Finding Waldo in the CBRS Band: Signal Detection and Localization in the 3.5 GHz Spectrum

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***Abstract*—Opening the Citizen Broadband Radio Service (CBRS) band in the US to secondary users offers unprecedented opportunities to LTE and 5G networks, as long as incumbent radar signals are protected from interference. Towards this aim, the US Federal Communications Commission (FCC) requires Environmental Sensing Capabilities (ESCs) to be installed along the coastal regions. Furthermore, FCC mandates that the secondary users transmit with low power levels, such that the aggregated interference and noise power in the vicinity of ESC sensors remains below -109 dBm/MHz. At this interference level, the ESC must detect 99% of radar pulses with peak power of at least -89 dBm/MHz. In this paper, we design an enhanced ESC sensor, called ESC+, that leverages the deep learning framework called 'you only look once' (YOLO) for signal detection using spectrograms. We propose a two-stage spectrogram-based coarse and fine signal analysis method for: (i) detecting, and characterizing radar pulses in environments where the aggregated noise and interference level goes beyond FCC restrictions, and (ii) detecting and characterizing other signal types (e.g., 5G and LTE) in the CBRS band, with a goal of determining unauthorized users. We generate a realistic spectrogram dataset in MATLAB consisting of three signal types of radar, 5G, and LTE where the aggregated interference and noise power occurring concurrently with the radar pulse is varied upto -104 dBm/MHz. We show 100% radar pulse detection in interference and noise levels of up to 3 dB higher than what is required today.**

***Index Terms*—Spectrogram, YOLO, CBRS band, Incumbent radar, PAL user.**

I. Introduction

The Citizens Broadband Radio Service (CBRS) band in the US offers new spectrum resources in the desirable mid-band frequencies between 3.55 and 3.7 GHz, for deploying 4G LTE and 5G networks as well as internet of things (IoT) applications. As a necessary condition to use this band, higher priority incumbent users of the CBRS band (e.g., naval radar signals) must be protected from interference [1]. Towards this aim, the Federal Communications Commission (FCC) defines regulations for hierarchical access priority in the CBRS band and transmission power level control in areas along the coastline [1], [2].

• *Hierarchical spectrum access priority in the CBRS band:* Spectrum access priority in the CBRS band has a three-tier structure as shown in Fig. 1 with: (i) naval radar at the apex of the pyramid, (ii) the Priority Access Licenses (PAL) users in the middle tier, and (iii) the General Authorized Access (GAA) users at the bottom tier. PAL users purchase a license

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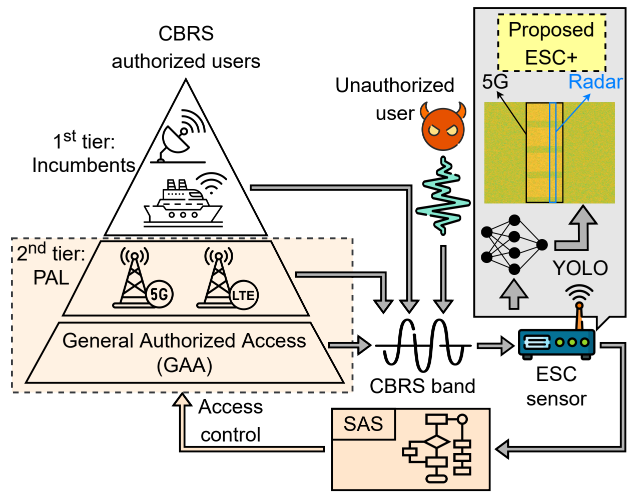

Fig. 1: The proposed ESC+ that detects, classifies, and localizes different signals in the shared CBRS spectrum, through YOLOv3 framework. The labels and frequency boundaries of each detected signal can be compared against SAS registered users to find unauthorized signals.

