

Article

Parameter Estimation Algorithm for Suppression Jamming Signals Based on an Improved YOLOv8

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Abstract

In military confrontations, intentional suppression jamming can significantly degrade the reliability of friendly communication systems. By integrating conventional frequency hopping with spectrum sensing, cognitive frequency hopping technology can proactively avoid jammed frequency bands, thereby enhancing anti-jamming performance. This paper proposes a jamming detection and parameter estimation algorithm based on an improved YOLOv8 model. The proposed method extracts the time–frequency features of jamming signals and predicts their bounding boxes in time–frequency images. Based on the coordinates of the predicted bounding boxes, the center frequency, bandwidth, and temporal parameters of the jamming signals are estimated, thereby supporting spectrum sensing. Simulation results under MATLAB-generated signal conditions show that the proposed method achieves high detection accuracy and low mean squared relative error in the considered simulation scenarios. In addition, the proposed method maintains effective detection and parameter-estimation performance in composite jamming scenarios. This study provides a useful simulation-based reference for spectrum sensing in cognitive frequency hopping systems.

Keywords: cognitive frequency hopping; spectrum sensing; jamming signal detection; jamming signal parameter estimation;

1. Introduction

With the continuous development of wireless communication and electronic countermeasure technologies, the electromagnetic environment has become increasingly complex. In military communication scenarios, intentional jamming can seriously degrade the reliability of wireless links. As a spread-spectrum technique, frequency-hopping communication reduces the probability of being jammed by frequently switching carrier frequencies [1]. However, conventional frequency-hopping systems lack real-time awareness of the electromagnetic environment and may still collide with jamming signals. By contrast, cognitive frequency hopping can proactively avoid jammed frequency bands by means of spectrum sensing technology [2]. Recent studies on frequency-hopping signal detection have further emphasized that reliable signal detection and real-time electromagnetic environment awareness are important for improving communication robustness in complex electromagnetic environments [3].



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Spectrum sensing and jamming detection are key techniques for cognitive frequency-hopping systems. Existing methods mainly include time-domain detection, frequency-domain detection, time–frequency-domain analysis, and other transform-domain methods. In the time domain, only the presence or absence of jamming can usually be determined, while frequency-domain methods can detect jamming frequency components and estimate occupied frequency bands [4–6]. However, these methods may suffer from estimation errors due to FFT resolution, threshold selection, noise uncertainty, and false alarms. In addition, some classical signal detection methods often require prior information, have limited robustness to noise, or involve relatively high computational complexity. Therefore, for cognitive frequency hopping, it is not sufficient to only detect jamming; key parameters such as center frequency, bandwidth, sweep period, pulse duration, and duty cycle are also required for frequency avoidance and adaptive decision-making.

With the development of computer vision and deep learning, time–frequency representations of jamming signals can be treated as images for feature extraction and target localization. By applying object detection algorithms to time–frequency images, single or compound jamming signals can be identified [7,8]. Some studies have further utilized the time and frequency information contained in time–frequency images for radar jamming detection, recognition, and information extraction [9,10]. More recently, spectrogram-based object detection has been extended to communication signal detection, frequency-hopping signal parameter estimation, and compound jamming signal detection [11–13]. Compared with classification-only methods, YOLO-based object detection models can provide both category and location information, which is useful for composite jamming detection and subsequent parameter estimation. Recent reviews also show that machine learning and neural-network-based methods have become important directions for jamming recognition in complex electromagnetic environments [14]. In addition, deep learning-based spectrum prediction has demonstrated the importance of accurate time–frequency information in intelligent jamming and anti-jamming scenarios [15].

Although existing studies have made progress in traditional spectrum sensing, time–frequency analysis, deep learning-based signal detection, and YOLO-based time–frequency target detection, several issues remain insufficiently addressed. Existing YOLO-based studies mainly focus on general communication signal detection, frequency-hopping signal parameter estimation, radar compound jamming detection, or radar jamming parameter estimation [9–13]. The application of improved YOLO-based detection to suppression jamming parameter estimation in cognitive frequency-hopping communication systems still requires further investigation. In particular, the explicit mapping between predicted bounding-box coordinates in time–frequency images and the physical parameters of suppression jamming signals needs to be further clarified.

Therefore, the objective of this work is to estimate the key physical parameters of suppression jamming signals from time–frequency images so as to support frequency avoidance in cognitive frequency-hopping systems. To address this objective, this paper proposes a jamming detection and parameter estimation method based on an improved YOLOv8 model. The received signal is first converted into a time–frequency image using STFT. Then, the improved YOLOv8 network is used to detect jamming regions. Finally, the predicted bounding-box coordinates are converted into physical parameters, including center frequency, bandwidth, sweep period, pulse period, and duty cycle.

The main contributions of this paper are summarized as follows:

1. A suppression-jamming-oriented time–frequency object detection framework is developed for cognitive frequency hopping systems, which integrates jamming type recognition, jamming region localization, and physical parameter estimation.

2. An improved YOLOv8 model is constructed by introducing the SE-C2f module and coordinate attention mechanism to enhance feature representation and localization capability in time–frequency images.
3. A bounding-box-based parameter estimation procedure is designed to convert image-domain detection results into physical jamming parameters, including center frequency, bandwidth, sweep period, pulse duration, and duty cycle.

2. Jamming Signal Model

This paper mainly studies the parameter estimation of four types of suppression jamming signals, and their mathematical expressions are as follows. During the silent period of the communication signal, the received signal can be expressed as

$$y(t) = J(t) + N(t) \quad (1)$$

where $J(t)$ represents the jamming signal and $N(t)$ represents the noise.

Partial-band noise jamming (PBNJ) refers to a jamming signal that continuously occupies a specific frequency band. Its time-domain expression is given by

$$J(t) = U_n(t)e^{j(2\pi f_c t + \theta_J)} \quad (2)$$

where $U_n(t)$ represents band-limited baseband Gaussian noise, f_c denotes the center frequency, and θ_J represents the random phase.

Comb-spectrum noise jamming (CSNJ) refers to a jamming signal whose energy is concentrated on a series of narrowband spectral lines with certain spacing intervals. It can be composed of multiple narrowband noise jamming (NBNJ) signals. Its time-domain expression is given by

$$J(t) = \sum_{i=1}^N U_n(t)e^{j(2\pi f_i t + \theta_i)} \quad (3)$$

where N represents the number of narrowband noise jamming signals.

Linear frequency modulation (LFM) jamming is a type of jamming signal whose energy sweeps across a specific frequency band over a certain period of time. Its instantaneous frequency varies linearly with time. Its time-domain expression is given by

$$J(t) = \sqrt{P_J} \exp \left\{ j \left[2\pi \left(f_L t + \frac{f_H - f_L}{2T_{SW}} t^2 \right) + \theta_J \right] \right\} \quad (4)$$

where T_{SW} is the sweep period, f_L and f_H are the starting and ending frequencies of the sweep jamming band, respectively, the sweep bandwidth is $(f_H - f_L)$, and the center frequency is $(f_H + f_L)/2$.

Periodic pulse noise jamming (PPNJ) is a type of jamming signal consisting of a sequence of short-duration, high-power noise pulses transmitted with a certain pulse repetition period. Its time-domain expression is given by

$$J(t) = U_n(t) U_{T,\tau}(t) e^{j(2\pi f_c t + \theta_J)} \quad (5)$$

where $U_{T,\tau}(t)$ denotes a periodic pulse signal, expressed as

$$U_{T,\tau}(t) = \begin{cases} 1, & kT \leq t \leq kT + \tau, \quad k = 0, 1, 2, \dots \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where T denotes the pulse period, and τ/T represents the duty cycle.

Unlike the frequency domain, the time–frequency domain can characterize the frequency components of a signal and the changes in their energy intensity over time, providing excellent differentiation between different types of jamming. There are many methods for time–frequency analysis; since the Short Time Fourier Transform (STFT) can flexibly balance time and frequency resolution, this paper uses STFT to obtain the time–frequency representation. For discrete signals, the STFT is given by the following equation:

$$\text{STFT}(m, k) = \sum_{n=0}^{N_{\text{STFT}}-1} y(n) w(n-m) e^{-j \frac{2\pi kn}{N_{\text{STFT}}}} \quad (7)$$

where m and k represent the time and frequency indices, respectively, $w(n)$ represents the window function, and N_{STFT} represents the number of STFT points. The time–frequency image is subsequently generated from the magnitude spectrum $|\text{STFT}(m, k)|$.

