Deep RP-CNN for Burst Signal Detection in Cognitive Radios

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ABSTRACT
This article proposes a convolutional neural network (CNN)-based signal detection scheme using image encoding techniques for burst signals in wireless networks. The conventional signal detection approach based on energy measurement performs poorly when detecting burst signals owing to the short signal length and relatively long sensing duration. To detect the presence of a burst signal, the proposed scheme encodes the received time-series signal into an image that is further fed to a CNN model. For image encoding techniques, recurrence plot algorithms are adopted in the proposed scheme with a CNN. In particular, the proposed scheme achieves the correct detection probability of 99% even in the presence of a short burst signal at SNR = −10 dB.

INDEX TERMS
Burst signal detection, cognitive radio, deep learning, recurrence plot, energy detection.

I. INTRODUCTION
Burst signals have become more prevalent in emerging communication systems because low latency is one of the crucial requirements for system design. In particular, the requirement for low latency is stringent in some cases of intelligent transportation, industrial control systems, and factory automation [1] because low latency is vital to guarantee real-time functionality in the interactive communications of devices. To enable low-latency communications, short packet communication, in which data is often compressed and transmitted over a very short period, is introduced to reduce the physical-layer transmission latency [2], [3]. Therefore, this burst nature of short packet transmission is expected to occur more frequently in emerging communication systems used in various industrial areas, especially in, smart factories, industrial manufacturing, and robot control, which are closely connected with mission-critical applications.

Cognitive radio (CR) has been established as an encouraging solution to resolve spectrum scarcity using dynamic spectrum sensing in wireless communications. It allows secondary users (SUs) to share a part of the idle spectrum without affecting the quality of service of primary users (PUs), which enables avoidance of the high cost of spectrum resetting and improves the utilization of spectrum resources. To achieve this goal effectively, the SUs need to sense the spectrum to determine the presence or absence of PUs. Thus, signal detection is one of the fundamental tasks in the CR systems.

Many signal detection algorithms have been studied in the past decades, including the optimal estimator-correlator detector, cyclo-stationary feature detection, and matched filters. Although the cyclo-stationary feature detection and matched filter scheme exhibited a good performance in signal detection, these schemes require information about the transmitting signal such as the transmitting period, which is not always available in practice and makes it highly complex. In contrast, energy detection (ED) is a simple and effective scheme to detect the presence of a signal, where the received signal energy collected over the sensing duration is compared with a pre-determined threshold to satisfy target detection or false alarm probability [4], [5]. Because the ED scheme is performed without any prior information about the transmitter, it has low complexity characteristics.

The recent widespread popularity of machine learning and deep neural network (DNN) permits learning-based signal processing techniques [6]–[8] to achieve a powerful capability of learning features out of data samples [9], which shows great potential in wireless communication systems. In [8], a cost-efficient convolutional neural network (CNN)-based method for a robust automatic modulation
classification (AMC) is proposed. In particular, it achieves over 93% of 24-modulation at 20 dB through an approach that considers the concurrent learning of the spatiotemporal signal correlation via different asymmetric convolution kernels. Deep learning has been introduced gradually into cognitive radio networks (CRN) for a range of tasks, most of which can be categorized as either signal classification or decision making. Reference [10] proposed a CNN-based modulation recognition scheme with two CNNs trained on different data sets: in-phase and quadrature-phase (IQ) components and an image of a constellation diagram. Reference [11] introduced a CNN-based feature-based fusion scheme for automatic modulation classification, where a parallel multi-CNN model was adopted to combine the different features. The authors of [12] discussed a cooperative spectrum sensing (CSS) based on the CNN scheme for CRNs, which is constructed using a sensing matrix that takes into account the spatial and spectral correlations of the channels [13]. In [14], the spectrum sensing of a single SU based on the CNN was taken into account, where the feature of the presence of the PU signal is extracted and adopted to the input data, which is fed to the CNN. References [13], [15] used the covariance matrix (CM) of signal samples as the input to the CNN. As CMs can be regarded as images, the CNN was adopted as the DNN structure. However, although [13] achieves good detection performance in a harsh environment, these learned features are mostly based on prior knowledge, such as a history of PU activity patterns.

