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CNN-Based Spectrum Sensing Method for Low Probability of Detection Communication Systems

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Abstract: In recent years, the development of Low Probability of Detection (LPD) communication systems has gained significant attention as a means to enhance communication security. Consequently, the need for effective signal interception technologies capable of detecting such signals has also increased. This paper proposes a novel spectrum sensing method based on Convolutional Neural Networks (CNNs) to determine the presence or absence of signals. The proposed method addresses the limitations of conventional energy detection techniques that rely on fixed thresholds, by learning diverse signal patterns to enable more accurate detection. Received signals are first sampled at a high rate and transformed into frequency-domain representations using the Fast Fourier Transform (FFT). These frequency spectra are then accumulated over time to form two-dimensional spectrograms, which are used as input to the CNN model. The proposed CNN classifier comprises four convolutional layers, along with batch normalization and pooling layers. Simulation results demonstrate that the proposed approach consistently outperforms traditional threshold-based energy detection methods, achieving approximately a 2 dB performance gain across all *SNR* conditions. Under –6 dB *SNR*, the method achieves an improvement of about 35% in detection accuracy.

Keywords: Binary Classification; Convolutional Neural Network; Low Probability of Detection (LPD); Spectrogram; Spectrum Sensing

1 INTRODUCTION

In modern communication environments, accurately detecting the presence or absence of a signal plays a crucial role not only in national security but also in industrial safety, autonomous system operation, and a wide range of other applications. Detecting various platforms such as naval vessels and unmanned or manned aerial vehicles poses a major challenge, as these systems often adopt stealth technologies to evade detection by radar and other sensing mechanisms. In response, Low Probability of Detection (LPD) techniques have been developed to reduce the detectability of signals in the electromagnetic, optical, and infrared domains, thereby enhancing the survivability of unmanned platforms [1]. Although initially driven by military demands, LPD technologies have also gained relevance in civilian applications such as drone-based infrastructure monitoring, industrial wireless sensor networks, and emergency communication systems for disaster response. In such systems, LPD communication minimizes signal exposure, making it difficult for third parties to detect transmissions. This allows for secure and reliable communication between unmanned systems [2]. Accordingly, the need for interception technologies capable of reliably identifying the existence of LPD signals has become increasingly critical. These systems must be able to detect signals with extremely low power levels while maintaining high accuracy.

One of the most commonly used approaches for signal detection is spectrum sensing [3]. Among various spectrum sensing techniques, the energy detection method based on a fixed threshold is the most widely adopted. This method determines the presence of a signal by comparing the received signal power against a predefined threshold [4]. While effective when noise power can be accurately estimated, its performance significantly degrades in practical scenarios where such estimation is unreliable [5]. To overcome this limitation, machine learning-based approaches have recently been proposed [6]. In particular, spectrum sensing methods based on deep learning [7] models such as Convolutional Neural Networks (CNNs) have been actively studied. These works have primarily focused on cognitive radio (CR) systems, with the goal of optimizing spectrum utilization and increasing spectral efficiency [8–11].

In contrast to CR-oriented studies, the present work targets the problem of signal detection in LPD communication systems, with the specific goal of supporting interception capabilities under challenging low-power signal environments. The key distinction of our approach is that it enables signal detection without requiring explicit noise power estimation significant advantage for practical deployment in unpredictable environments. Recently, there has been a growing body of research on RF signal detection that leverages real-world RF environments, addresses signal interference robustness, and adopts lightweight CNN architectures capable of maintaining performance even with low-resolution spectrograms [12]. These advancements have paved the way for practical spectrum monitoring solutions, expanding the application potential of spectrum sensing to civilian drone communications, industrial IoT surveillance, and public safety networks.

Reflecting this trend, this paper proposes a CNN-based spectrum sensing technique for detecting weak LPD signals without requiring noise power estimation. The received signal is transformed into a time–frequency domain spectrogram and fed into a CNN model for binary classification of signal presence. The proposed model is capable of autonomously learning diverse signal patterns, offering a clear advantage over traditional threshold-based methods. Simulation results confirm that longer observation durations improve detection performance. The proposed method outperforms the conventional energy detection approach by approximately 2 dB across all SNR conditions and achieves up to 35% higher detection accuracy at –6 dB.