To improve the reproducibility of the dataset construction process, the simulation and annotation procedures are further described. For each sample, the time-domain jamming signal and its ground-truth physical parameters were generated simultaneously by MATLAB R2018a (MathWorks, Natick, MA, USA) simulation. PBNJ was generated by filtering complex Gaussian noise and modulating it to a randomly selected carrier frequency. CSNJ was generated by superimposing multiple narrowband noise components at different center frequencies. LFM jamming was generated as a periodic linear chirp signal, while PPNJ was generated by applying a periodic pulse gate to filtered noise and then modulating it to a carrier frequency.

For each generated signal, STFT was used to construct the time–frequency image. A Hamming window with a length of 256 and an FFT length of 512 was used. The displayed frequency range was limited to 0–50 MHz, and the observation time range was 0–0.1 ms. Since all samples were generated by simulation, the ground-truth time–frequency parameters were known. Therefore, the bounding-box labels were automatically generated according to the ground-truth parameters and stored in the standard YOLO format. PBNJ and CSNJ were both assigned to the BNJ category because they share similar frequency-band estimation requirements, while LFM and PPNJ were assigned to separate categories. This merging is only applied at the detection-category level. For PBNJ, one BNJ bounding box corresponds to the occupied partial band. For CSNJ, each narrowband component is annotated and detected as an individual BNJ bounding box. Therefore, the center frequency and bandwidth of each occupied frequency component can still be estimated from its corresponding bounding box.

The time–frequency images of the four jamming types are shown in Figure 1.

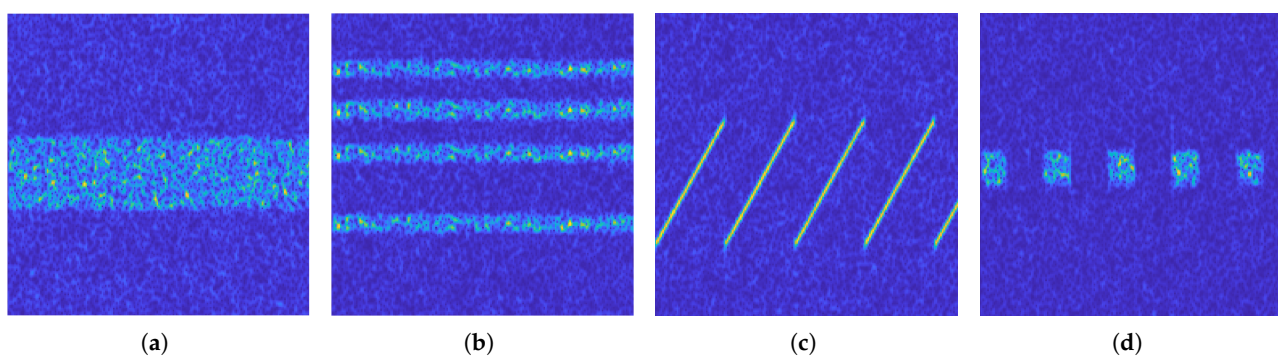


Figure 1. Time–frequency images of different jamming signals: (a) PBNJ. (b) CSNJ. (c) LFM. (d) PPNJ.

As shown in Figure 1, different suppression jamming signals exhibit distinct time–frequency characteristics. PBNJ appears as a continuous band-like region occupying a certain frequency range, while CSNJ consists of several separated narrowband components. LFM jamming presents oblique stripe-like structures because its instantaneous frequency changes linearly with time. PPNJ appears as intermittent pulse-like blocks along the time axis. These distinguishable time–frequency patterns provide the basis for jamming detection and parameter estimation using object detection methods.

3. Proposed Method

3.1. Improved YOLOv8

YOLOv8 is one of the YOLO (You Only Look Once) series object detection algorithms released by Ultralytics in 2023, and it belongs to the category of one-stage object detection models [16]. YOLOv8 mainly consists of three components: the Backbone, Neck, and Head. The Backbone is responsible for extracting deep features from the input image; the Neck is used to fuse feature information at different scales; and the Head is responsible for outputting the target categories and bounding box locations. YOLOv8 mainly consists of the Conv, C2f, and SPPF modules. In the Backbone network, the Conv module performs progressive downsampling to extract high-level semantic features, and is composed of Conv2d, Batch Normalization (BN), and the SiLU activation function. The SPPF module is used for feature aggregation at the end of the Backbone. Through successive max-pooling operations, it expands the receptive field and fuses contextual information across different scales.

The C2f module serves as the core feature extraction and fusion component in the Backbone and Neck of YOLOv8, and its structure is illustrated in Figure 2. Concat represents the concatenation of feature maps along the channel dimension. By introducing the channel-splitting operation, the Bottleneck module extracts features from only half of the split channels, thereby substantially reducing the computational complexity and parameter count. Meanwhile, Concat fuses shallow features with the intermediate- and deep-level features extracted by Bottleneck modules of different depths, which facilitates richer gradient flow.

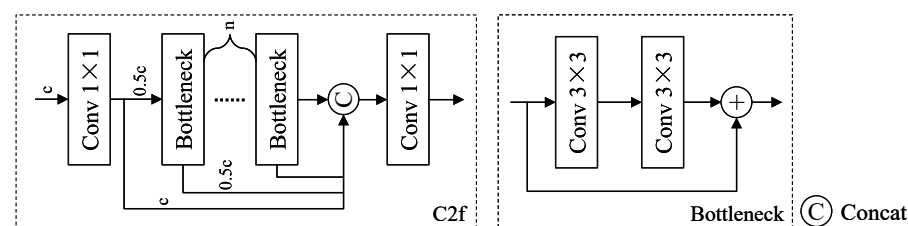


Figure 2. Structure of the C2f module. The arrows indicate the feature propagation direction, and the ellipsis denotes repeated Bottleneck operations. The ellipsis does not affect the scientific understanding of the module structure.

However, the shallow features retained by C2f may contain redundant information and are more susceptible to noise under low jamming-to-noise ratio (JNR) conditions. To alleviate this problem, a squeeze-and-excitation (SE) attention mechanism [17] is introduced into the C2f module in the Backbone to perform channel-wise redundancy suppression on the shallow features to be concatenated, thereby enhancing the quality of shallow feature representations. The structure of the SE-C2f module is illustrated in Figure 3.

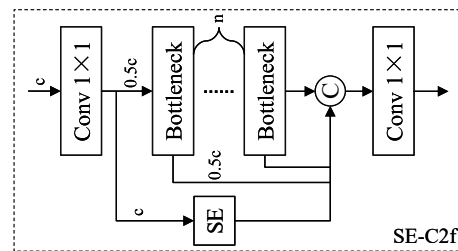


Figure 3. Structure of the SE-C2f module. The arrows indicate the feature propagation direction, and the ellipsis denotes repeated Bottleneck operations. The SE block represents channel-wise feature recalibration before feature concatenation.

To effectively detect targets at large, medium, and small scales, YOLOv8 employs three detection heads at different scales and integrates a feature pyramid network (FPN) and a path aggregation network (PAN) in the Neck, forming a bidirectional multi-scale feature fusion structure. To improve the sensitivity of the multi-scale features output from the Backbone to the Neck to the spatial locations of targets, a coordinate attention (CA) mechanism [18] is introduced between the Backbone and the Neck in this study. This enables the network to select and recalibrate key information, thereby enhancing its localization capability. Finally, the network architecture of the improved YOLOv8 is shown in Figure 4.

To further enhance the model's generalization ability and robustness, data augmentation techniques are introduced during the training phase. The core idea is to construct a richer training distribution by randomly transforming the input image and its annotations, thereby reducing overfitting of the model to specific backgrounds, target scales, and poses. The augmentation methods used in this section include vertical flipping, horizontal flipping, color jittering, scaling down, and scaling up, and these methods can be combined.

