SMARTSAT
COOPERATIVE RESEARCH CENTRE

RMIT UNIVERSITY

Spectrum Sensing using Semantic Segmentation

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Introduction

The radio frequency (RF) spectrum is a shared scarce natural resource utilised by both the defence and commercial sectors. Cognitive radio (CR) aims to address the scarcity problem by intelligently sharing the spectrum. Spectrum sensing is the first CR step with energy detection (ED) being the popular traditional method. However, ED requires a threshold which limits its performance when the signal is close to the noise floor [1].

Aims

The research project's objective is to investigate mitigation strategies to inhibit interference efforts whilst maximising the throughput and capacity. The project aims to develop advanced physical layer security algorithms and strategies, suitable for defence and commercial systems. To accomplish this, development of spectrum sensing is required.

Methods

Convolutional neural networks (CNN) are used in this research project due to their known feature extraction qualities. The features include the power from a hybrid satellite-terrestrial shared downlink frequency band. The satellite system is modelled after Inmarsat downlink broadband global area network (BGAN) and the terrestrial system is a 5G new radio (NR) physical downlink shared channel (PDSCH). Greyscale spectrogram images are generated and used to train a semantic segmentation spectrum sensing (SSSS) agent. The SSSS agent uses the CNN extracted features to detect signal occupancy in low signal-to-noise ratio (SNR) fading environments. Statistical analysis was applied to the SSSS agent's softmax layer output to verify its performance results. Lastly, a threshold-based detector (TD) with a dynamic threshold was used as the baseline spectrum sensing method.