in the first 100 MHz of the CBRS band to acquire transmission rights in the band, while GAA users opportunistically use the band when no other transmission is going on. Spectrum access is managed by a central entity known as Spectrum Access System (SAS) that has no control over the incumbent users, but grants access to the registered PAL and GAA users [1]. Both PAL and GAA users need to register with SAS to be considered as authorized users, and to be granted access based on their priority. The SAS relies on sensing information from an array of geographically distributed Environmental Sensing Capabilities (ESCs) for allocating the spectrum to PAL and GAA users. The frequency bands are allocated only if no radar pulse is detected in them. Furthermore, based on the noise floor information received from ESC sensors and PAL/GAA locations, SAS mandates the latter to transmit with a power level such that the aggregated noise and interference level in the vicinity of ESC sensors remains below -109 dBm/MHz [2]. The areas in the vicinity of ESC sensors, where the PAL/GAA transmission power level restrictions are enforced with a goal of protecting the radar signal, are called *whisper zone*s. With radar pulses having at least -89 dBm/MHz power, ESCs should be designed such that detection of 99% of radar pulses in SINR 20 dB is guaranteed [3].

• *Problem definition:* Previous work show promising results in the use of deep learning for detecting radar pulses in unoccupied bands [4], [5] and in the presence of a weak LTE signal in the radar band [6]. However, two interesting questions remain: (i) Could advanced signal analysis methods help in relaxing FCC regulations regarding the limited power levels of the secondary users [2] in the whisper zone? Deep learning-based approaches may eliminate the need for hand-crafted detection of signal features. Furthermore, given the ability to learn subtle signal variations across time-frequency axes, our hypothesis is that deep learning may be able to detect radar pulses embedded within stronger LTE and 5G signals. (ii) Could the ESC sensor perform a larger role beyond detecting only radar pulses? Currently, there is no standards-defined requirement within ESCs to detect *unauthorized* transmissions such as LTE/5G users that are not registered with SAS to operate in the band. Clearly, without such safeguards, paying LTE/5G service providers are not incentivized to use the CBRS band.

• *Proposed solution:* In this paper, we propose an enhanced ESC sensor, called ESC+, that addresses the two aforementioned gaps: (i) ESC+ can detect radar pulses within the time-frequency boundaries of an existing PAL signal with power higher than FCC-mandated level. This provides the opportunity to relax FCC restrictions in the whisper zone and helps achieve better LTE/5G network connectivity. (ii) ESC+ detects, classifies, and localizes different signal types in the spectrograms obtained within the CBRS band. The list of detected signals and their occupied bands can be shared with SAS, which is then compared against SAS list of registered users in order to label each transmission as authorized or unauthorized. Compared to previous work [4], [6], [5], we assume a more complex environment where (either authorized or unauthorized) LTE and 5G signals occupy different bands concurrently with radar signals. We formulate signal detection, classification, and localization as an object detection problem. We train YOLOv3 framework [7] to effectively detect, classify, and localize three signal types of 5G, LTE, and radar in the spectrograms of the CBRS band, as shown in Fig. 1.

• *Paper contributions:* Our contributions are as follows:

- We propose the design of an enhanced ESC sensor called ESC+, as shown in Fig. 1. ESC+ detects weak radar signals within overlapping LTE/5G PAL-allocated frequencies, as well as 5G and LTE signals in the CBRS spectrum.
- We use a deep-learning-based approach, specifically YOLOv3, for not only signal detection, but also determining the signal type, and localizing the signal by marking the specific lower and higher end points of the spectrum band that it occupies.
- We propose a *two-stage signal detection* process using two differently trained YOLOv3 frameworks. In the first stage, spectrograms showing the whole 100 MHz CBRS band are fed to a YOLOv3 framework that is trained on 100 MHz-extent spectrograms, for a coarse signal detection. Then, the detected signals from this stage are cropped, stretched, and fed to another YOLOv3 in the second stage for fine signal detection.
- The proposed ESC+ is validated on a diverse simulated MATLAB dataset generated for a complex but realistic environment, where multiple LTE/5G transmissions of different bandwidths exist in close proximity along the frequency scale with possible overlapping radar pulses.

II. Related Work

In this section, we first present a review of the existing literature on spectrogram-based signal detection. Then, we review the work focusing on radar detection in the CBRS band.