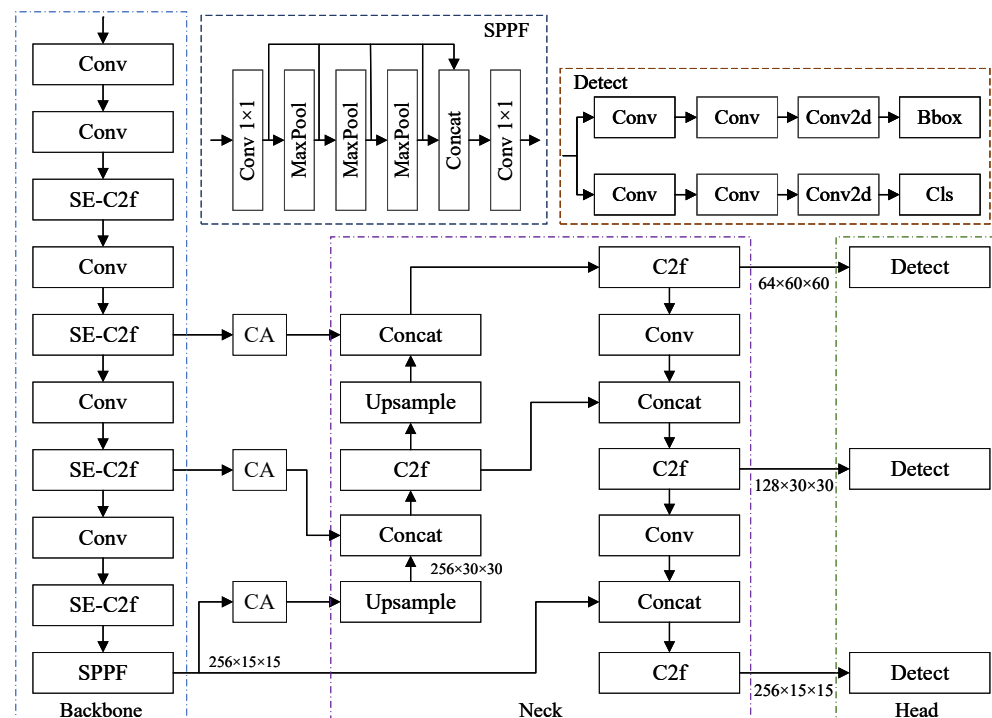


Figure 4. The improved YOLOv8 network architecture. The arrows indicate the feature propagation and feature-fusion directions. The dashed colored boxes distinguish the Backbone, Neck, and Head components, and the orange dashed boxes indicate the classification and bounding-box prediction branches. The colors are used only to visually distinguish different network modules and do not represent additional quantitative values.

3.2. Parameter Estimation Principle

A schematic of object detection in the time–frequency image is shown in Figure 5. The predicted outputs include the coordinates of the upper-left corner of the bounding box (x_1, y_1) , the coordinates of the lower-right corner (x_2, y_2) , the category label, and the confidence score. Then, the center, height, and width parameters of the predicted bounding box are calculated based on the output coordinates. Combined with the frequency on the vertical axis and the time on the horizontal axis of the time–frequency image, the parameters of the jamming signal can be estimated. Since both PBNJ and CSNJ are continuous jamming generated by noise, PBNJ and CSNJ are collectively referred to as BNJ during detection.

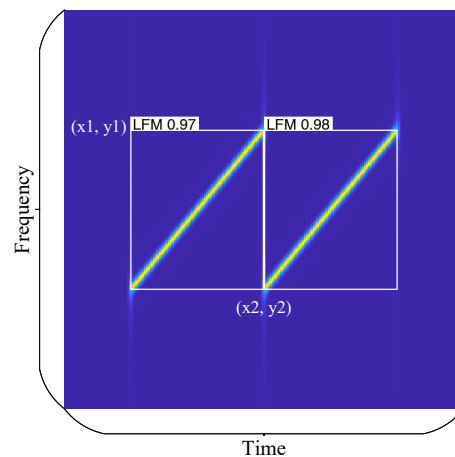


Figure 5. Schematic diagram of object detection based on time–frequency image of jamming signals. The background color represents the time–frequency energy distribution, where brighter regions indicate stronger spectral energy. The white rectangles indicate predicted bounding boxes, and the labels show the detected jamming category and confidence score.

For a predicted bounding box (x_1, y_1, x_2, y_2) , its center coordinate, width, and height are calculated as

$$x_c = \frac{x_1 + x_2}{2}, \quad y_c = \frac{y_1 + y_2}{2}, \quad (8)$$

$$w = x_2 - x_1, \quad h = y_2 - y_1. \quad (9)$$

Let the input image size be $W \times W$, the effective time–frequency region be $W_{\text{eff}} \times W_{\text{eff}}$, the observation bandwidth be B_{obs} , and the observation time be T_{obs} . Since the frequency axis increases from bottom to top in the time–frequency image, the center frequency and bandwidth are estimated as

$$\hat{f}_c = \frac{W - y_c - m}{W_{\text{eff}}} B_{\text{obs}}, \quad (10)$$

$$\hat{B} = \frac{h}{W_{\text{eff}}} B_{\text{obs}}, \quad (11)$$

where $m = (W - W_{\text{eff}})/2$ denotes the image margin introduced by resizing or padding. For LFM, the sweep period is estimated from the average width of the retained boxes:

$$\hat{T}_{\text{LFM}} = \frac{\bar{w}}{W_{\text{eff}}} T_{\text{obs}}. \quad (12)$$

For PPNJ, the pulse period is estimated from the average horizontal interval between adjacent pulse boxes, and the duty cycle is calculated as

$$\hat{T}_{\text{PPNJ}} = \frac{\bar{\Delta x}}{W_{\text{eff}}} T_{\text{obs}}, \quad \hat{D} = \frac{\bar{w}}{\Delta x}. \quad (13)$$

This mapping explicitly converts image-domain detection results into physical jamming parameters, including center frequency, bandwidth, sweep period, pulse period, and duty cycle.

In this study, B_{obs} is expressed in MHz and T_{obs} is expressed in ms. Therefore, the estimated frequency-domain parameters $\hat{f}_c$ and $\hat{B}$ are obtained in MHz, while the estimated temporal parameters $\hat{T}_{\text{LFM}}$ and $\hat{T}_{\text{PPNJ}}$ are obtained in ms. The predicted bounding-box coordinates used in the above equations are pixel-domain coordinates in the input image. If YOLO-format normalized labels are used during training, the normalized coordinates are first converted back to pixel coordinates by multiplying by the input image size. During detection, only the image intensity values are normalized for network input, and this normalization does not change the spatial coordinate mapping from image pixels to physical frequency and time parameters.

For LFM and PPNJ, one or more complete or incomplete periods may appear within the observation interval, depending on the randomly generated period. Therefore, the 3-sigma criterion is applied only when a sufficient number of candidate boxes or period intervals are available. When the number of detected candidates is insufficient for statistical filtering, all available candidates are retained and the corresponding parameters are estimated directly according to Equations (10)–(13). After obtaining the object detection bounding boxes, the image-domain parameters are first calculated and then converted into physical jamming parameters according to Equations (10)–(13). The parameter estimation process for different jamming types is shown in Algorithm 1.

Algorithm 1 Parameter estimation algorithm for jamming signals.