When a PU transmits a packet whose signal duration is much shorter than the sensing duration, the conventional ED scheme is less likely to detect the presence of the burst signal correctly. This is because the energy of the burst signal is much smaller than the total energy measured over the sensing duration. As a result, the burst signal is diluted into the total energy with no noticeable indication. Therefore, the conventional ED scheme does not work well in scenarios where signals with a burst characteristic are present because the measurement of the received signal energy is generally performed over the regular sensing duration [16]–[18].

Motivated by the aforementioned issue and possibility, this article proposes a novel CNN-based signal detection scheme that focuses primarily on detecting burst signals using image encoding techniques. CNN is designed to take advantage of 2D structure data, such as image-type data. Hence, recurrence plot (RP) algorithms are exploited to imagify burst signals and for CNN detectors to extract the burst signal features for classification in the proposed scheme. The RP algorithm is designed to detect dynamical transition and properties of system dynamics represented by time series data [19]. In particular, the RP algorithm can capture important and interpretable feature information in a time domain as an image using time correlation information which is represented by the trajectories in phase space [20]. Two RP algorithms and CNN models are used in the proposed scheme and show good performance through the simulation results. The contributions of this article are summarized as follows.

1) A deep RP-CNN detector (DRC) is proposed, which is a signal detection scheme for burst signals in CRNs that does not require any prior information for detection. To the best of our knowledge, this is the first work that applies deep learning along with image encoding techniques for detecting burst signals in CRNs.

2) The implementation verifies that the proposed scheme achieves a higher detection accuracy in detecting burst signals even with a single detector than the conventional CSS scheme with multiple SUs. Because cooperative schemes generally involve considerable overhead and performance loss due to communication errors in reality, the proposed scheme can be a practical solution.

3) Numerous simulations show that the proposed scheme achieves a superior F-score with a high probability of correct detection, under various signal-to-noise ratios (SNRs), with high precision. This proves that the proposed scheme improves both correct detection and false-alarm robustness simultaneously while maintaining a balance between recall and precision.

The remainder of this article is organized as follows. In Sections II and III, the system model of CRN and conventional ED are presented, respectively. The proposed scheme is described in Section IV. The simulation environment and numerical simulation results are presented in Section V followed by the conclusion in Section VI.

II. SYSTEM MODEL

Consider a CRN with a scenario where a PU transmits a burst signal, such as a small data packet, infrequently in the spectrum, and an SU attempts to detect the presence of the PU and access the spectrum opportunistically when the spectrum is not occupied. For successful spectrum access without interference to the licensed user, the SU is required to perform spectrum sensing to determine accurately whether the spectrum is occupied or not.

Fig. 1 illustrates a received signal in the presence of a burst signal over the sensing period in the time domain. Assuming the conventional ED scheme used in spectrum sensing, the SU collects measurement samples to compute the average energy over the sensing period. The $n$-th sample in the measurement follows a binary hypothesis and is given as

$$ y(n) = \begin{cases} \begin{array}{c} w(n) \\ H x(n) + w(n) \end{array} & \begin{array}{c} H_0 \\ H_1 \end{array} \end{cases} $$

FIGURE 1. Illustration of a burst signal in a time domain; the length of the burst signal in terms of samples is relatively too short (2.5%) than that of the total samples.
where $x(n)$ is the $n$-th sample of a signal from PU whose power is $\sigma_x^2$, $h$ is a complex Rayleigh fading channel gain between PU and SU, and $w(n)$ is additive white Gaussian noise (AWGN) with variance $\sigma_w^2$. $H_0$ and $H_1$ represent the states of the PU that are silent and active, respectively.

### III. CONVENTIONAL DETECTION SCHEMES

#### A. ENERGY DETECTION (ED)

ED computes the energy of the measurement samples given in (1) as the squared magnitude of the average over those samples and compares it with a pre-determined threshold to obtain the sensing decision. If this energy is higher than the threshold, the PU is deemed present; otherwise, the PU is considered absent. This technique is simple and practical because it does not require any prior information about the PU signal. However, the performance of this technique is highly dependent on the value of the threshold, the received signal, and the noise. Prior knowledge of the signal and noise is thus very useful to enhance the detection performance. Regarding the state of the PU, the test statistics for determining the presence of a burst signal are given as

$$T = \frac{1}{N} \sum_{n=1}^{N} |y(n)|^2 \leq \lambda$$

where $T$ is the average energy and $\lambda$ is a pre-determined threshold. Given the threshold, the false alarm probability is computed as

$$P_{FA} = P(T < \lambda | H_0) = Q\left(\frac{\lambda - \mu_{H_0}}{\sigma_{H_0}}\right)$$

where $\mu_{H_0}$ and $\sigma_{H_0}$ are the average and the standard deviation under $H_0$, respectively [21]. From (3), the threshold can be calculated by satisfying the target false alarm probability as

$$\lambda = \sqrt{\frac{\sigma_x^2}{N} Q^{-1}(P_{FA}) + \sigma_w^2}$$

where $Q^{-1}(\cdot)$ is the inverse Q-function [22].