The remainder of this paper is organized as follows. Section 2 describes the system model and preprocessing steps, including the operation of the conventional energy detection method and the proposed CNN-based method. Section 3 details the CNN architecture and evaluates the performance of the proposed method through simulations. Finally, Section 4 concludes the paper and discusses future directions.

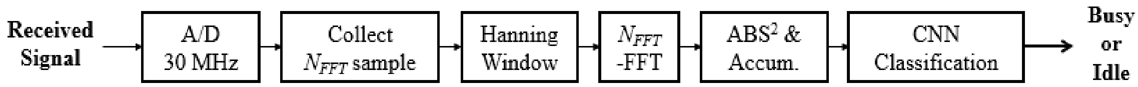

Figure 1 System Model

2 MATERIALS AND METHODS

Fig. 1 illustrates the system model of the spectrum sensing method considered in this study. The received signal at the antenna is processed through an analog-to-digital converter (ADC) with a sampling rate of 30 MHz, converting it into a baseband digital signal, denoted as $x_a(n)$. The signal $x_a(n)$ is received in units of N_{FFT}, corresponding to the FFT size, and adjacent N_{FFT} samples are collected for processing. The process of receiving $x_a(n)$ and collecting signal samples is illustrated in Fig. 2. The total number of observed signal samples, referred to as the observation length, is denoted as B. The $(i+1)^{th}$ collected signal sample is expressed as follows:

$$x_{a,i}(n) = \left[x_a(i), ..., x_a(i+k-1)\right], \text{ for } i = 0, ..., (B-1) \tag{1}$$

Since the spectrum sensing method must be performed in the frequency domain, all B collected signal samples are first processed using a Hanning window, and the signals are then stacked in a matrix form and transformed into frequency spectra by applying an FFT of size N_{FFT}. Subsequently, the squared magnitude of each FFT element is computed, and the results are accumulated along the time axis to generate a spectrogram, which visualizes spectral variations in the time-frequency domain. Finally, the spectrogram is fed into a CNN model, which classifies the presence of a signal as "Busy" and the absence of a signal as "Idle."

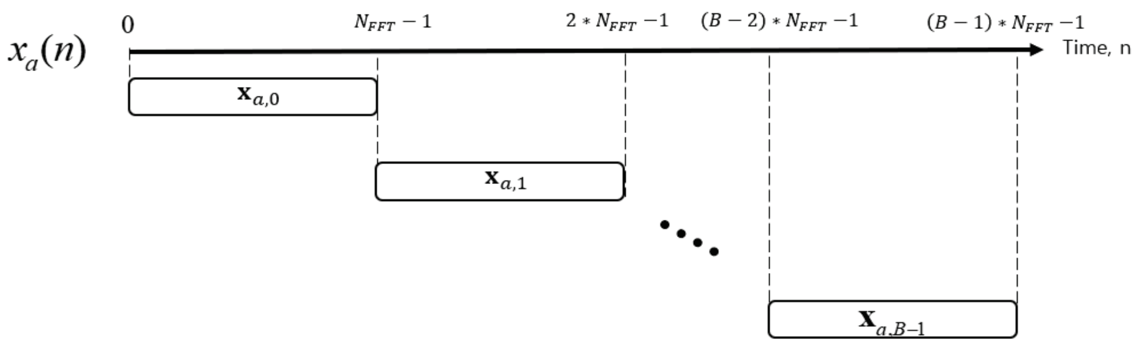

Figure 2 Sample Collection Process of the Received Signal

2.1 Spectrogram

The spectrogram used as the input to the CNN is represented as a grayscale image, where the vertical axis corresponds to the FFT size in units of N_{FFT}, and the horizontal axis represents the observation length, which consists of B collected signal samples. As the FFT size increases, the vertical length of the spectrogram also increases, indicating that a larger frequency range can be represented within a single block. Additionally, as the observation length increases, the detection latency also increases.