Require: Predicted bounding box parameters output by the object detection model

Ensure: Jamming category, center frequency, bandwidth, and temporal parameters

- 1: Obtain the class label, x_{center} , y_{center} , width, and height of each predicted bounding box:

$$x_{\text{center}} = (x_2 + x_1)/2, y_{\text{center}} = (y_2 + y_1)/2, \text{width} = x_2 - x_1, \text{height} = y_2 - y_1.$$
 - 2: **if** the class label is BNJ **then**
 - 3: Calculate the center frequency and bandwidth according to Equations (10) and (11).
 - 4: **else if** the class label is LFM **then**
 - 5: Sort all predicted boxes of the same class in descending order according to width. Calculate the mean values μ_W , μ_H and standard deviations σ_W , σ_H of the width and height of the first $N - 2$ predicted boxes, where N is the number of predicted boxes of the same class and $N \geq 3$. Traverse all predicted boxes.
 - 6: **for all** predicted boxes **do**
 - 7: **if** the width and height do not satisfy $\mu_W - 3\sigma_W \leq \text{width} \leq \mu_W + 3\sigma_W$ **or** $\mu_H - 3\sigma_H \leq \text{height} \leq \mu_H + 3\sigma_H$ **then**
 - 8: Remove the predicted box.
 - 9: **end if**
 - 10: **end for**
 - 11: Calculate the mean values of y_{center} , width, and height of the remaining predicted boxes, denoted as μ'_Y , μ'_W , and μ'_H , respectively.
 - 12: Convert the mean box coordinates into the center frequency, bandwidth, and sweep period according to Equations (10)–(12).
 - 13: **else if** the class label is PPNJ **then**
 - 14: Calculate the mean value μ_H and standard deviation σ_H of the height of all predicted boxes of the same class.
 - 15: **for all** predicted boxes **do**
 - 16: **if** the height does not satisfy $\mu_H - 3\sigma_H \leq \text{height} \leq \mu_H + 3\sigma_H$ **then**
 - 17: Remove the predicted box.
 - 18: **end if**
 - 19: **end for**
 - 20: Calculate the mean values of y_{center} and height of the remaining predicted boxes, denoted as μ'_Y and μ'_H , respectively.
 - 21: Convert the mean box coordinates into the center frequency and bandwidth according to Equations (10) and (11).
 - 22: Sort the remaining predicted boxes of the same class in descending order according to width. Calculate the mean value μ_W and standard deviation σ_W of the width of the first $N - 2$ predicted boxes.
-

