)	Accuracy 2 (%)	Training Time 1 (Hr)	Training Time 2 (Hr)
AlexNet	98.50	96.51	7.73	7.10
GoogleNet	97.80	98.30	16.21	16.19
ResNet-101	98.60	98.90	31.62	31.00

Network	Europe Orbit Agreement with SMAP detection (%)	Middle East Orbit Agreement with SMAP detection (%)
AlexNet	97.58	88.31
AlexNet (no coast)	98.85	92.23
GoogleNet	95.89	82.10
GoogleNet (no coast)	96.84	85.03
RestNet-101	96.09	85.77
Restnet-101 (no coast)	97.09	88.05



# Results – Europe Pass



#### L1B\_TB 28923\_D



- 19405 footprints tested
- RFI > 5 K or > 50% of spectrogram blanked = 4088
- 7407 fps detected by deep learning
- Deep Learning agreement = 3989 or 97.6 %
- 256 fps detected by deep learning had 10 or less pixels detected by MAXPD , 1.3 %
- 4125 fps had RFI < 5 K



- Red: agree on RFI
- Grey: agree no RFI
- Blue: DL detects RFI but SMAP detection does not
- Yellow: DL does not detect RFI but SMAP detection does



### Results







# Results – Middle East Pass



DLodetection – AlexNet coastlines excluded

- 98467 footprints tested
- RFI > 5 K or > 50% of spectrogram blanked = 3113
- 11232 fps detected by deep learning
- Deep Learning agreement = 2871 or 92.2 %
- 4470 fps detected by deep learning had 10 or less pixels detected by MAXPD , 4.54 %
- 8667 fps had RFI < 5 K



- Red: agree on RFI
- Grey: agree no RFI
- Blue: DL detects RFI
  but SMAP detection
  does not
- Yellow: DL does not detect RFI but SMAP detection does



### Results – Middle East Pass





#### Example RFI cases in this orbit





### More wideband and continuous RFI in this orbit

#### DL missed detection footprints









- Deep Learning has high performance at detecting RFI localized in time and frequency and lower performance for broadband RFI
- Classification is highly dependent on input data as demonstrated by the coastline/no coastline experiments
- To improve detection especially for broadband RFI improved ground truth can be used such as simulated data