In the spectrogram, higher power values are represented as white, while lower power values, approaching zero, appear as black. Fig. 3(a) shows a spectrogram at SNR = 20 dB, where the white bands indicate Busy state, representing the presence of a signal in specific frequency bands, whereas the black regions indicate the absence of a signal. Fig. 3(b) displays a spectrogram for an Idle state, where only noise is observed without any active signal. As the SNR decreases, the distinction between Busy and Idle states becomes less clear, as the signal power becomes increasingly similar to the noise power, making detection more challenging.

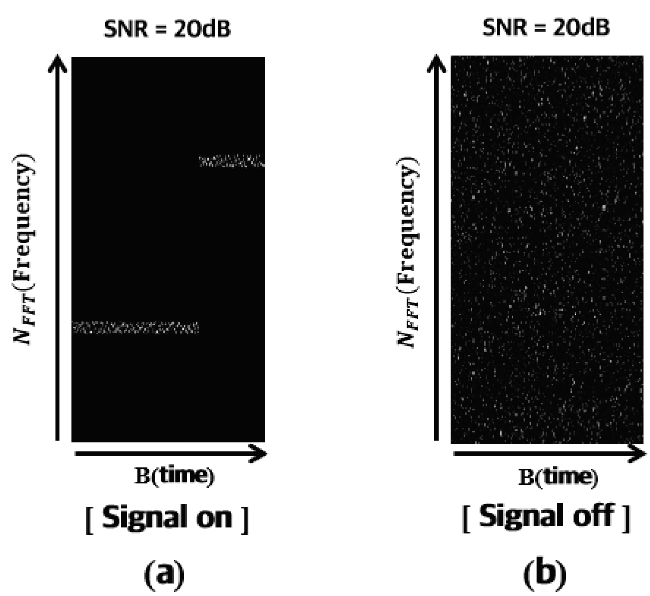

Figure 3 Spectrogram Image (SNR = 20 dB, B = 128) (a) Signal on (b) Signal off

2.2 Threshold-Based Spectrum Sensing

The conventional energy detection method first estimates the noise power and sets a threshold based on this estimation. Then, if the received signal power exceeds the predetermined threshold, the presence of a signal is determined; otherwise, the absence of a signal is assumed. Fig. 4 illustrates the threshold-setting process in the threshold-based spectrum sensing method.

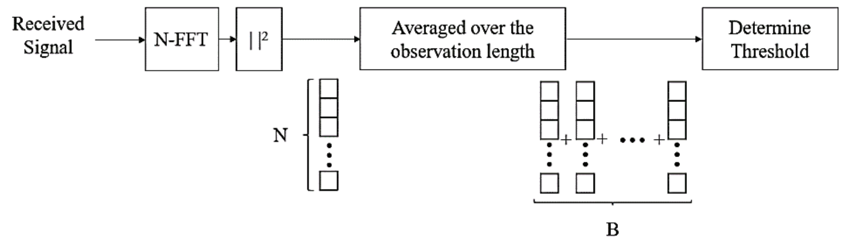

Figure 4 Threshold-Setting Method in Conventional Threshold-Based Spectrum Sensing

First, following the same process as in Fig. 2, an FFT of size N_{FFT} is applied to the signal, and the resulting spectra are stacked in a matrix form. Then, the squared magnitude of each FFT element is computed. Afterward, the average is taken over B collected signal samples to determine the threshold. This approach ensures a fair comparison by matching B with the CNN-based spectrum sensing method.

2.3 CNN-Based Spectrum Sensing

A Convolutional Neural Network (CNN) is a type of deep neural network that is optimized for tasks such as image recognition and video processing [13-15]. CNNs were introduced to address various challenges in conventional deep neural networks, including long training times, large network sizes, and excessive parameter counts. By utilizing convolutional layers, CNNs autonomously learn features from input images and generate results based on the extracted features. The spectrogram, as described earlier, can be represented as a two-dimensional matrix, which can be interpreted as a grayscale image. Therefore, in this study, the CNN model is trained to take a two-dimensional grayscale spectrogram as input and perform binary classification to determine the presence or absence of a signal.