Signal Detection using YOLO: A variant of YOLO, called as tiny-YOLO, was used in [8] to detect the boundaries of signals of 20-modulation classes as one single class.Vagollari *et al.* [9] combine signal detection and modulation classification into a single problem, using YOLO. They consider a 10-class modulation classification spectrogram dataset and retrain the last few layers of YOLOv1 pretrained on ImageNet dataset, with their spectrogram dataset. Fonseca *et al.* [10] detect and classify WiFi and LTE signals in over-the-air spectrograms besides extracting transmission features such as center frequency, bandwidth, and duty cycle through YOLO object detection framework. Basak *et al.* [11] train a variant of YOLO-lite framework to classify 10 classes comprising 2 WiFi versions and 8 drone signals in the ISM band. They consider scenes from an over-the-air dataset of single or multiple signals with overlapping and non-overlapping cases. Ghanney *et al.* [12] detect radio frequency interference in a National Radio Astronomy Observatory dataset. They create images of power spectral density graphs for each recording. They use two methods of supervised learning through YOLOv3 and unsupervised using convolutional autoencoder for interference detection.

Radar Detection in the CBRS Band: Lees *et al.* [4] show the superiority of deep learning over classical algorithms for radar detection by creating independent spectrograms of each of the 10 MHz channels in the CBRS band, and classifying them in parallel in terms of the presence or absence of radar signals. While they use a wide variety of machine learning and deep learning classifiers, they do not localize the signals or estimate their bandwidths. Sarkar *et al.* [6] propose a Spectrogram Image Learning (SIL) framework based on YOLO for real-time detection of radar (incumbent) signals and estimating their bandwidths. This work focuses on detecting radar signals in the presence of noise and weak interference from secondary users. Caromi *et al.* [5] detect radar signals in the CBRS band using a variety of Convolutional Neural Networks (CNNs). They perform both raw signal magnitude-based and spectrogram-based binary classification indicating the presence or absence of the radar signal.

None of the studied previous work on the CBRS band propose detecting and characterizing different types of signals, or radar detection in environments with noise higher than FCC regulations in the whisper zone.

III. Spectrogram Dataset Description

To evaluate our proposed ESC+ sensor, we generate a dataset in MATLAB with 1300+ spectrogram scenes of simulated time domain signals in the CBRS band. These signals are of the three following types: (i) Ship-borne radar as the incumbent user of the CBRS band. For realistic evaluation, we allow the radar pulses to appear at any frequency in the spectrogram, both overlapping or non-overlapping with other signals, (ii) LTE, and (iii) 5G signals that may or may not be registered within SAS. At the end of the detection process, the ESC+ sensor generates a list of detected 5G and LTE signals that is shared with the SAS. By comparing against the list of registered users, the SAS can identify unauthorized 5G and LTE users.

The main properties of the three signals in our dataset are described below.

Power values: As mandated by FCC regulations, the cumulative power of Additive White Gaussian Noise (AWGN) and other sources of interference must be no more than -109 dBm/MHz around the ESC sensor [2]. We define SINR as $10 \times \log_{10}(P_{\text{radar}}/P_{\text{noise}})$, where P_{radar} is peak radar power per MHz, and P_{noise} is average noise and interference power per MHz of the radar band. In this case, radar pulses with at least -89 dBm/MHz of peak power (at least 20 dB SINR) must be detected with 99% accuracy [3]. We vary the power of radar pulses in the range of -89 to -79 dBm/MHz to emulate SINRs in the range of 20 to 30 dB. For the noise and interference power, we go upto 5 dB beyond FCC limit, and allow the noise and interference power to vary in the range of -109 to -104 dBm/MHz. In the scenes where radar overlaps with the PAL user signal (i.e., LTE or 5G), we allocate 25% of the power to AWGN and 75% to the LTE/5G signal, to ensure the SINR is in the range of 15 and 30 dB.

Signal bandwidth: According to FCC regulations, each CBRS vendor can purchase and aggregate up to four 10 MHz channels in the CBRS band. Therefore, the largest bandwidth that PAL users can transmit is 40 MHz. Based on this, we randomize the bandwidth of 5G and LTE signals to have all the standard bandwidths in the range of 5 to 40 MHz.

Radar parameters: We use standard compliant radar type-1 that is used in naval radars [3]. We use the tool released by National Institute of Standards and Technology (NIST) in [13], and set the pulse width of radar pulses to 0.5 μs. We set the pulse per burst parameter as 20 and pulse repetition rate as 1010 per second.