Algorithm 1 *Cont.*

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23:   for all predicted boxes do
24:     if the width does not satisfy  $\mu_W - 3\sigma_W \leq \text{width} \leq \mu_W + 3\sigma_W$  then
25:       Remove the predicted box.
26:     end if
27:   end for
28:   Calculate the mean width  $\mu'_W$  of the remaining predicted boxes and convert it into the pulse
duration using the time-axis mapping.
29:   Sort the remaining predicted boxes in ascending order according to  $x_{\text{center}}$ . Calculate the differ-
ences between adjacent  $x_{\text{center}}$  values to obtain the image-domain period intervals  $T_1, T_2, \dots, T_{n-1}$ ,
where  $n$  is the number of remaining predicted boxes. Calculate the mean value  $\mu_T$  and standard
deviation  $\sigma_T$  of the estimated periods.
30:   for all  $T_i$  do
31:     if  $T_i$  does not satisfy  $\mu_T - 3\sigma_T \leq T_i \leq \mu_T + 3\sigma_T$  then
32:       Remove  $T_i$ .
33:     end if
34:   end for
35:   Calculate the mean value  $\mu'_T$  of the remaining estimated period intervals.
36:   Calculate the final pulse period and duty cycle according to Equation (13).
37: end if

```

4. Experimental Results

The evaluation metrics for object detection mainly include precision P, recall R, and mean average precision (mAP). Their formulations are given as follows:

$$P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \quad AP = \int_0^1 P(R) dR, \quad mAP = \frac{1}{N_C} \sum_{i=1}^{N_C} AP_i \quad (14)$$

where TP denotes true positive predictions, FP denotes false positive predictions, FN denotes missed detections, and N_C denotes the number of categories. AP represents the area under the precision–recall (P - R) curve for a single category, while mAP denotes the mean average precision across all categories. In this study, mAP@90 is adopted to evaluate the detection performance of the model, where a prediction is considered correct only when the intersection over union (IoU) between the predicted bounding box and the ground-truth box is greater than or equal to 0.9. For bounding boxes b and b' , their IoU can be expressed as

$$\text{IoU}(b, b') = \frac{|b \cap b'|}{|b \cup b'|} \quad (15)$$

where $|b \cap b'|$ denotes the intersection area between boxes b and b' , and $|b \cup b'|$ denotes their union area.

The deviation of parameter estimation is evaluated using the mean squared relative error (MSRE), which is calculated as follows:

$$\text{MSRE} = \frac{1}{N} \sum_{i=1}^N \left(\frac{\rho_i - \hat{\rho}_i}{\rho_i} \right)^2 \quad (16)$$

where N denotes the number of samples, ρ_i represents the true value of the i -th sample, and $\hat{\rho}_i$ represents the estimated value of the i -th sample.

The data were generated by MATLAB simulation, with a sampling frequency of 120 MHz, 12,000 samples, and an observation bandwidth of 50 MHz. The STFT window length is set to 256, the time–frequency image size is 480×480 , the vertical axis span is 50 MHz, and the horizontal axis span is 0.1 ms. The parameter settings for different jamming types are shown in Table 1.

Since the dataset used in this study is generated by MATLAB simulation, the experimental results should be interpreted as simulation-based performance under the considered signal models and STFT settings. Further validation using measured RF, over-the-air,

or hardware-captured data is still needed to evaluate the generalization ability of the proposed method in practical electromagnetic environments.

Table 1. Parameter settings of different jamming types

Jamming Type	Parameter Description
CSNJ	Number of NBNJs: 3–7; bandwidth of each NBNJ: 2–3 MHz; center-frequency distribution: 0.5–50 MHz.
PBNJ	Bandwidth: 5–25 MHz; center-frequency distribution is the same as that of CSNJ.
LFM	Bandwidth: 5–25 MHz; sweep period: 0.01–0.1 ms.
PPNJ	Bandwidth: 4–8 MHz; pulse period: 0.01–0.1 ms; duty cycle: 0.2–0.5; center-frequency distribution is the same as that of CSNJ.

The JNR sampling points of the training samples were set to $([-8:2:10])$ dB. For each JNR value, 150 samples were generated for each single jamming type. In addition, composite jamming samples were introduced by randomly selecting two to three types from the four jamming types and assigning equal power to each jamming component. For each JNR value, 150 composite jamming samples were generated. The JNR range of the test samples was consistent with that of the training samples. For each JNR value, 50 samples were generated for each single jamming type and for the composite jamming type. In summary, the training set contained 7500 samples, and the test set contained 2500 samples. The training framework is based on PyTorch 2.12.1 (Meta AI, Menlo Park, CA, USA), and the parameter settings are shown in Table 2. During inference, the confidence threshold is set to 0.4, and the IoU threshold is set to 0.6.

Table 2. Training parameter settings.

Parameter	Configuration
Input size	480×480
Epochs	80
Batch size	16
Learning rate	$1 \times 10^{-3} \rightarrow 1 \times 10^{-5}$
Optimizer	AdamW

Figure 6 shows the detection results of the proposed method under single and composite jamming scenarios.

It can be observed from Figure 6 that the proposed method can accurately localize jamming features under both single and composite jamming conditions. In the single-jamming case, the proposed model can locate the main time–frequency regions of BNJ, LFM, and PPNJ. In the composite-jamming case, multiple jamming components coexist in the same time–frequency image, which increases the difficulty of detection. Nevertheless, the proposed method can still distinguish different jamming components and provide relatively accurate bounding boxes. This indicates that the improved YOLOv8 model has good localization capability for both single and composite jamming scenarios.

Table 3 shows the performance of YOLOv8n and the improved YOLOv8 on object-detection indicators. In terms of mAP@90, introducing SE-C2f improved the performance by 0.21% compared with YOLOv8n, while introducing the CA mechanism resulted in a 1.09% improvement. Moreover, the combination of the two modules achieved a further improvement of 1.25%. Furthermore, this improvement was achieved without a significant increase in the number of parameters or computational cost. These results show that the proposed modules mainly improve localization accuracy rather than simply increasing

