






An Intelligent Wireless Signal Detection and Recognition Platform

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Abstract. The detection and recognition of wireless signals play an essential role in the communications security of the Internet of Things (IoT). In order to monitor wireless signals, a platform that can detect and recognize wireless signals in real time is needed. This paper describes an intelligent wireless signal detection and recognition platform. The platform can monitor the presence or absence of wireless signals in real time and perform parameter analysis and modulation classification of wireless signals. We design and implement an integrated detection and recognition scheme based on the You Only Look Once for Signal Detection (YOLO-SD) and the Convolutional Neural Networks (CNN). The YOLO-SD algorithm has a fast running speed, thus the platform can work in real-time. The platform is designed and implemented on Field Programmable Gate Array (FPGA) platform. The result shows that our proposed platform achieves a detection accuracy of 80% and recognition accuracy of 93%, thus demonstrating the significant potential for analyzing RF spectral activity with high accuracy.

Keywords: Radio frequency (RF) signal acquisition · time-frequency map analysis · signal detection and recognition · deep learning · YOLO target detection

1 Introduction

Nowadays, billions of IoT devices arise around us. IoT systems are becoming more widespread in various areas of applications, namely in industry, power engineering, systems of implantable medical devices for monitoring vital characteristics of the human body, transport systems, and mobile operational control systems in emergency situations [1], etc. Thus, it is important to ensure the safety of the communication system by detecting the signals in real-time [2–4].

Due to the low response latency for IoT services, the wireless signals need to be detected in real-time. Nowadays, the most commonly used equipment for wireless signal analysis is the spectrum analyzer. The primary role of a spectrum

analyzer is the measurement of signal power versus frequency [5]. A method used for spectrum analyzer is the Discrete Fourier Transform (DFT). The classical general-purpose swept spectrum analyzer has the disadvantage of having less access to information about the wireless signals. In addition, it is not suitable for real-time detecting [6]. In [7], the authors proposed Passive IoT Radar (PIoTR) to perform RF sensing. PIoTR is designed based on passive radar technology, with a generic architecture to utilize various signal sources including the WiFi signal and wireless energy at the Industrial, Scientific and Medical (ISM) band. The PIoTR systems typically make use of relative narrowband signals for detecting large targets at long distances. However, variations in bandwidth, signal strength and data rate can significantly affect the sensing performance of PIoTR systems.

Traditionally, non-cooperative signal detection tasks are accomplished through energy detection [8]. The authors detect the signal by comparing the output of the energy detector with a threshold which depends on the noise floor. The energy detection method obtain the signal bandwidth and center frequency. However, at low signal-to-noise ratios (SNR), the accuracy of the energy detection method greatly reduced. In [9], the authors detected and recognized signals by converting them to pictures and using the YOLO algorithm, which reduce the effect of noise on detection accuracy. However, this method requires a more demanding window length for the short-time Fourier transform [10], which is difficult to determine.

In this paper, we describe an intelligent platform for wireless signal detection and recognition. To the best of our knowledge, this is the first work to integrate signal acquisition, signal detection, and signal recognition in an FPGA-based platform. The hardware model is implemented inside the FPGA that addresses the development of complex applications for continuous data acquisition and processing. Moreover, We propose YOLO-SD algorithm to detect wireless signal in real-time, which substantially improves the signal detection results in the case of low SNR.

The rest of the paper is structured as follows. Section 2 presents the overview of the platform. Section 3 explains the theoretical description of the platform, including the detection algorithm and the recognition algorithm. Section 4 presents the FPGA real-time implementation. Section 5 presents the performance evaluation. The conclusion is drawn in Sect. 6.

2 Overview of the Platform

The platform automatically detects and analyses wireless signals. The wireless signal collected by the antenna is sufficient.

Output parameters of the platform are the following.

- 1) Bandwidth of all received signals $B \leq 2f_s$. Where f_s is the sampling rate. Limited by Nyquist's sampling theorem, the platform can only correctly acquire and analyze wireless signals with a bandwidth no greater than twice the sampling rate.