Sampling rate and duration: The 10 MHz channels in the CBRS band can be monitored separately for radar pulses with sampling rate of 10 MHz, or the whole CBRS band can be monitored at once with a higher sampling rate. As the PAL users can exist in the first 100 MHz of the CBRS band between 3.55 GHz and 3.65 GHz, our proposed ESC+ monitors the entire 100 MHz at once and samples the wireless channel with 100 MHz sampling rate. Consequently, the spectrograms that we create out of the sampled data span 100 MHz on the horizontal axis. We sample the CBRS band for 20 ms, and so the time-scale of the spectrogram spans to 20 ms. We assume that all the three signals of radar, 5G, and LTE that might appear in each scene span throughout this 20 ms, while occupying different frequency bands as shown in Fig. 2.

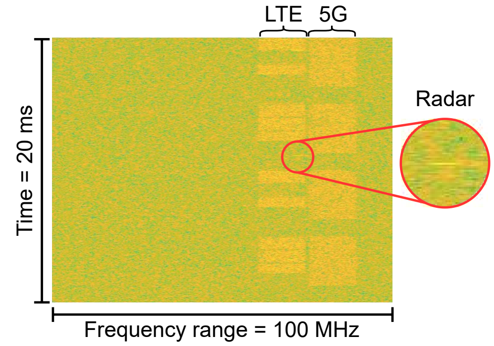

Fig. 2: A sample spectrogram in the dataset with 10 MHz 5G and 10 MHz LTE. A fade radar pulse is overlapping with the LTE, which can be seen in the red circle. The radar pulse has peak power of -89 dBm/MHz and the aggregated LTE and noise power in its background are -104 dBm/MHz, which leads to 5 dB lower SINR compared to FCC regulations for the whisper zone.

LTE and 5G spectrum usage technique: As per FCC regulations in the CBRS band [1], we create LTE and 5G signals in the Time Division Duplex (TDD) mode.

In the next section, we describe the proposed signal detection method within the proposed ESC+.

IV. Proposed Method

Our vision of ESC+ enhances the standard ESC, thereby allowing it to detect the radar pulses that are overlapping with secondary user signals (i.e., 5G or LTE) even when the aggregated interference and noise power in the radar band is higher than the FCC-specified limit [2]. To make radar detection possible in high noise regimes, we propose the use of deep learning for the ESC+ design. Specifically, we formulate signal detection and localization as an object detection problem, where a deep learning framework is trained to detect, classify, and localize different objects in an image. For the object detection framework, we use YOLOv3 [7] that provides signal detection, classification, and localization in spectrograms of the CBRS band, in one pass. The proposed ESC+ system is described next.

A. ESC+ System Overview

The ESC+ sensor consists of a two-stage detection process, as shown in Fig. 3. In the beginning, the ESC+ senses the CBRS band between 3.55 GHz and 3.65 GHz in one shot for 20 ms with 100 MHz sampling rate and creates a spectrogram. In the first stage, this spectrogram with 100 MHz frequency content is processed through YOLOv3 framework. The output of YOLOv3 consists of detected signals attributed with parameters including (i) label, (ii) detection probability, and (iii) bounding boxes around each detected signal that

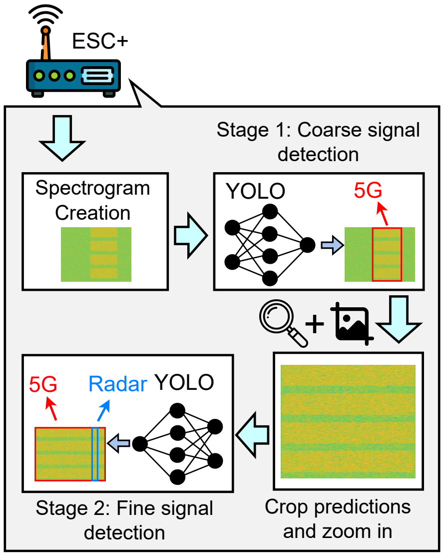

Fig. 3: The proposed ESC+ with two-stage signal (i.e., radar, 5G, and LTE) detection and localization using YOLOv3 object detection framework.