#### B. FEATURE-BASED FUSION SCHEME

The feature-based fusion scheme (FFS) is proposed in [11] for automatic modulation classification and uses a CNN-based architecture for feature extraction. Fig. 2 illustrates the workflow of the feature-based fusion scheme where $K$ is the number of SUs. In the FFS, a parallel multi-CNN is considered, where the input of the CNN is composed of the IQ components of the received signal in two columns of the matrix. Each CNN consists of two convolution layers and two fully connected layers. The exponential linear unit (ELU), which is very similar to a rectified linear unit (ReLU), is applied as the activation function for all layers. The ELU works differently to the output values; it produces negative values to avoid the dying ReLU problem. Unlike the CNN architecture in different studies, owing to the pulling operation that can result in data feature loss as downsampling,

FFS replaces pulling with dropout operation, which does not ignore important features. The received data of an SU are input to each CNN, which are combined to obtain different feature vectors at the last fully connected layer of each CNN. Then, all of the feature vectors are linearly fused at the Softmax layer, and the category with the highest probability is chosen as the decision result.

### IV. DEEP LEARNING-BASED DETECTOR DESIGN

This section introduces the proposed burst signal detector scheme based on image encoding algorithms and deep learning. The proposed scheme aims to detect burst signals in a robust and reliable manner even in a very low SNR environment regardless of the burst signal duration. Note that the signal detection capability of the proposed scheme at low SNR is not limited to burst signals, but can be extended to detect a signal with any signal duration.

#### A. RECURRENCE PLOT

Recurrence plot (RP) is a visualization algorithm that aims to analyze the $m$-dimensional phase space through a 2-dimensional representation of its recurrences, where $m$ is the embedding dimension that is found by false nearest neighbors. Let $S = [s_1, s_2, \ldots, s_k]^T$ denote the matrix of the $m$-dimensional phase space of a received signal energy, where $s_k$ indicates the state vector. The state vector can be constructed from the received signal energy as

$$s_i = [u_i, u_{i+d}, \ldots, u_{i+d(m-1)}], \text{ where } i = 1, \ldots, k,$$

where $d$ is the time delay that can be obtained by mutual information, $k$ is the trajectory length; $k = N - d(m - 1)$ [23], and $u_{i+d(m-1)} = |y(i + d(m - 1))|^2$. The state vector $s_i$ represents the trajectories in an $m$-dimensional space. The recurrence matrix ($R$) is defined as

$$R_{ij}(\epsilon) = \Theta(\epsilon - \|s_i - s_j\|), \text{ where } i, j = 1, \ldots, k,$$

where $\Theta(\cdot)$ is the Heaviside function, and $\|\cdot\|$ is a $L_2$-norm. In the $m$-dimensional phase space, a recurrence is considered to occur between two state vectors in the phase space over time, if the distance between the two state vectors is less than a threshold $\epsilon$ [24].

From (6), an RP image is generated from the $k \times k$ matrix of the RP with the same size as the matrix. Then, we converted the RP image into an RGB RP image with depth to take advantage of the CNN, which can extract the spatial features from the data using its kernel. According to [25], the diagonal
The choice of the adequate recurrence threshold is a challenging and important task for the RP algorithm. If the threshold \( \epsilon \) is chosen to be too small, many distinguishable lines appear in the results of the RP algorithms, and it leads to high false positives (false alarms). If it is large, true signals can be filtered out, and the result of RP algorithms may not show any indication of the signals, which results in high false negatives (missed detections) [26]. Thresholding of the RP image is the operation of converting a multi-level Const-RP image into a binary image by assigning ‘0’ for values lower than the threshold and ‘1’ for values higher than the threshold, or vice versa. It comprises the assumption that the RP image consists of burst signals and noise, which have a distinct bimodal distribution. If this assumption holds, the RP image histogram may contain two unique peaks, and a proper threshold value for separating them can be obtained. In general, there are two groups for threshold selection: global algorithms and local algorithms. A global thresholding algorithms is easier to implement and has a lower complexity compared to a local thresholding algorithm. It filters the image with a single threshold value obtained by using the histogram of the image.