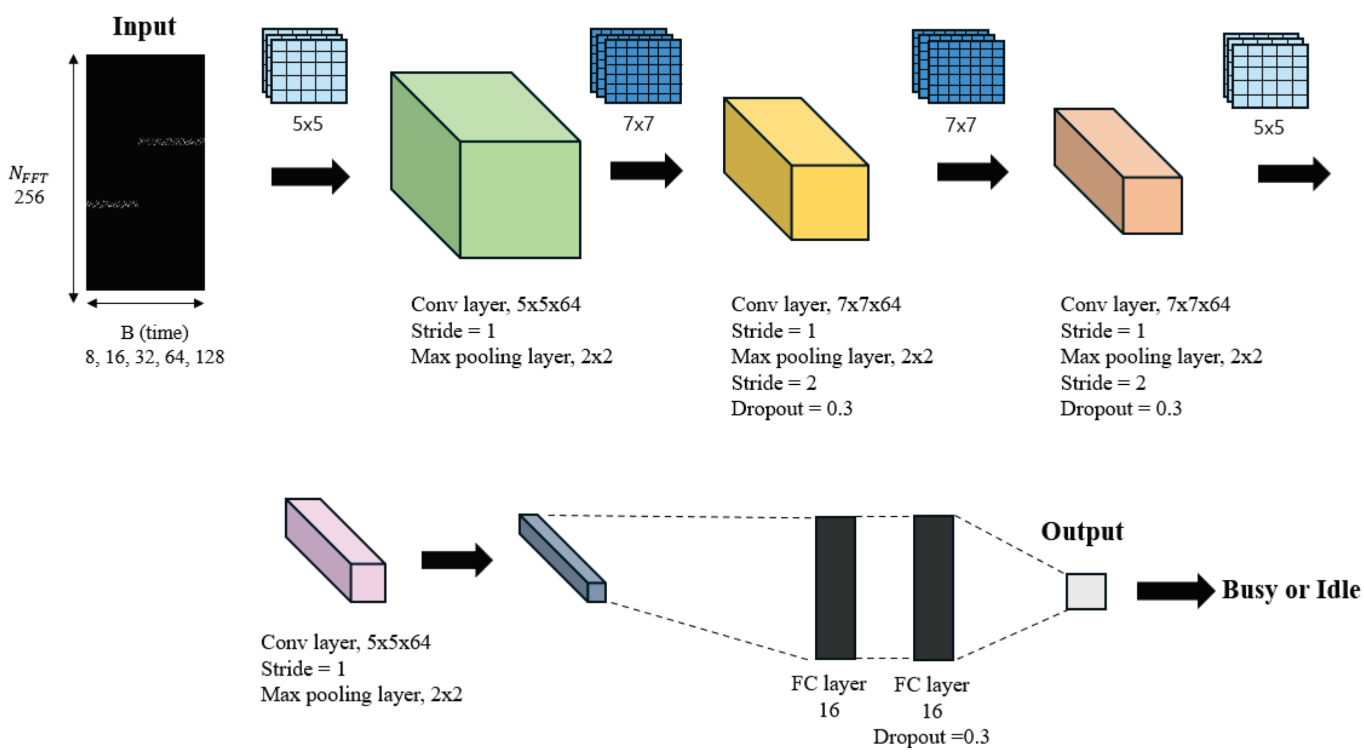

Figure 5 Network Architecture of the CNN-Based Spectrum Sensing Method

In this section, we describe the CNN-based spectrum sensing method, which utilizes deep learning techniques. Figure 3 illustrates a two-dimensional matrix represented as a grayscale image under conditions where SNR = 20 dB, N_{FFT} = 256, and B = 128. The spectrogram is used as an input to the CNN model, which determines the presence or absence of a signal. The network architecture of the CNN model, as shown in Fig. 5, takes the spectrogram as input and consists of a total of four convolutional layers and two fully connected layers. Each convolutional layer includes a batch normalization layer and a pooling layer. The number of filters in the convolutional layers is 64, 64, 64, and 64, respectively. The filter size is 5×5 in the first and last layers and 7×7 in the two middle layers. The stride is set to 1 for all convolutional layers. The pooling layers apply 2×2 max pooling with a stride of 2. The activation function used in the convolutional layers is ReLU (Rectified Linear Unit). In the final output layer, the Sigmoid activation function is applied to perform binary classification, determining the presence or absence of a signal. The hyperparameters for training the CNN-based spectrum sensing method are summarized in Tab. 1.