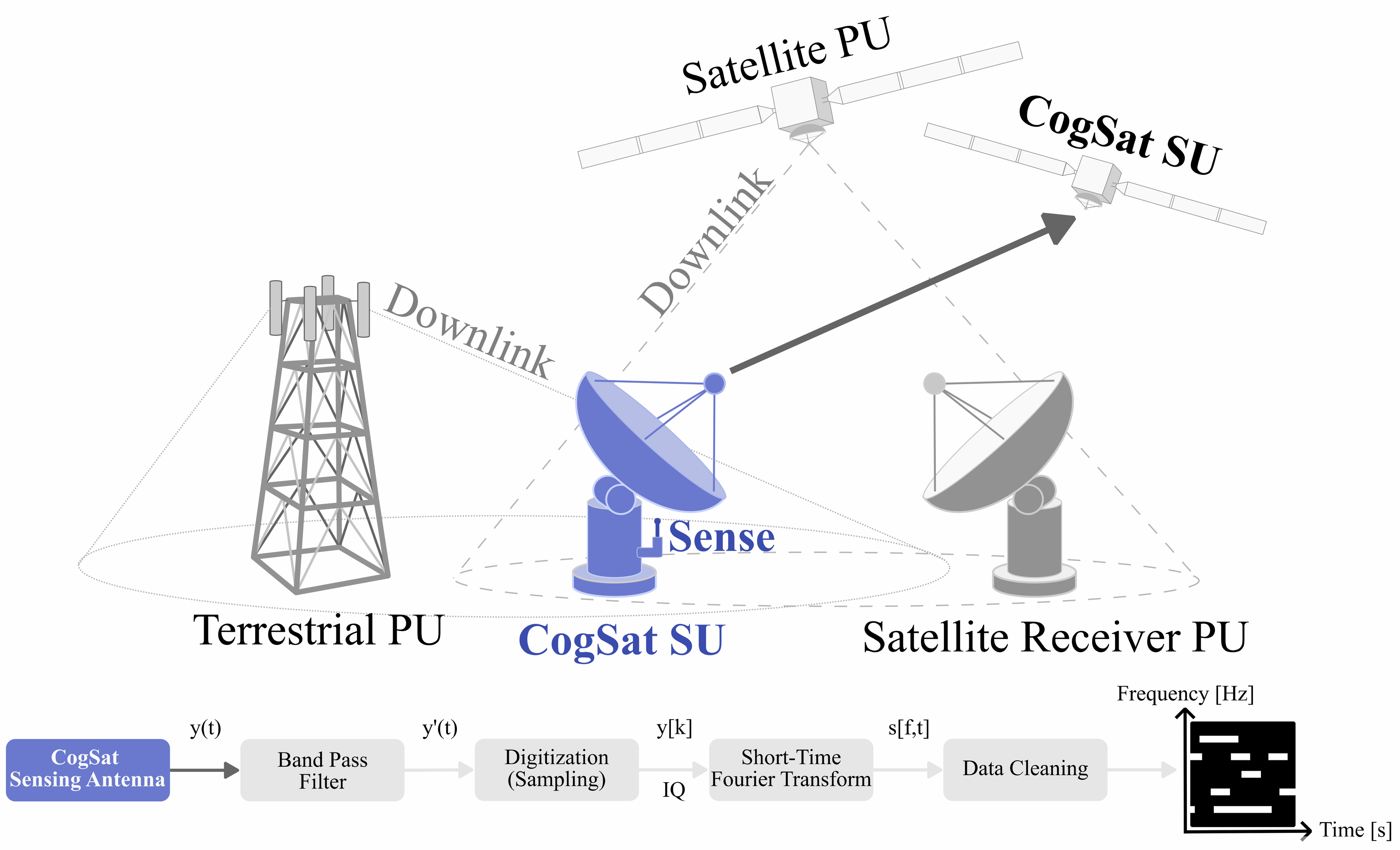

Fig. 1: Hybrid Satellite-Terrestrial Downlink Scenario

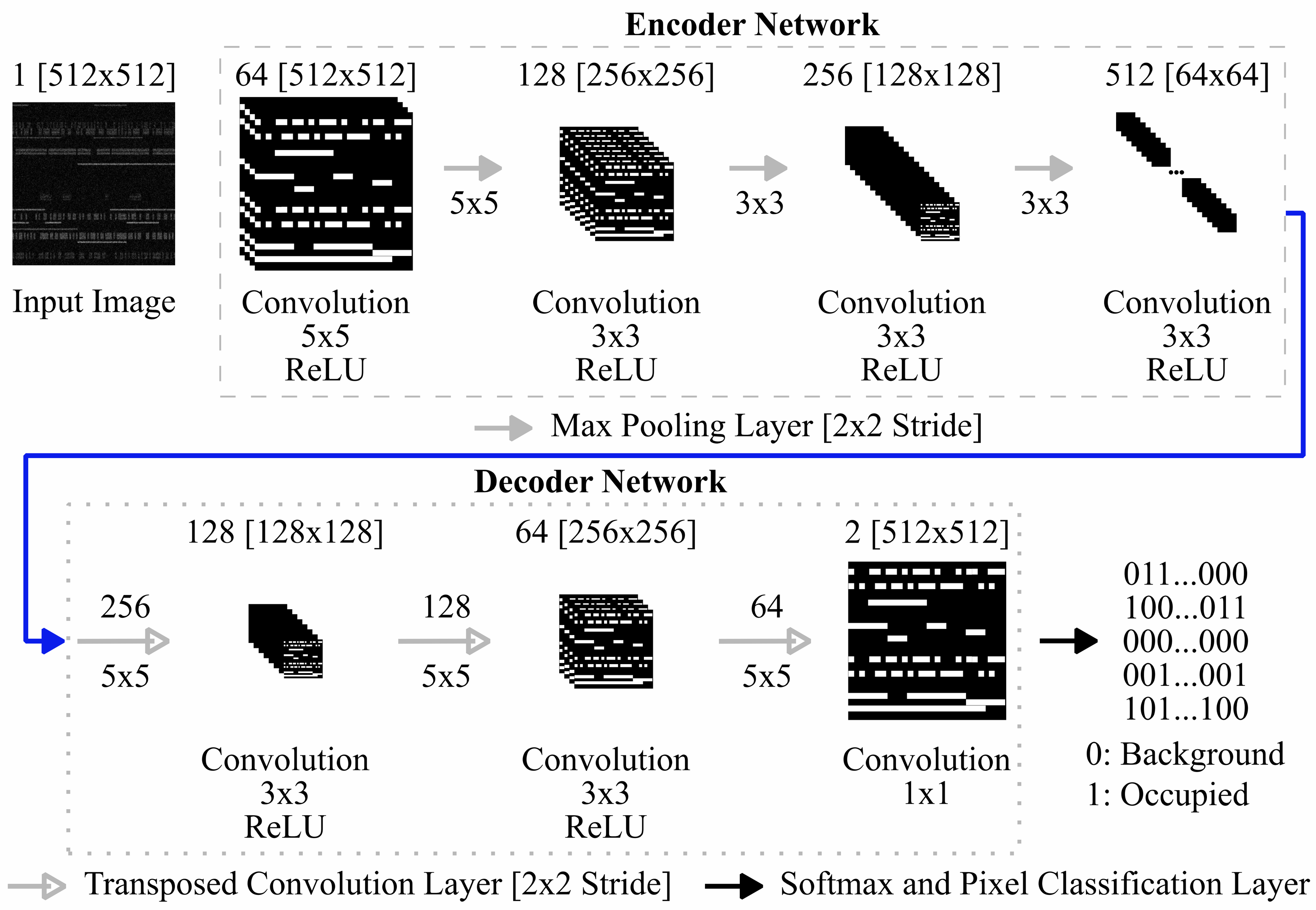

Fig. 2: SSSS Encoder-Decoder Network Architecture

Results

The downlink scenario is portrayed in Fig. 1 where the cognitive satellite (CogSat) secondary user (SU) senses the spectrum for occupancy and then creates a grayscale spectrogram image (512-by-512 pixels). A joint additive white Gaussian noise (AWGN) and Rician fading channel was considered.

The number of training images was skewed to be larger at low SNRs (-20 dB) and smaller at high SNRs (30 dB) with a total of 10000 images. The SSSS agent architecture is shown in Fig. 2 which classifies every pixel as either "Background" or "Occupied". A pruned variant of the trained SSSS agent was made to reduce the memory footprint and inference timing.

The SSSS agent requires 1.56s to classify the 512-by-512 image while the pruned agent was 0.76s. The probability of false alarm (P_{FA}), probability of detection (P_D), intersection over union (IoU), and overall accuracy were the performance metrics. The SSSS agent and pruned variant both perform significantly better than TD at low SNR fading environments. The SSSS agent should be used over the pruned one if timing is not critical.

Table 1: Performance Metric Comparison at $\mathrm{SNR} = -20$ dB

Agent	P_{FA}	P_D	IoU	Accuracy
SSSS	11.76%	**68.64%**	**52.39%**	82.85%
Pruned SSSS	**4.90%**	52.13%	46.16%	**83.29%**
TD	36.90%	45.95%	23.28%	58.38%

References

[1] R. Tandra and A. Sahai, "Fundamental limits on detection in low SNR under noise uncertainty," in 2005 Int. Conf. on Wireless Networks, Communications and Mobile Computing, vol. 1, 2005, pp. 464–469 vol.1.

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