The proposed threshold obtained using the global thresholding algorithm [27], [28], which is used for changing the Const-RP image into a binary-RP image. The algorithm for determining the threshold is organized as follows:

1) Normalize the \( R \) with the range of \([0, 1]\), and save as \( \hat{R} \).
2) Estimate the initial threshold \( \epsilon \)
\[
\epsilon = (\max(\hat{R}) + \min(\hat{R}))/2
\]
3) The \( \hat{R} \) is divided into two parts \( \hat{R}_1 \) and \( \hat{R}_2 \) by using \( \epsilon \). \( \hat{R}_1 \) includes the \( \hat{R} \) in which the values are \( \geq \epsilon \), and \( \hat{R}_2 \) includes the rest of the values.
4) Calculate the average value \( \epsilon_1 \) and \( \epsilon_2 \) of \( \hat{R}_1 \) and \( \hat{R}_2 \), respectively.
5) Update \( \epsilon \) as follows
\[
\epsilon := (\epsilon_1 + \epsilon_2)/2.
\]
6) Repeat 2~5), until the difference between the two calculation results of \( \epsilon \) is less than 0.001.
7) Bin-RP, \( R_{Bin} \) can be described,
\[
R_{Bin} = \begin{cases} 
1 & \hat{R} \geq \epsilon \\
0 & \text{otherwise, }
\end{cases}
\]
8) Output \( R_{Bin} \)

Owing to the threshold, the difference between the RP images shown in Fig. 3(a) is clearly recognizable to the human eye, especially in the case of Bin-RP. The Const-RP includes more information than the Bin-RP, including noise information. In contrast, the Bin-RP focuses on the representation of the burst signal.

C. CNN STRUCTURE

Various CNN models have been widely exploited in the field of cognitive radio [14], which uses CNN-based spectral sensing, where the input data consist of a two-dimensional matrix composed of the cyclo-stationary feature and energy feature. In the proposed scheme, the received time-series signal is converted into an RP image that is used as input data for the subsequent CNN.

The proposed DRC employs a CNN with a relatively small structure, compared to the CNN structure normally exploited for automatic modulation classification or image classification [11], [29]–[31]. The proposed DRC achieves a high sensing accuracy because it only needs to classify two classes, unlike image classification, where typically a number of classes have to be distinguished. The CNN structure of the proposed DRC for detecting a burst signal consists of two parts, a convolution part and a fully connected part, as shown.
TABLE 1. Structure of the CNN model in the proposed scheme.

| Layer                | Output dimension |
|----------------------|------------------|
| Input                | 224 × 224 × 3    |
| Conv2D (128 × 3 × 3) + ReLU | 128 × 224 × 224 |
| Maxpooling (size=2, stride=2) | 128 × 112 × 112 |
| Conv2D (64 × 3 × 3) + ReLU | 64 × 112 × 112  |
| Maxpooling (size=2, stride=2) | 64 × 56 × 56    |
| Conv2D (32 × 3 × 3) + ReLU | 32 × 56 × 56    |
| Maxpooling (size=2, stride=2) | 32 × 28 × 28    |
| Dense + ReLU         | 32               |
| Dense + Softmax      | 2                |

FIGURE 4. Proposed DRC workflow for burst signal detection.

in Fig. 4. For the input layer, we used a CNN input size of 224 × 224. The convolution part contains three sub-blocks that are sequentially connected, where each sub-block includes a convolution layer with zero padding, an activation function, and a max pooling layer, connected in tandem. The convolution layer performs 2D spatial convolution of the input data to extract the spatial features of the input data with a spatial filter, which is set to 3 × 3. It is sufficient to extract the spatial features of an image [32]. In addition, each convolution layer of the sub-blocks has a different number of filter channels that extract features in the image sequentially from a fine level at the front of the network to a rough level. After feature extraction, the ReLU offers non-linearity to the CNN. The ReLU layer is followed by the max pooling layer, which efficiently reduces the computational overhead without performance loss. The two fully connected layers at the back of the network perform classification based on the output of the convolution, using the results of the extraction feature. The network structure is shown in Table. 1. The ReLU is selected as the activation function for all layers except the last fully connected layer, in which Softmax is applied to compute the probability distribution matrix of the last layer.