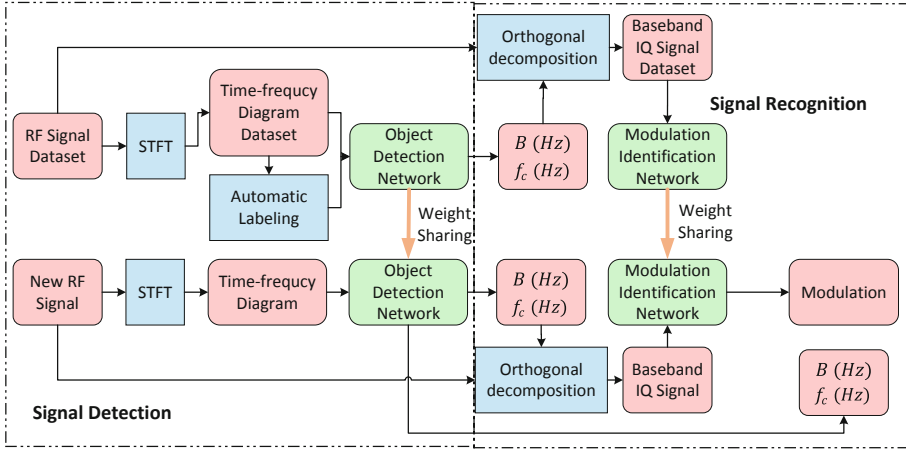


Fig. 1. RF signal detection and recognition algorithm block diagram.

- 2) Center frequency of all received signals f_c . To be transmitted in the channel, the signal usually needs to be upconverted. f_c is the frequency of the center of the signal after upconversion.
- 3) Modulation of all received signals such as Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK), 16-Quadrature Amplitude Modulation (16QAM), 2-Amplitude Shift Keying (2ASK), 2-Frequency Shift Keying (2FSK) etc.

Due to the high sampling rate of the acquisition module and the high processing rate of the signal processing algorithm, the platform can monitor and analyze the parameters of all signals received in real-time.

The proposed solution consists of an FPGA-based RF signal acquisition module and deep learning based signal processing module. The signal processing module consists of two steps: signal detection and signal recognition.

3 Deep-Learning-Based Wireless Signal Processing Method

The integrated wireless signal processing is divided into two phases as shown in Fig. 1. Firstly, the valid signals are detected and located. The bandwidth and center frequency of the valid signals are obtained. Afterwards, the signal recognition module downconverts and filters the signals according to the bandwidth and center frequency to extract the valid signals as baseband IQ signals. The CNN is used for recognition. The specific schemes are as follows.

Signal Detection. This phase detects if one or more wireless signals are received. If a signal is detected, this phase will output the bandwidth and center frequency of the signal.

- a) The short-time Fourier transform (STFT) can convert the RF signal into a two-dimensional time-frequency map. RF signal shows a banded geometry on the time-frequency diagram. Therefore, the signal detection task can be converted into an image target detection task.
- b) As a one-stage detection algorithm, YOLO has a high detection speed. In consideration of the real-time requirements of the platform, YOLO v3 is selected as the target detection network for the time-frequency map. And we have improved YOLO to fit the banded geometry characteristics of RF signals on the time-frequency diagram.

Signal Recognition. This phase recognizes the modulation of the signal. The modulation recognition algorithm is a two-step process: orthogonal decomposition then CNN completes signal feature extraction and modulation recognition.

- a) This phase downconvert every valid signal with f_c and filter with a low-pass filter of bandwidth B (orthogonal decomposition). This phase will output N baseband IQ signals. Where N is the number of valid signals.
- b) The baseband IQ signals can be used as input to the CNN for modulation type classification.

3.1 YOLO-SD Object Detection Network

YOLO is a state-of-the-art object detection algorithm, which is divided into two parts: a backbone feature extraction network and a feature prediction network. The backbone feature extraction network uses a residual network for extracting the main features of the target in the image. This backbone feature extraction network uses only convolutional layers and is a fully convolutional network. The feature prediction network constructs an Feature Pyramid Networks (FPN) feature pyramid for feature enhancement extraction [11]. Using the feature pyramid, three feature matrices of the enhanced features can be obtained. Each cell inside each feature matrix can predict three bounding boxes. The input image is equally divided into $S \times S$ grid, and each cell predicts B bounding boxes. This allows multiple targets to be detected and located on a single image.

Improving the Prior Bounding Box. The common YOLO v3 network is mainly used for the target detection of objects in images, and its prior bounding box is usually more similar to the objects in life. The signal target in the RF signal time-frequency diagram is in the shape of bars, and the prior bounding box of YOLO v3 cannot fit the characteristics of the RF signal time-frequency diagram well. To solve this problem, this paper adopts the K-means clustering algorithm to statistically cluster the signal borders in the constructed time-frequency map data set. The results that can fit the bars in the time-frequency diagram of the RF signal are used as the prior bounding box.