Table 1 Network Hyperparameters of the CNN-Based Spectrum Sensing Method

Hyper Parameters	Epochs	7
	Params.	638,065
	Optimizer	Nadam
	Loss Function	Binary Cross-Entropy
	Batch Size	64
	Learning Rate	0.001

3 RESULTS AND DISCUSSION

3.1 Received Signal Parameters for Spectrum Sensing

To evaluate the performance of the proposed CNN-based spectrum sensing method, computer simulations are conducted. The dataset for the simulation is generated using MATLAB, while model training is performed using TensorFlow. The key parameters used in the spectrum sensing method are summarized in Tab. 2. The sampling frequency of the received signal is set to 30 MHz, with a bandwidth of 1.25 MHz. The *SNR* range is configured from −10 dB to 20 dB, and the FFT size is fixed at 256. The number of observed signal samples B varies from 8 to 128, increasing by a factor of 2 for performance comparison. A smaller *B* enables faster sensing by observing a shorter duration of the signal, while a larger *B* results in slower sensing speed but improves sensing accuracy.

Table 2 Received Signal Parameters

Parameters	Value
Sampling Frequency	30 MHz
Bandwidth	1.25 MHz
SNR Range	–10 ~ 20 dB
FFT Size	256
Number of observation signal blocks	B = 8, 16, 32, 64, 128

The training, validation, and test datasets used to train the proposed CNN model in this study are as follows. The training and validation datasets are randomly generated within an *SNR* range from –10 dB to 20 dB, with 50,000 and 10,000 samples, respectively. The test dataset, used for performance evaluation, is generated within the same *SNR* range at 1 dB intervals, with 10,000 samples per *SNR* value. All datasets are evenly distributed between cases where a signal is Busy or Idle. The performance of signal detection is evaluated using two key metrics: Detection Probability, which represents the probability of correctly identifying the presence of a signal, and False Alarm Rate (FAR), which indicates the probability of falsely detecting a signal when none is present.

3.2 Simulation Results

3.2.1 Detection and False Alarm Performance by Observation Length

Figs 6. and 7 illustrate the simulation results of the proposed CNN-based spectrum sensing method based on the observation length *B*. Fig. 6 shows that as B increases by a factor of 2, the detection performance improves by approximately 1 dB. Notably, when *B* = 128, a 100% detection probability is achieved from *SNR* = −4 dB onward. Similarly, Fig. 7 demonstrates that the false alarm performance also improves as the observation length *B* increases. The results indicate that the best performance is achieved when *B* = 128. Therefore, in the subsequent analyses, *B* is fixed at 128 for comparison.