V. NUMERICAL SIMULATIONS AND RESULTS

A. SIMULATION ENVIRONMENT

To evaluate the performance of the proposed scheme by comparison, two conventional schemes are implemented: a feature-based fusion scheme with CNN models [11] and an ED scheme with thresholds satisfying the target false alarm probability, \( P_{FA} = 0.05 \).

For the training process of the proposed scheme, pre-collected labeled data with SNR ranging from -16 dB to 0 dB are generated with an interval of 2 dB, where the total training data size is 20,000 for each SNR. After the training process, the test data set of 2,000 was used for each SNR. A burst signal is generated by BPSK modulation with a signal duration of \( \tau_b = 100 \mu s \). For performance comparisons, both the conventional scheme and the proposed scheme used the same simulation parameters, which are listed in Table 2 [6], [33]. The number of samples for sensing and transmission signals are computed as \( \tau_f \) and \( (\tau - \tau_f) f_s \), respectively. Here, the recurrence matrix was constructed with \( m = 6 \) and \( d = 2 \). All data generation, RP processing, network training and testing were accomplished using MATLAB 2019b.

For model evaluation, we analyzed the detection performance using the classification performance metrics. Here, the classification performance metrics included accuracy, recall, precision and F-score, which are principally used in many classification studies. In the statistical analysis of binary classification, the F-score indicates a measure of test accuracy. To compute the score, it takes into account both the precision and recall of the test in computing the score. The F-score can be obtained from the harmonic mean of the precision and recall. The precision is the fraction of true positives among the positive results. The recall is defined as the ability of a test to correctly identify positive results to obtain the true positive rate. The “positive” indicates the presence of a burst signal. Note that the recall is the same as the correct detection probability and indicates the sensitivity of a model, while precision is a measure of robustness to the false alarms. The F-score reaches its best value at one when the precision and recall are perfect, and is the worst at zero. The energy efficiency is also given as a benchmark for performance comparison of the proposed DRC. Energy efficiency is defined as [33]

\[
E_{eff} = \frac{F}{C},
\]

where \( F \) is the average throughput and \( C \) is the energy cost for spectrum sensing, which is composed of sensing and transmission durations with lengths \( \tau_s \) and \( (\tau - \tau_s) f_s \) in a frame, respectively. There are four possible scenarios according to the state of the PU and the decision of the SU: \( P(H_0) \) and \( P(H_1) \) are the probabilities of \( H_0 \) and \( H_1 \), respectively. Then, the a priori probabilities for the possible scenarios are defined as follows:

1. \( P_1 = P(H_0)(1 - P_{FA}) \): PU (burst signal) is absent, and SU detects the absence of PU correctly;
2. \( P_2 = P(H_0)P_{FA} \): False alarm occurs;
3. \( P_3 = P(H_1)(1 - P_{FA}) \): PU (burst signal) is present, and SU correctly detects the presence of PU;
4. \( P_4 = P(H_1)P_{FA} \): True detection occurs.

TABLE 2. Parameters for simulation.

| Simulation parameters | Value |
|-----------------------|-------|
| The sampling frequency \( f_s \) | 6 MHz |
| The length of one time frame \( \tau \) | 300 ms |
| The sensing duration \( \tau_s \) | 5 ms |
| The symbol duration for burst signal \( \tau_b \) | 100 \( \mu s \) |
| The transmit power \( P_t \) | 3 Watt |
| The sensing power \( P_s \) | 0.1 Watt |
| The occurrence probability of \( H_1 \), \( Pr(H_1) \) | 0.2 |
| The occurrence probability of \( H_0 \), \( Pr(H_0) \) | 0.8 |
| The energy detection throughput \( F_0 \) | 0.6658 bits/sec/Hz |
3) \[ P_3 = P(H_1)(1 - P_{MD}) \]; PU is present, and SU detects the presence of PU successfully;
4) \[ P_4 = P(H_1)P_{MD} \]; Missed detection occurs, where \( P_{MD} \) is the missed detection probability, which can be expressed as \( P_{MD} = 1 - P_D = 1 - P(T > \lambda|H_1) \). In the first scenario, the SU transmits its data after finishing the spectrum sensing. \( F_0 \) is the throughput of the SU in the case of \( H_0 \). Thus, the energy cost \( C_1 \) and throughput \( F_1 \) for this scenario are derived as

\[
C_1 = E_e \tau_s + E_i(\tau - \tau_s), \quad F_1 = \frac{\tau - \tau_s}{\tau} F_0. \tag{8}
\]