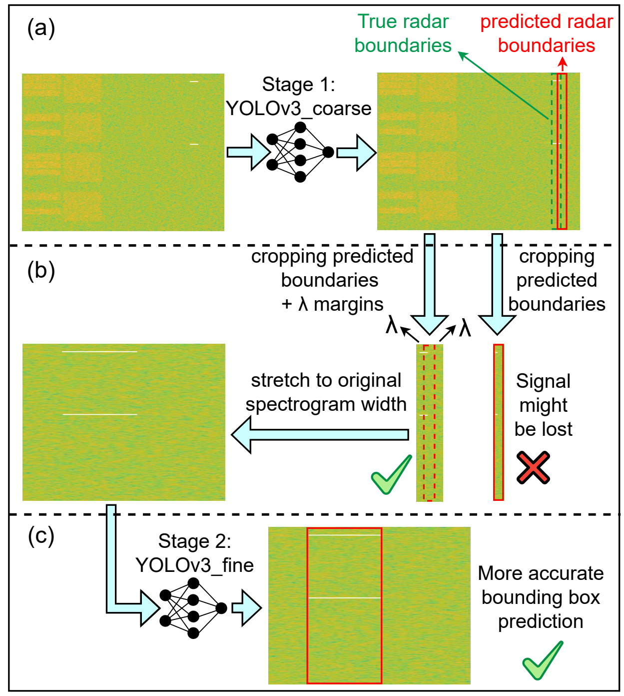

Fig. 4: The two-stage coarse and fine signal detection. (a) Stage 1: Coarse signal detection, (b) Proper cropping and stretching the predicted signals of stage 1, (c) Stage 2: Fine signal detection on the stretched (zoomed) spectrogram that leads to more accurate localization of narrow signals. In all spectrograms in this diagram, the originally faded radar pulses are manually whitened to be visible in the diagram.

determine signal frequency and time boundaries. In this stage, signals with wider occupied frequency bands that are easily visible in the spectrogram are detected with high bounding box precision. However, narrower signals that occupy a smaller portion of the 100 MHz spectrum extent inside the wider LTE and 5G might be missed, or if detected, might not be localized with accurate bounding boxes. To solve this, we propose to crop the detected signals in the spectrogram, and zoom into them to perform a fine signal detection with a second YOLOv3 framework. These two stages are described in the remainder of this section.

B. Stage 1: Coarse Signal Detection

For coarse signal detection in stage 1, we train a YOLO framework, denoted as `YOLOv3_coarse`, with spectrograms that have the full frequency content of 100 MHz. We follow the YOLOv3-specific steps of anchor generation before training, and adjusting the learning rate during training [7], [14]. For the signal labels, we use 3 labels of radar, 5G, and LTE to characterize each signal pattern separately. As seen in Fig. 2, 5G and LTE signals have different patterns in the spectrogram. Furthermore, the faded radar pulse –that is overlapping with the LTE and is shown by zooming in the red circle– shows a completely different pattern. The detected signals are distinguished and labeled by trained YOLOv3 framework based on their distinct patterns in the spectrogram. Fig. 2 further shows our complicated scenario in high noise regime with faded signals that are in close proximity to each other.

In the first stage of signal detection within ESC+, we perform a coarse detection of the signals that exist in the spectrogram of the CBRS band. In this stage, wider band signals of 5G and LTE that occupy at least 5 MHz bandwidth, which corresponds to at least 5% of the frequency content of each frame, are detected with accurate bounding boxes. However, the narrow radar pulses that may exist within 5G and LTE frequency boundaries might be missed, or if detected, the bounding boxes might not be accurate. These pulses have less than 2 MHz of bandwidth and occupy less than 2% of the spectrogram frequency content, and hence, might not be detected accurately by YOLO in stage 1.

To solve this issue, we propose a second stage of YOLOv3 spectrogram processing for fine signal detection.

C. Stage 2: Fine Signal Detection

For finer detection of narrower signals, we further analyze the signals that are detected in stage 1. We increase the scale of the narrow signals that potentially exist within the boundaries detected in stage 1, by stretching the detected signal along the frequency axis. As explained in Section IV-B, the predicted bounding box of the detected signal might not be accurate. Therefore, if the detected signal is cropped using the predicted boundaries, portions of the signal might be lost, as shown in Fig. 4 (b). To prevent this, we consider a margin of λ pixels at each side of the predicted bounding box to account for inaccurate bounding box prediction, and ensure that the original signal is fully within the cropped spectrogram. Next, the cropped spectrogram is stretched along the frequency axis (horizontally) so that it is now the same width as the original

100 MHz spectrogram. This stretched spectrogram with the stretched (and more visible) signal inside it is then fed to another YOLOv3 framework, denoted as `YOLOv3_fine`, for more accurate localization of the signal within it. The proper cropping and stretching of the detected signal is shown in Fig. 4 (b).