Detection Accuracy Metric. The metric is called generalized Intersection over Union (gIoU), which is defined as:

$$\text{gIoU} = \text{IoU} - \frac{C - (A \cup B)}{C}, \quad (1)$$

where A is the predicted box and B is the actual box. C is the smallest box that can enclose both A and B boxes. The Intersection over Union (IoU) is $(A \cap B)/(A \cup B)$. Compared with the IoU metrics, gIoU applies to the case of the bounding boxes do not overlap each other. In this case, IoU is 0, which does not reflect any information about the proximity of the bounding boxes. The gIoU is the lower bound of IoU, in the case of infinite overlap of two boxes, $\text{IoU} = \text{gIoU} = 1$. IoU takes values in the range $[0, 1]$ and gIoU takes values in the range $(-1, 1]$. The gIoU converges to -1 when $(A \cup B)/C \approx 0$ and there is no intersection between A and B . For the problem of signal detection, this property of gIoU can be helpful in high noise scenarios where the network is expected to predict many error detections and bounding boxes that do not overlap with any signal. The gIoU-based loss for error detection can be high, thus forcing the network to gradually penalize such false predictions during training. Based on the above, we replace IoU with gIoU in the general YOLO algorithm and thus propose the YOLO-SD algorithm to adapt to the signal detection task.

3.2 Deep Learning Based Wireless Signal Modulation Recognition Method

To facilitate the recognition of the signal by the convolutional neural network, we decompose the signal orthogonally and thus downconvert the signal from RF to baseband. The process of quadrature decomposition is to multiply the received signal by the cosine signal and pass it through a low-pass filter so that the I-way and Q-way baseband signals can be obtained. The process of orthogonal decomposition to obtain the I-way baseband signal can be described as

$$y_I(t) = [r(t) \cos 2\pi f_c t] * h(t) = \frac{1}{2}x_I(t) + n_I(t), \quad (2)$$

where $r(t)$ is the signal, $h(t)$ is the low-pass filter, $x_I(t)$ is the I-way baseband signal and $n_I(t)$ is the I-way noise. Similarly, the Q-way baseband signal can be obtained by

$$y_Q(t) = [r(t) \sin 2\pi f_c t] * h(t) = \frac{1}{2}x_Q(t) + n_Q(t), \quad (3)$$

where $x_Q(t)$ is the Q-way baseband signal and $n_Q(t)$ is the Q-way noise.

The CNN uses four convolutional layers with different sizes of convolutional kernels for feature extraction, including shallow features with a perceptual field slightly larger than the symbol rate, and deep features with a global field of view. This is a network structure designed to address the characteristics of modulated signals. The IQ signal can be viewed as two channels, each of which is one-dimensional sampled data. Both channels use a one-dimensional convolutional layer and convolutional kernel at the same time.

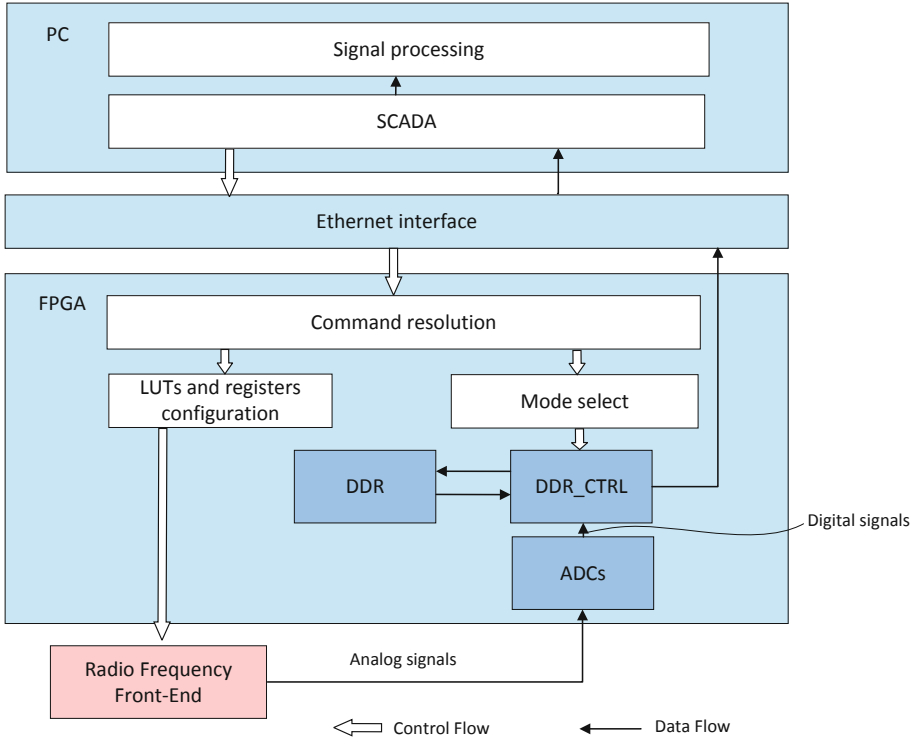


Fig. 2. Block diagram of the platform.