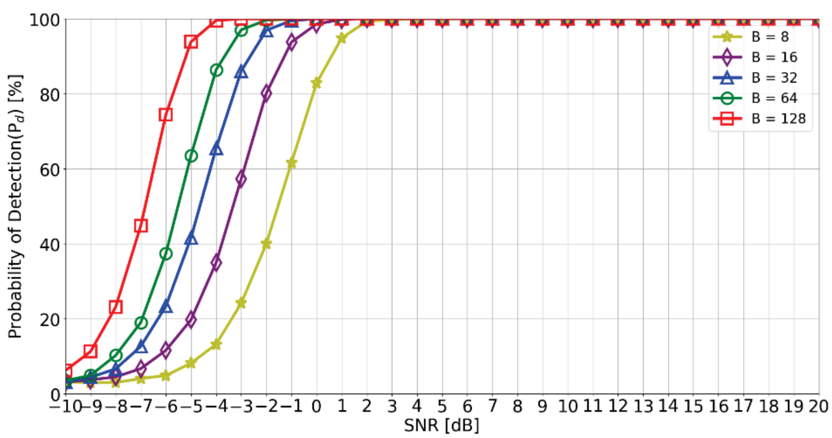

Figure 6 Detection Performance of the Proposed Method by Observation Length

3.2.2 Detection Performance of the Proposed Method Compared to the Conventional Threshold-Based Energy Detection Method

Fig. 8 presents the simulation results comparing the proposed method with the conventional threshold-based method. As shown in Fig. 7, when the FFT size is 256 and the observation length *B* = 128, the average false alarm rate of the proposed method ranges between 1.5% and 2%. At a similar false alarm rate, the proposed method demonstrates an approximately 2 dB improvement over the conventional method.

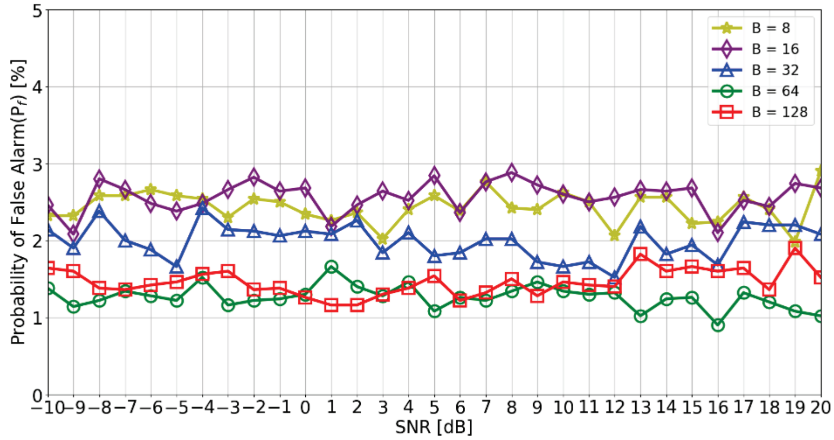

Figure 7 False Alarm Performance of the Proposed Method by Observation Length

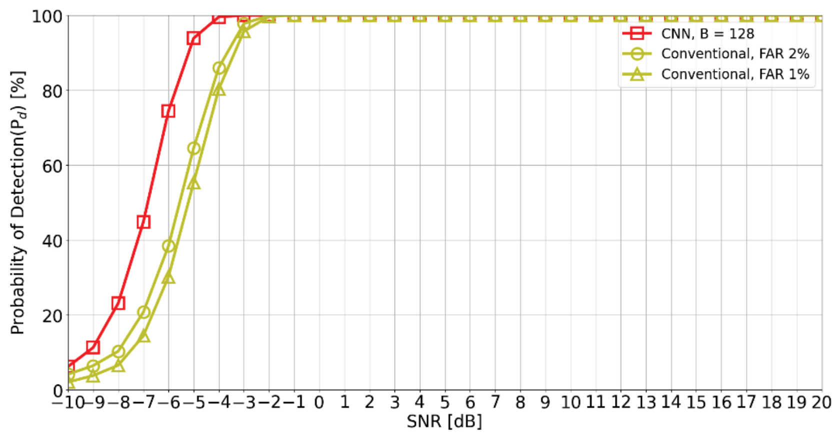

Figure 8 Detection Performance of the Proposed Method Compared to the Threshold-Based Method

4 CONCLUSION

This study proposed a CNN-based spectrum sensing method for Low Probability of Detection (LPD) communication systems, using time–frequency domain spectrograms as input to a CNN to determine signal presence without explicit noise power estimation. Simulation results showed that the proposed method achieved approximately a 2 dB performance gain over conventional threshold-based energy detection. Notably, under an SNR of –6 dB, the proposed method demonstrated an improvement of about 35% in detection accuracy. Furthermore, the detection performance improved consistently as the observation length increased. The key contribution lies in enabling accurate detection of weak signals by learning diverse spectral patterns directly from spectrograms, without relying on prior noise estimation. However, this study was limited to simulation-based evaluation, and future work will include over-the-air validation in real RF environments, comparison with lightweight deep learning models, and enhancement of robustness to interference and spectral distortion.

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