model complexity, since the mAP@90 is improved while the number of parameters and GFLOPs remain almost unchanged.

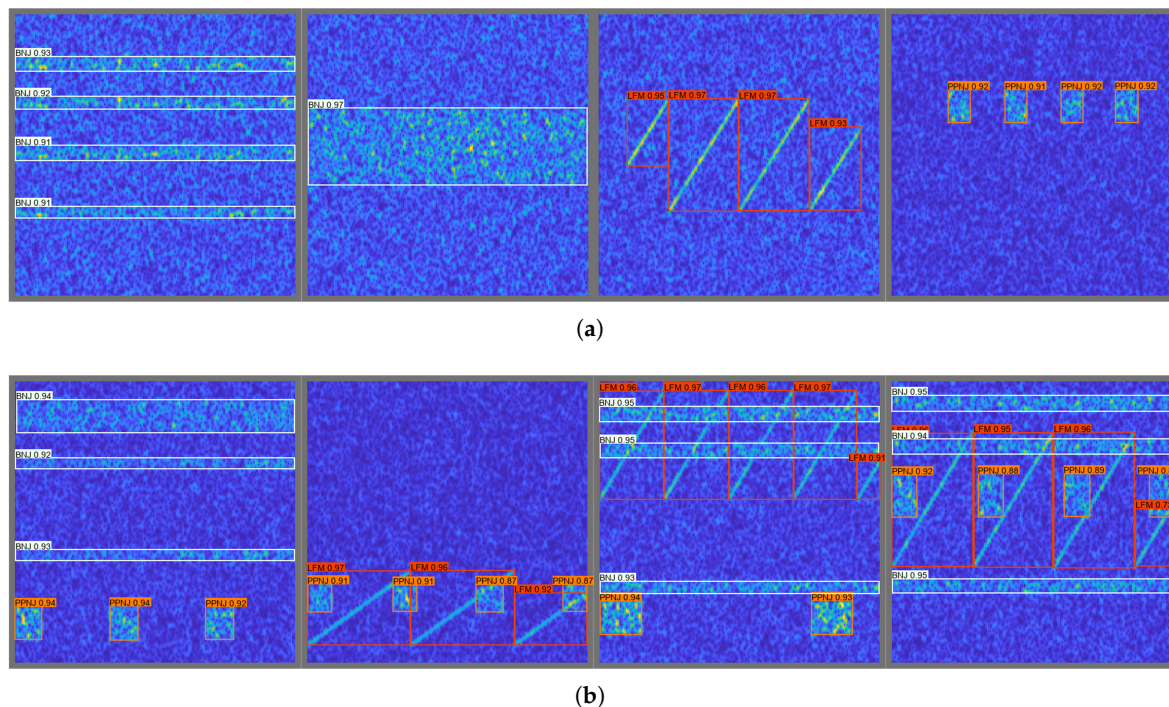


Figure 6. Performance of the improved YOLOv8 in detecting different jamming types: (a) Single jamming. (b) Composite jamming. Different colored boxes represent predicted bounding boxes for different jamming categories. The overlapping boxes in the composite-jamming examples indicate coexisting jamming components in the same time–frequency region and do not affect the scientific understanding of the detection results.

Table 3. Single-run ablation comparison of different models on the test set.

Model	P (%)	R (%)	mAP@90 (%)	Params (M)	GFLOPs
YOLOv8n	99.74	99.76	96.20	3.01	4.6
YOLOv8n + SE-C2f	99.76	99.79	96.41	3.05	4.6
YOLOv8n + CA	99.75	99.78	97.29	3.02	4.6
Improved YOLOv8	99.76	99.79	97.45	3.07	4.6

To further evaluate the statistical stability of the performance improvement, YOLOv8n and the proposed improved YOLOv8 were independently trained five times with different random seeds under the same dataset split, input size, training configuration, and validation settings. The mean and standard deviation of the detection metrics are reported in Table 4.

Table 4. Statistical stability comparison over five independent runs.

Model	P (%)	R (%)	mAP@90 (%)
YOLOv8n	97.7604 ± 1.1977	98.0053 ± 0.9270	92.1434 ± 2.2401
Improved YOLOv8	97.2106 ± 0.3555	97.9635 ± 0.0641	92.2667 ± 0.2052

As shown in Table 4, the proposed improved YOLOv8 achieves a slightly higher average mAP@90 than YOLOv8n over five independent runs. More importantly, the standard deviation of mAP@90 is reduced from 2.2401% to 0.2052%, indicating that the proposed model shows smaller performance fluctuations across different random seeds. These results

suggest that the observed performance improvement is generally stable rather than being caused by a single random training run.

As shown in Table 5, the proposed improved YOLOv8 achieves the highest mAP@90 and recall among the compared models. Compared with YOLOv8n, the proposed method improves mAP@90 by 1.14%, while increasing the number of parameters only slightly from 3.01 M to 3.07 M and maintaining the same GFLOPs. Although YOLOv8s obtains the highest precision, it requires 11.14 M parameters and 16.1 GFLOPs, which are much larger than those of the proposed model. These results indicate that the proposed method provides a better balance between detection accuracy and model complexity for suppression jamming detection in time–frequency images.

Table 5. Comparison with representative object detection models on the test set.

Model	P (%)	R (%)	mAP@90 (%)	Params (M)	GFLOPs
YOLOv5n	96.86	96.96	90.14	2.51	4.0
YOLOv8n	97.04	97.54	91.22	3.01	4.6
YOLOv8s	97.82	97.87	92.21	11.14	16.1
YOLO11n	96.84	97.30	90.77	2.59	3.6
Improved YOLOv8	97.39	97.93	92.36	3.07	4.6

It should be noted that the absolute mAP@90 values in Tables 3–5 are not identical because they correspond to different experimental purposes and independent training runs. Table 3 focuses on the relative contribution of each proposed module in the ablation study, Table 4 reports the mean and standard deviation over five random seeds, and Table 5 provides representative comparisons with other detectors. Therefore, the results are interpreted mainly through within-table comparisons rather than by directly comparing the absolute mAP@90 values across different tables.

As shown in Table 6, the proposed improved YOLOv8 achieves an inference latency of 12.564 ms per image and a throughput of 79.59 images/s on an NVIDIA GeForce RTX 3050 Ti Laptop GPU with an input size of 480×480 . The result was measured on 2500 test images using the trained model. This indicates that the proposed method has the potential to support near-real-time spectrum sensing and cognitive frequency hopping anti-jamming applications.

Table 6. Inference speed of the proposed method on a realistic platform.

Platform	Input Size	Batch Size	Latency (ms/Image)	Throughput (Images/s)
RTX 3050 Ti Laptop GPU	480×480	1	12.564	79.59

To further evaluate the performance of the proposed method in composite jamming scenarios, additional quantitative experiments were conducted on multi-class composite samples and overlapped samples. The validation set contains 500 multi-class composite jamming images and 252 overlapped images in which the IoU between at least two ground-truth components is larger than 0.1. Each jamming component in a composite time–frequency image was treated as an individual detection object. The missed-detection rate (MDR) is defined as

$$\text{MDR} = \frac{N_{\text{miss}}}{N_{\text{gt}}} \times 100\%, \quad (17)$$

where N_{gt} denotes the number of ground-truth jamming components and N_{miss} denotes the number of components without matched predictions.

As shown in Table 7, the proposed method can still detect the main jamming components in composite jamming scenarios. For the composite subset, the overall recall and AP@90 reach 91.93% and 89.75%, respectively. For the overlapped subset, the overall recall and AP@90 are 90.92% and 82.68%, respectively. These results indicate that the proposed model has the ability to localize multiple jamming components in the same time–frequency image. However, the detection performance is not uniform across different component types. In particular, the BNJ component shows lower precision, recall, and AP@90 than LFM and PPNJ, and its missed-detection rate is relatively high in both the composite and overlapped subsets. This is mainly because BNJ components, especially narrowband components, have more fragmented time–frequency distributions and are more likely to overlap with other jamming components, leading to boundary ambiguity and missed detections. Therefore, although the proposed method is effective at the overall composite-scenario level, BNJ detection under fragmented and overlapped conditions remains a challenging case.