4 Platform Implementation

The key to hardware implementation is to pipeline the acquired signals to the signal processing module. The architecture of the platform is shown in Fig. 2. The PC sends commands to the FPGA via Supervisory Control and Data Acquisition (SCADA). SCADA controls the RF parameters of the platform (RF frequency point, receive gain, etc.) by configuring the through look-up tables (LUTs) and registers of the FPGA. The RF front-end reads RF parameters to complete the setup of the acquisition module and starts to acquire signals.

The analog signals are converted to digital signals by ADC. The ADC is included in the ADRV9009. The ADRV9009 RF transceiver uses the JESD204B protocol and communicates via a GTX high-speed serial transceiver. The ADC continuously transmit digital signals to Double Data Rate Synchronous Dynamic Random Access Memory (DDR) via Advanced eXtensible Interface (AXI) bus. Due to the advanced RF front-end, the platform supports frequencies from 123 MHz to 6000 MHz with a bandwidth of up to 200 MHz.

The input data is continuous. The rate of acquisition and the rate of transmission to the PC are different. To achieve continuous data transfer, a ping-pong storage structure is used. Due to the fast acquisition rate and a large amount

of data, DDR was chosen as the buffer device instead of fifo and ram. Although there is only one bus for DDR read and write, DDR read and write is fast enough to meet the demand of ping pong operation. Therefore, we can directly use the bank inside the DDR to perform ping pong operations. A ping-pong operation is a time-sharing operation (write and read) of two memory cells. DDR controller controls data in and out of DDR to enable ping pong operations. In the first cycle of the entire data transfer process, DDR controller deposits the input data into bank A. No data is output at this time. In the second cycle, DDR controller turns the data to deposit into bank B, while DDR controller outputs the data in bank A. In the third cycle, DDR controller transfers the data to bank A and outputs the data in bank B. This is repeated for subsequent cycles. From the output and input of the DDR controller, the data stream is constantly being transferred.

FPGA transfers data to PC via Ethernet interface. To ensure continuous data transmission, the Ethernet rate must be greater than the rate of the RF front-end acquisition. The sampling rate of the RF front-end $f_s = 245.76$ MHz. ADC converts the analog signal to a 16 bit digital signal. Therefore the input data flow rate can be calculated as

$$R = 16 \times f_s = 4 \text{ Gbps.} \quad (4)$$

As a result, Small Form Pluggables (SFP) optical network port with a transmission rate of 10 Gbps is used. Therefore, the platform can continuously acquire, store, and process signals.

5 Performance Evaluation

5.1 Dataset Generation

Signal detection and signal recognition algorithms are both based on deep learning. So it is necessary to build an efficient and comprehensive RF signal dataset. The centre frequency of the signal is set in the range of 10 MHz to 110 MHz. The signal bandwidth is set from 3 MHz to 10 MHz. The RF signal data is modulated by choosing digital modulation methods such as 2FSK, 16QAM, QPSK, BPSK, 2ASK, etc.

5.2 Results

Figure 3 shows the detection accuracy of YOLO-SD, YOLO-general, and energy Detection at 0–20 dB SNR. The detection accuracy is characterized by the IoU metric. We choose YOLO-general [10] and energy detection [12] as the base-lines. The energy detection method detect the signal by comparing the output of the energy detector with a threshold which depends on the noise floor. So the energy detection method will mistakenly detect noise lines as signals. At the same time, due to the existence of intraband splitting of signals (e.g. FSK), the energy detection method misclassify a signal as multiple signals. In addition,