However, the SU does not transmit data in the second and third scenarios, where the energy cost \( C_i \) and throughput \( F_i \) can be derived as

\[
C_2 = C_3 = E_e \tau_s, \quad F_2 = F_3 = 0. \tag{9}
\]

In scenario \( P_4 \), the SU missed the detection of the PU and thus transmitted its data even if the PU was present. However, the transmitted data cannot be perfectly decoded owing to a collision with the PU signal, and the throughput may be zero. Therefore, the energy cost and throughput are obtained as

\[
C_4 = E_e \tau_s + E_i(\tau - \tau_s), \quad F_4 = 0. \tag{10}
\]

By combining equations (8) to (10), the energy efficiency for spectrum sensing is computed as

\[
E_{eff} = \frac{P_1 F_1}{\sum_{i=1}^{4} P_i C_i} = \frac{P_1 \frac{\tau - \tau_s}{\tau} F_0}{E_e \tau_s + (P_1 + P_4) E_i(\tau - \tau_s)} \tag{11}
\]

Note that the energy efficiency is reduced as the missed detection probability increases.

### B. SIMULATION RESULTS

In this section, various simulation results are provided to evaluate the performance of the proposed DRC, especially the classification performance of the proposed DRC for detecting a burst signal under various SNR levels. Fig. 5 compares the performance of the proposed DRC with that of the feature-based fusion scheme and conventional ED in terms of accuracy, recall, precision, and F-score, respectively. For a fair comparison, the feature-based fusion scheme was performed with \( K=1 \). Here, it was observed that the proposed DRC has a higher classification accuracy than the conventional schemes. In addition, the proposed scheme outperforms the feature-based fusion scheme by providing approximately 20% higher recall (correct detection probability) at an SNR of \(-14\) dB. In particular, it can be easily observed that the Bin-RP performs better than the Const-RP on recall. This is straightforward because the threshold filters the Bin-RP, which makes it more focused on the presence of burst signals than the Const-RP. Furthermore, compared with the conventional schemes, the recall gain of the proposed DRC over the conventional schemes is significant, especially at low SNR. In contrast, precision represents the robustness of the false-alarms, which shows that the precision of the Bin-RP is lower than that of Const-RP.

The feature-based fusion scheme is not able to accurately learn the model parameters at low SNR, and its detection performance deteriorates significantly. Furthermore, all of the performance metrics of the proposed DRC outperform those of the comparison schemes. In terms of F-score, the performance of the proposed DRC is significantly higher than that of the comparison schemes. In particular, the F-score of the proposed DRC reaches its best value at one at an SNR of approximately \(-10\) dB, while the feature-based fusion scheme reaches it at approximately \(-8\) dB.

Fig. 6 shows the detection performance and energy efficiency of the proposed DRC. As observed, the correct detection probability of the proposed DRC with a single detector is higher or comparable to the performance of the FFS with three SUs for various SNRs. Specifically, it shows the best performance in terms of missed detection and error probability even with a single SU. In addition, the proposed DRC shows a significant reduction in the error probability, thereby demonstrating its superiority. To further evaluate the performance, the energy efficiency performance of the proposed DRC is higher than that of the comparison schemes owing to its low missed detection probability. Note that the conventional ED scheme has a higher missed detection probability at a low SNR because the burst signal energy is diluted when the total sensing samples are averaged out.
This article proposes a CNN-based detector scheme with RP algorithms for burst signal detection, where a time-series signal is first converted to an RP image by applying the RP algorithms. Then, the RP image is used by the CNN model to extract the features and further detect a burst signal. The implementation and simulation results show that the proposed CNN-based detector shows excellent and stable detection performance (99% accuracy at -10 dB) even in a low SNR environment without the need for multiple detectors for cooperative detection. In particular, it performs well even with a small number of burst samples collected from a single SU. The significant point of our proposed DRC is that it operates on a high energy efficiency based on the low missed detection probability; hence, it can be applied to various sensors in industrial manufacturing facilities where burst signals may exist.

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