To train `YOLOv3_fine`, we take the training set of `YOLOv3_coarse` in stage 1, and crop out the independent signals from their true boundaries plus the λ margins on their sides. Independent signals include all LTE/5G signals and those radar pulses that do not overlap with LTE/5G signals. We stretch the cropped portion of the spectrogram horizontally to match the width of stage 1 spectrograms. In this way, the training set spectrograms for `YOLOv3_fine` is structured the same way that the test spectrograms will be structured.

Determining $\boldsymbol{\lambda}$: We define λ as the margin at both sides of the predicted bounding boxes and use it to ensure the original signal is fully within the cropped image, even if the predicted boundaries are not accurate. Proper determination of this margin is essential for increasing the performance of `YOLOv3_fine` at stage 2. We determine a specific λ per signal type by testing the trained `YOLOv3_coarse` on the validation set spectrograms. We compare the predicted bounding boxes against the true bounding boxes, and record pixel errors at both frequency borders. After passing all the validation set spectrograms through the trained `YOLOv3_coarse` and recording all the pixel errors, we calculate λ as the maximum of pixel errors for each signal type. We achieve 3 λ values, one for each signal type. These λs are used for properly cropping each signal, and preparing a cropped and stretched spectrogram for `YOLOv3_fine`, during training and during testing it after stage 1 coarse detection.

V. Evaluation

We shuffle our dataset of 1300+ spectrograms and partition it into 70%, 10%, and 20% to construct training, validation, and test sets, respectively. We train `YOLOv3_coarse` for stage 1 and `YOLOv3_fine` for stage 2, using the training set and the stretched version of the training set, respectively, as described in Section IV.

A. Metrics

We use the following object detection metrics for statistically evaluating our proposed 2-stage ESC+.

Recall: Recall is the ratio of true positives to the total number of signals in all the test set spectrograms.

Intersection over Union (IoU): For each detected signal with predicted bounding box, IoU is the area where the true bounding box and the predicted one overlap, divided by the area of their union.

False Positives (FPs): In our experiments, FPs are the detected objects whose predicted bounding boxes have no overlap with true bounding boxes of the object with the same labels (i.e., IoU < 0.001).

Average Precision (AP): Average Precision for each label is the true positive count divided by the total number of positives for that label.

TABLE I: Different performance metrics for different signal types of radar, 5G, and LTE after stage 1 and after stage 2. The metrics are calculated over all SINRs in the test set from 15 to 30 dB.

	Metric	Signal Type		
		Radar	5G	LTE
Stage 1	Recall	98%	100%	100%
	Average IoU	0.75	0.95	0.94
	False Positives	30	1	1
	Average Precision	0.89	0.99	0.99
Stage 2	Recall	99%	100%	100%
	Average IoU	0.85	0.97	0.97
	False Positives	10	0	0
	Average Precision	0.96	1.00	1.00

B. Evaluation of Stage 1

After the training of `YOLOv3_coarse` is completed, we perform stage 1 (coarse object detection) on the test set as shown in Fig. 3, and calculate the aforementioned metrics for stage 1 that are shown in Table I. For evaluation, we set IoU threshold to a small value of 0.001, which ensures that any detected object with a certain label whose predicted bounding box has the slightest overlap with true bounding box of an object with the same label is counted as true positive. We observe 100% recall for 5G and LTE signals, and 98% recall for radar. The high recall for 5G and LTE compared to radar is due to their more widely spread energy and higher bandwidth of 5G and LTE signals compared to narrow and sparse radar pulses that are more difficult to detect, as seen in Fig. 2.