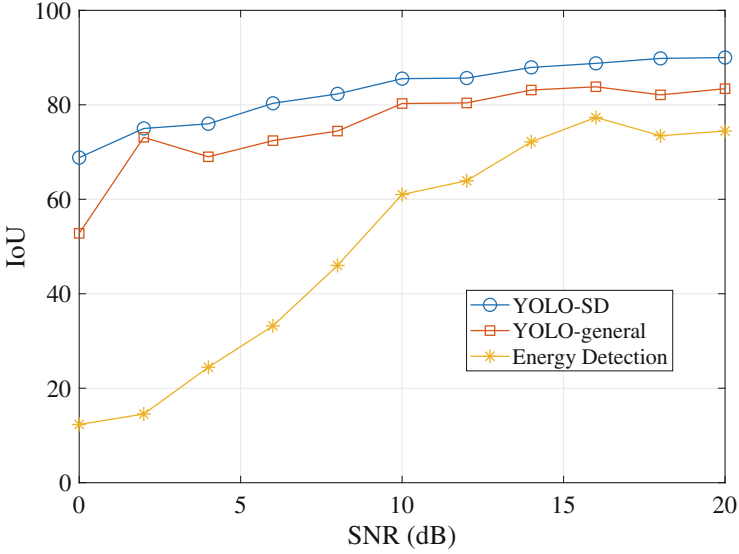


Fig. 3. IoU with different schemes and SNR

The detection accuracy of the energy detection method decreases rapidly as the SNR decreases. This is mainly due to the fact that the signal in the experiment will have some random noise lines in the spectrum at low SNR with similar or even stronger amplitude than the signal. The YOLO-general algorithm, compared to the energy detection method, is no longer affected by the random noise spectrum. However, it sometimes appears that the accuracy in the high SNR case is lower than that in the neighboring low SNR case. This is mainly due to the poor fit of the box and signal identified by the algorithm when using IoU as the metric, and this error exceeds the effect of 2–4 dB noise. It is also found that when IoU is used as the metric, the accuracy drops abruptly at low SNR. This is mainly because the IoU is 0 when there is no intersection between the prediction box and the actual box, and the loss function is also 0 at this time. So it is impossible to perform gradient calculation and training. Therefore, the algorithm using IoU as a metric has a poor learning ability for low SNR data, which leads to a weak detection ability for low SNR signals.

YOLO-SD uses a computer vision approach to reduce the effect of noise on signal detection. In addition, the priori bounding box and accuracy metric are improved. So it can be seen that Compared with the other two detection methods, the YOLO-SD algorithm shows a significant improvement in detection accuracy at each SNR.

To analyze the modulation classification performance, Fig. 4 shows the confusion matrix of all detections and recognition in the dataset acquired with hardware. The data set was collected in an environment with SNR = 34.7 dB. From the experimental results, it can be seen that the intelligent wireless signal

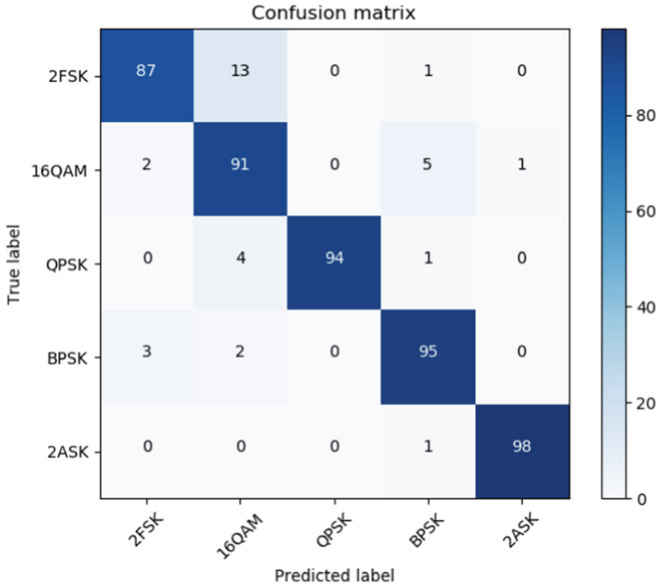


Fig. 4. Acquisition and analysis platform experimental results with SNR = 34.7 dB.

detection and recognition platform achieves an average recognition accuracy of 93% for six modulation types of RF signals.

6 Conclusions

This paper designed and implemented an intelligent IoT signal Monitoring platform, which could automatically detect the wireless signals and output the bandwidth, center frequency, and modulation of the signals. The YOLO-SD algorithm is adopted as the detection algorithm, which has improved the detection accuracy and the performance in terms of low SNR compared with YOLO-general. Adopting the method of orthogonal decomposition followed by a neural network for recognition, the modulation mode can be recognized for signals of any frequency. Due to the hardware sampling frequency of up to 245.76 MHz, the platform can detect and recognize signals with a wide bandwidth (no larger than 245.76 MHz). In addition, due to the ping-pong structure of the hardware part, the data can be continuously collected, transmitted, and processed, thus realizing the function of collecting signals and processing them in real-time.

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