The parameter estimation results in Table 8 show that the proposed bounding-box-based mapping method can still estimate the main physical parameters in composite scenarios. The center-frequency estimation errors remain relatively low for BNJ, LFM, and PPNJ. Compared with the composite subset, the overlapped subset generally shows larger bandwidth and duty-cycle estimation errors, indicating that component overlap may introduce additional boundary uncertainty in time–frequency images.

Table 7. Detection performance of the proposed method in composite jamming scenarios.

Subset	Component	GT	P (%)	R (%)	AP@90 (%)	MDR (%)
Composite	BNJ	1243	66.10	78.76	75.00	21.24
Composite	LFM	1053	98.59	99.62	96.23	0.38
Composite	PPNJ	1038	99.52	99.90	98.02	0.10
Composite	All	3334	85.45	91.93	89.75	8.07
Overlap-IoU > 0.1	BNJ	737	66.13	78.70	74.10	21.30
Overlap-IoU > 0.1	LFM	605	98.52	99.34	95.17	0.66
Overlap-IoU > 0.1	PPNJ	431	99.08	100.00	97.76	0.00
Overlap-IoU > 0.1	All	1773	83.87	90.92	82.68	9.08

Table 8. Parameter estimation performance of the proposed method in composite jamming scenarios.

Subset	Component	Parameter	MSRE
Composite	BNJ	Center frequency	2.4×10^{-5}
Composite	BNJ	Bandwidth	0.002267
Composite	LFM	Center frequency	0.000120
Composite	LFM	Bandwidth	0.002130
Composite	LFM	Sweep period	0.000210
Composite	PPNJ	Center frequency	4.2×10^{-5}
Composite	PPNJ	Bandwidth	0.001613
Composite	PPNJ	Pulse period	2.0×10^{-5}
Composite	PPNJ	Duty cycle	0.000397
Overlap-IoU > 0.1	BNJ	Center frequency	2.4×10^{-5}
Overlap-IoU > 0.1	BNJ	Bandwidth	0.002502
Overlap-IoU > 0.1	LFM	Center frequency	0.000137
Overlap-IoU > 0.1	LFM	Bandwidth	0.002421
Overlap-IoU > 0.1	LFM	Sweep period	0.000158
Overlap-IoU > 0.1	PPNJ	Center frequency	5.0×10^{-5}
Overlap-IoU > 0.1	PPNJ	Bandwidth	0.002930
Overlap-IoU > 0.1	PPNJ	Pulse period	2.8×10^{-5}
Overlap-IoU > 0.1	PPNJ	Duty cycle	0.000549

It should also be noted that the parameter-estimation results are based on detected or matched jamming components. In practical cognitive frequency hopping applications, missed BNJ components may lead to incomplete jammed-band awareness and affect subsequent frequency-avoidance decisions. Therefore, improving BNJ component detection and separation in composite scenarios is an important direction for future work.

In addition to the composite-scenario evaluation, the parameter estimation performance was further analyzed under different JNR conditions for each type of jamming signal. To evaluate the parameter estimation error, 400 samples were regenerated for each type of jamming, and MSRE was calculated under different JNRs. For CSNJ, the MSRE of each narrowband jamming component was calculated separately. The MSRE estimates for the center frequency (f_c) and bandwidth (B_W) parameters of PBNJ and CSNJ are shown in Figures 7 and 8. For f_c , the proposed method outperforms YOLOv8n, while for B_W , it is slightly inferior to YOLOv8n under high-JNR conditions.

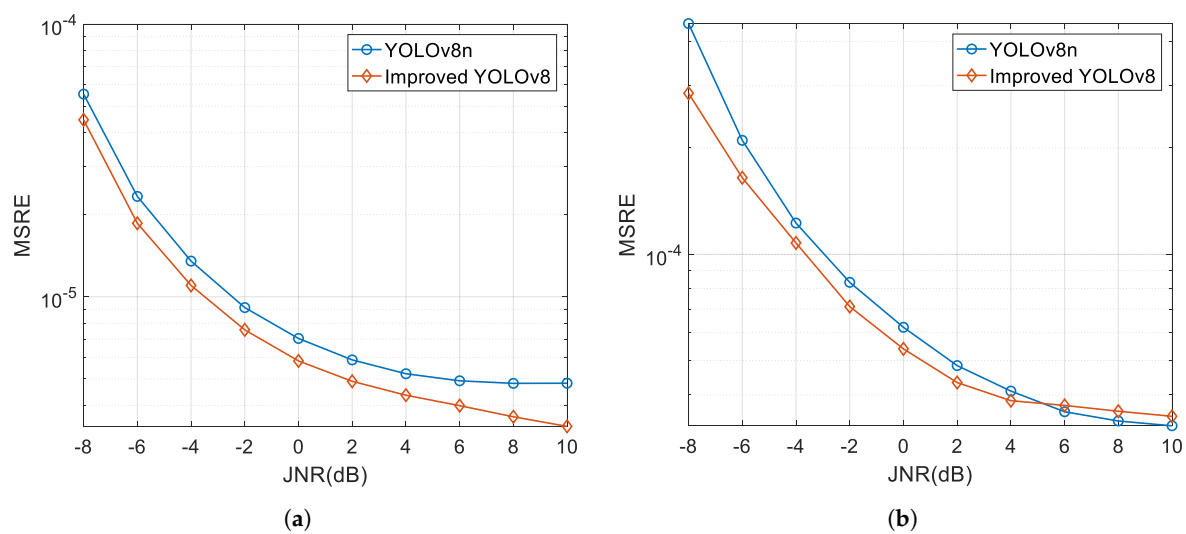


Figure 7. Performance of parameter estimation on PBNJ: (a) Center frequency. (b) Bandwidth.

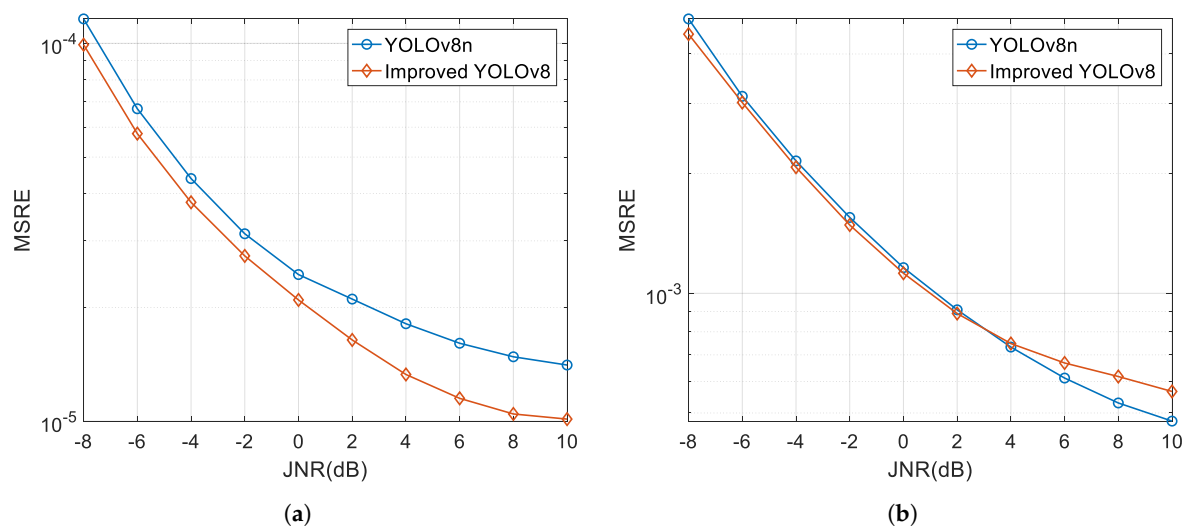


Figure 8. Performance of parameter estimation on CSNJ: (a) Center frequency. (b) Bandwidth.

Although PBNJ and CSNJ are merged into the BNJ category during detection, their parameter estimation performance is evaluated separately in Figures 7 and 8. For CSNJ, each narrowband component is estimated from its own bounding box. Since CSNJ components usually have relatively narrow bandwidths, the bandwidth estimation is more

sensitive to bounding-box height errors, which is consistent with the slightly inferior bandwidth-estimation performance under high-JNR conditions.

To allow more precise verification of the numerical results, the detailed MSRE values corresponding to Figures 7 and 8 are further reported in Tables 9 and 10.

Figures 9–11 show the MSRE performance of LFM and PPNJ parameter estimation. For LFM, the proposed method outperforms YOLOv8n in estimating f_c , B_W , and the period T when $\text{JNR} \geq -6$ dB. For PPNJ, the proposed method improves the estimation performance for most parameters, although it performs slightly worse than YOLOv8n in estimating T .

Figures 7–11 show the MSRE curves of different jamming parameters under different JNR conditions. Overall, the MSRE decreases as the JNR increases, indicating that clearer time–frequency features lead to more accurate bounding-box localization and parameter estimation. For PBNJ and CSNJ, the proposed method achieves better center-frequency estimation in most JNR cases, while the bandwidth estimation of CSNJ is slightly inferior to YOLOv8n under high-JNR conditions. For LFM, the proposed method provides lower MSRE values for center frequency, bandwidth, and period estimation when JNR is higher than approximately -6 dB. For PPNJ, the proposed method improves most parameter estimates, although the period estimation is slightly worse than YOLOv8n in some cases. These results indicate that the proposed method generally improves parameter-estimation accuracy, while some parameters remain sensitive to bounding-box width or interval estimation.

Table 9. Numerical MSRE values corresponding to Figure 7 for PBNJ.

JNR (dB)	YOLOv8n- f_c	Improved- f_c	YOLOv8n- B_W	Improved- B_W
−8	5.5387×10^{-5}	4.4547×10^{-5}	4.5049×10^{-4}	2.8569×10^{-4}
−6	2.3340×10^{-5}	1.8603×10^{-5}	2.1024×10^{-4}	1.6470×10^{-4}
−4	1.3518×10^{-5}	1.1004×10^{-5}	1.2259×10^{-4}	1.0770×10^{-4}
−2	9.1279×10^{-6}	7.5445×10^{-6}	8.3303×10^{-5}	7.1139×10^{-5}
0	7.0328×10^{-6}	5.8176×10^{-6}	6.2150×10^{-5}	5.3984×10^{-5}
2	5.8684×10^{-6}	4.8980×10^{-6}	4.8408×10^{-5}	4.3342×10^{-5}
4	5.2213×10^{-6}	4.3552×10^{-6}	4.1002×10^{-5}	3.5118×10^{-5}
6	4.9183×10^{-6}	3.9877×10^{-6}	3.5835×10^{-5}	3.6420×10^{-5}
8	4.8137×10^{-6}	3.7301×10^{-6}	3.7403×10^{-5}	3.5152×10^{-5}
10	4.8185×10^{-6}	3.5482×10^{-6}	3.2697×10^{-5}	3.4386×10^{-5}

Table 10. Numerical MSRE values corresponding to Figure 8 for CSNJ.

JNR (dB)	YOLOv8n- f_c	Improved- f_c	YOLOv8n- B_W	Improved- B_W
−8	1.1607×10^{-4}	9.9177×10^{-5}	4.9012×10^{-3}	4.6462×10^{-3}
−6	6.7121×10^{-5}	5.7675×10^{-5}	3.1302×10^{-3}	3.0170×10^{-3}
−4	4.3864×10^{-5}	3.7948×10^{-5}	2.1529×10^{-3}	2.0696×10^{-3}
−2	3.1297×10^{-5}	2.7373×10^{-5}	1.5198×10^{-3}	1.4353×10^{-3}
0	2.4433×10^{-5}	2.0921×10^{-5}	1.1026×10^{-3}	1.0781×10^{-3}