C. Evaluation of Stage 2

To suitably tailor the training set for `YOLOv3_fine` in stage 2, we need to calculate λ for each signal type. To do this, we test `YOLOv3_coarse` on the validation set, and record pixel errors. We calculate λ values as the maximum of pixel errors for each signal type over the whole validation set, and achieve numerical values of 13, 8, and 9, for radar, 5G, and LTE, respectively. We crop and stretch the training set using these values, and train `YOLOv3_fine` with the stretched training set. Similarly, in the test phase after `YOLOv3_coarse` detection, we use the same λ values as margins to crop the predicted objects, as shown in Fig. 4. Next, we stretch the cropped spectrograms to have the same pixel width as the stage 1 spectrograms and feed them to `YOLOv3_fine` at stage 2.

To evaluate stage 2, first, we show the effect of our 2-stage signal detection by illustrating an example spectrogram with YOLOv3 bounding boxes after stage 1 and stage 2 in Fig. 6. We observe that the narrow radar signal within the wider 5G is missed in stage 1, as shown in Fig. 6 (a). However, after proper cropping and stretching the spectrogram as described in Section IV and proceeding through stage 2, we observe that the radar pulse is detected in Fig. 6 (b).

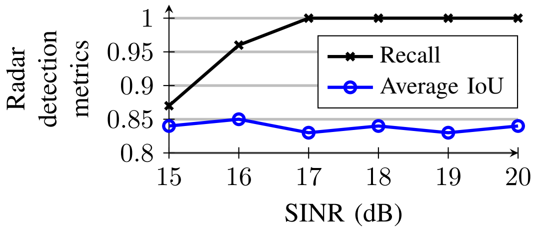

Fig. 5: ESC+ radar detection metrics in SINRs lower than the standard. 20 dB is the standard SINR in the whisper zone.

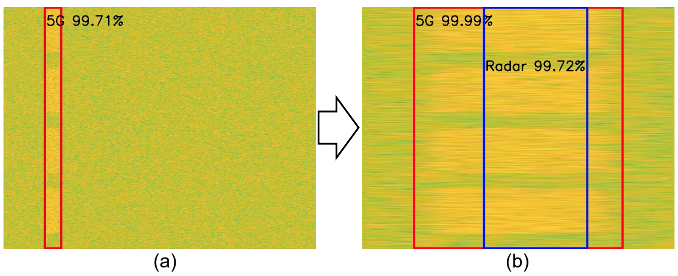

Fig. 6: An example of YOLOv3 output bounding boxes during test (a) After stage 1, where the narrow radar signal within the 5G signal is missed, and (b) After stage 2, where the stretched radar is detected.

Next, similar to stage 1, we calculate the aforementioned metrics for stage 2 and show them in Table I. We observe that stage 2 improves the coarse signal detection metric of recall by 1% for radar. Furthermore, average IoU is increased by 13%, 2%, and 3% for radar, 5G, and LTE, respectively. Similarly, FPs are decreased by 66% for radar signals, while they become 0 for LTE and 5G signals.

We further calculate recall and average IoU per SINR for radar pulses and present them in Fig. 5. Compared to the standard ESC that promises 99% radar detection in SINRs 20 dB and higher [3], our results provide 100% radar detection in SINR 17 dB and higher, which indicates 3 dB higher noise and interference than the standard. We also observe average IoU of around 0.84 for radar detection in different SINRs between 15 dB to 20 dB. This implies that we are able to detect radar signals in environments with 3 dB higher noise compared to what is realized today in whisper zones.

Achievements: Our proposed ESC+ achieves recall of 100% for radar, 5G, and LTE signals in SINRs of 17 dB and higher, which shows that FCC regulations regarding secondary user transmission power in the CBRS band in whisper zones can be reduced by 3 dB. This higher transmission power can potentially improve cellular connectivity for 5G and LTE networks in the whisper zone.

VI. Conclusion

In this paper, we proposed an enhanced ESC sensor, called ESC+, for detecting signals using the spectrograms of the CBRS band. The proposed ESC+ is based on YOLOv3 object detection framework and leverages a two-stage design to perform coarse and fine signal detection, respectively. The proposed ESC+ can detect wide and narrow radars (incumbent users) and LTE/5G signals (PAL users) in complex setting and in close spectral proximity. By achieving 100% radar pulse detection in SINR 17 dB, which is 3 dB below the standard SINR, we show the possibility for relaxing FCC regulations related to transmission power in whisper zones. Our proposed design will allow the LTE/5G networks to transmit with higher power, potentially resulting in better connectivity to end users.

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