2	2.1040×10^{-5}	1.6404×10^{-5}	9.8926×10^{-4}	8.5213×10^{-4}
4	1.8104×10^{-5}	1.3288×10^{-5}	7.3236×10^{-4}	6.9977×10^{-4}
6	1.6074×10^{-5}	1.1490×10^{-5}	6.1211×10^{-4}	5.9137×10^{-4}
8	1.4805×10^{-5}	1.0445×10^{-5}	5.2987×10^{-4}	5.1351×10^{-4}
10	1.4075×10^{-5}	1.0124×10^{-5}	4.7700×10^{-4}	4.6421×10^{-4}

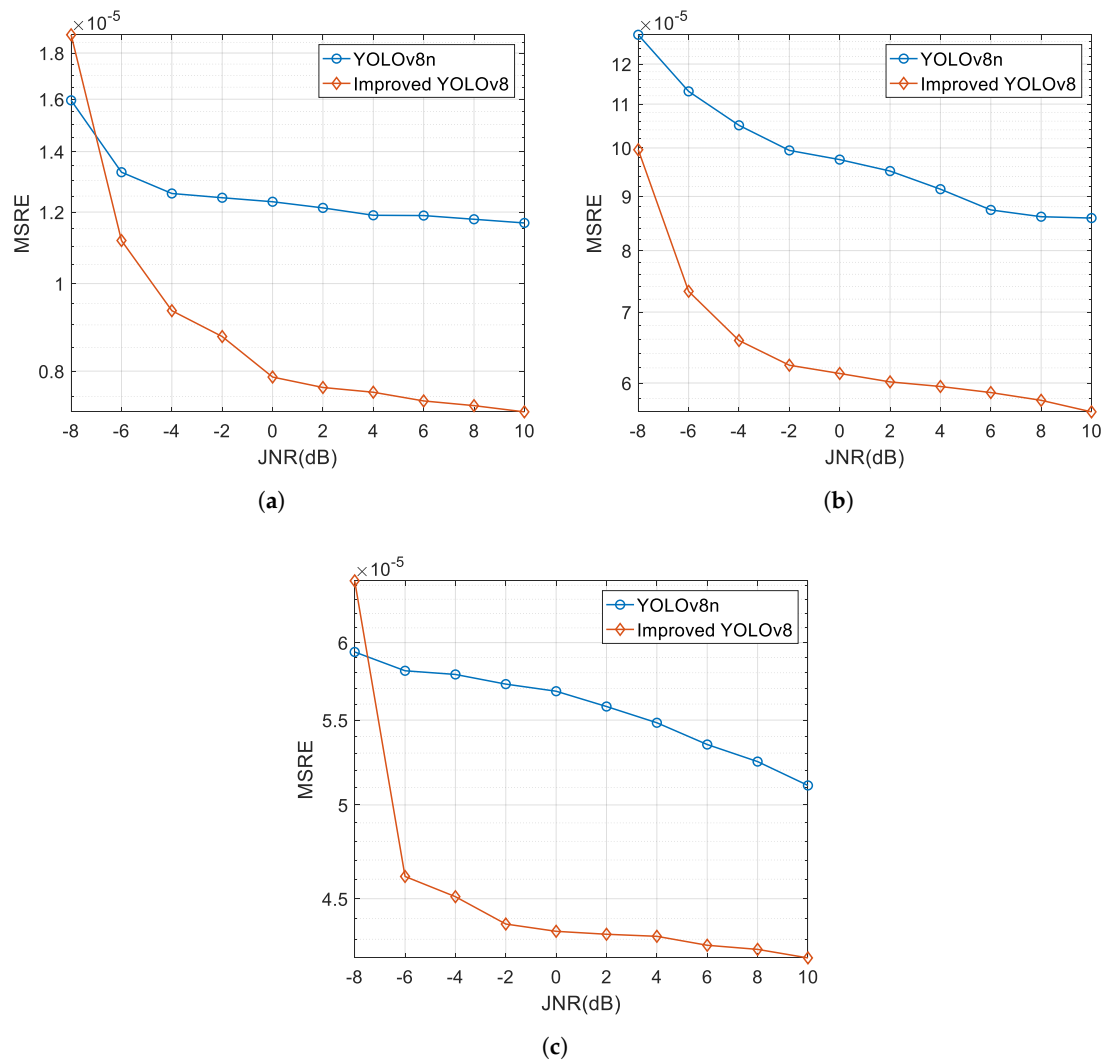


Figure 9. Performance of parameter estimation on LFM: (a) Center frequency. (b) Bandwidth. (c) Period.

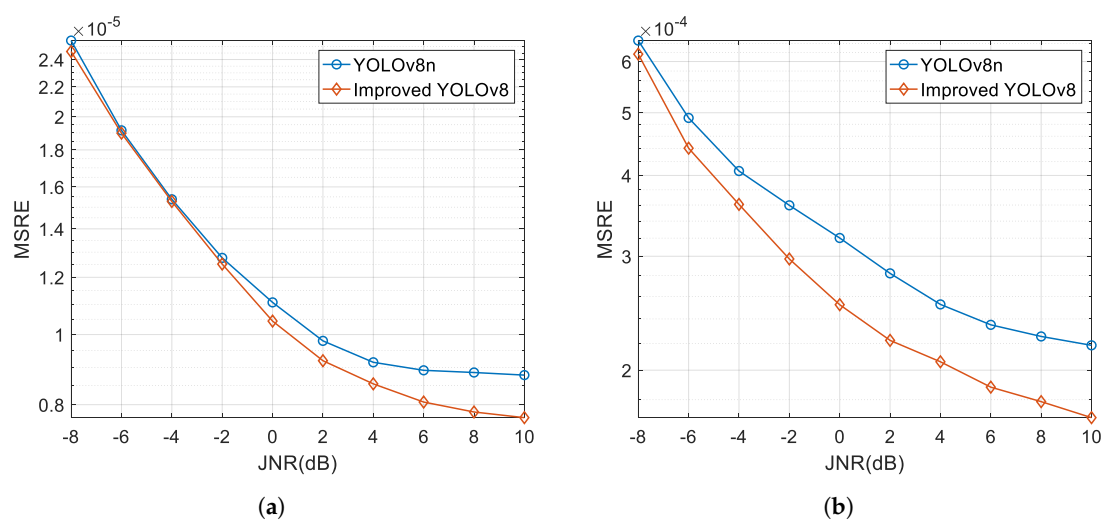


Figure 10. Performance of parameter estimation on PPNJ: (a) Center frequency. (b) Bandwidth.

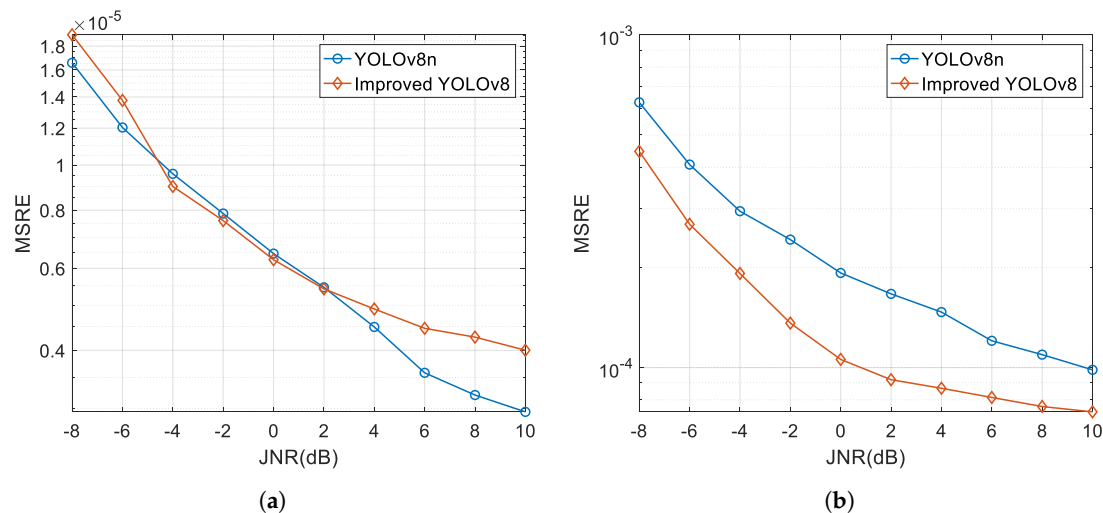


Figure 11. Performance of parameter estimation on PPNJ: (a) Period. (b) Duty cycle.

5. Discussion

The experimental results indicate that the improved YOLOv8 model can effectively localize different types of suppression jamming signals in time–frequency images. The performance improvement mainly comes from the enhanced feature representation and localization capability introduced by the SE-C2f module and the CA mechanism. The SE-C2f module helps suppress redundant channel information in shallow features, which is beneficial for extracting weak jamming features under noisy conditions. The CA mechanism further strengthens the sensitivity of the network to spatial location information, which is important for accurate bounding-box regression and subsequent parameter estimation. The ablation experiments confirm the contribution of these two modules, and the comparison with representative object detection models further shows that the proposed improved YOLOv8 achieves the highest mAP@90 and recall under the same training and validation settings. This indicates that the proposed modifications are beneficial for time–frequency localization of suppression jamming signals, rather than only improving the performance over a single YOLOv8n baseline.

The influence of JNR on parameter estimation can also be observed from the simulation results. Under low-JNR conditions, the time–frequency features of jamming signals are more easily submerged by noise, leading to larger bounding-box localization errors and higher MSRE values. As the JNR increases, the jamming features become clearer in the time–frequency image, and the parameter estimation errors decrease accordingly. However, for some parameters, such as the bandwidth of CSNJ and the period of PPNJ, the improved model does not always outperform YOLOv8n under all JNR conditions. This is mainly because CSNJ bandwidth estimation is sensitive to bounding-box height errors, while PPNJ period estimation is affected by incomplete pulse periods within the observation interval.

In addition, the composite-scenario results show that BNJ detection is more vulnerable to component overlap and fragmented time–frequency distributions than LFM and PPNJ detection. This limitation is important for cognitive frequency hopping because BNJ components directly correspond to occupied frequency bands that should be avoided. If some BNJ components are missed, the subsequent frequency-avoidance decision may be incomplete. Therefore, future work should further improve boundary modeling, narrowband component separation, and overlap-aware detection for BNJ in composite jamming scenarios.

The advance of this work is not limited to modifying the YOLOv8 architecture. More importantly, the proposed framework connects time–frequency object detection with phys-

ical parameter estimation of suppression jamming signals. By converting bounding-box localization results into center frequency, bandwidth, sweep period, pulse period, and duty cycle, the method provides a direct link between deep learning-based detection and cognitive frequency hopping anti-jamming applications. From the perspective of practical application, the estimated frequency-domain and temporal parameters can support jammed-band avoidance, spectrum sensing, and adaptive anti-jamming decision-making.

Nevertheless, this study still has some limitations. The experimental results are based on MATLAB-generated signals under controlled STFT settings, and therefore should be interpreted as simulation-based performance under the considered signal models. Moreover, the same level of performance cannot be directly assumed on other independently generated datasets because differences in signal models, parameter distributions, STFT configurations, noise conditions, and hardware-related distortions may affect the generalization ability of the proposed method. Further validation using measured RF, over-the-air, or hardware-captured data is needed in future work. In addition, the current method relies on the quality of time–frequency images and bounding-box localization, and its robustness should be further evaluated under more complex and dynamic jamming scenarios.

6. Conclusions

This paper combines time–frequency analysis with object detection to estimate the frequency and temporal parameters of four types of suppression jamming signals. By incorporating the SE attention mechanism and the CA mechanism into YOLOv8, an improved YOLOv8 model is proposed to achieve more accurate localization. Simulation results show that, without significantly increasing the number of parameters or computational complexity, the improved YOLOv8 achieves a 1.25% improvement over YOLOv8n in terms of mAP@90. In addition, as measured by MSRE, the improved YOLOv8 generally outperforms YOLOv8n in parameter-estimation accuracy. The estimated jamming center frequency and bandwidth parameters can be applied to cognitive frequency hopping, enabling active avoidance of jammed frequency bands. In composite jamming scenarios, the proposed method can detect the main jamming components, but BNJ components remain more challenging under fragmented and overlapped conditions, which may affect complete jammed-band awareness in cognitive frequency hopping applications. However, it should be noted that the above results were obtained using MATLAB-generated signals under controlled STFT settings, and further validation using measured RF, over-the-air, or hardware-captured data is still needed in real-world application scenarios.

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