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Jamming Recognition Based on Adaptive Feature Focusing Convolutional Neural Network for Agile Cognitive Radar

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Highlights

Faced with the performance dilemma between jamming recognition and agile anti-jamming, this study proposes an adaptive feature-focusing (AFF) network. By pre-training the AFF module, the network establishes the mapping relationship between agile parameters and adaptive feature scales, which can effectively resolve the feature mismatch caused by parameter agility. Specifically, the AFF module is employed to process real-time High Resolution Range Profile (HRRP) and Short-Time Fourier Transform (STFT) features, and the fused features are then fed into a dual-branch feature fusion network for jamming recognition. This method enables the recognition of multiple typical noise and deception jamming signals using a single pulse without accumulation, and thus is well-suited for radar jamming recognition under inter-pulse parameter agility.

What are the main findings?

- A new formulation of the jamming recognition problem. This paper proposes a problem framework that captures the dilemma between parameter agility and jamming recognition performance, and establishes a corresponding dataset to facilitate validation.
- An adaptive feature focusing processing module. This paper demonstrates that the AFF module can effectively facilitate radar jamming recognition under both parameter-agile and non-agile scenarios.
- A feature fusion paradigm that balances information extraction and computational efficiency. This paper proposes a fusion CNN network that incorporates 1D HRRP and 2D STFT features. These two features can respectively provide the range scattering features and joint time-frequency component features of the signal. Integrated with the AFF module, this network exhibits high efficiency and comprehensiveness.

What are the implications of the main findings?

- Electromagnetic environment perception and radar jamming recognition.

Abstract

With the advancement of cognitive radar, the application of deep neural networks for radar jamming recognition has become an indispensable research. However, as a common anti-jamming measure, the agility of radar waveform parameters will degrade the effectiveness of jamming recognition, resulting in a effectiveness dilemma to balance jamming recognition, and anti-jamming agility. Specifically, for the same type of jamming, the agility of the radar in frequency, pulse width and bandwidth will alter the profile and scale features of the jamming, thus posing challenges to jamming recognition based on conventional CNN networks. To address this challenge, this paper proposes an Adaptive Feature-Focusing CNN (AFF-CNN), a pre-trained AFF module is designed to establish the mapping relationship between agile parameters and adaptive feature scales. Operating on time-domain high-resolution range profiles (HRRP) and time-frequency domain short-time Fourier transform (STFT) data, this module contributes to calibrating the deviations induced by radar inter-pulse parameter agility while enhancing the capability of salient signal feature focusing.

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Furthermore, a lightweight 1D-2D feature fusion CNN is designed to process these adaptive features and recognize jamming using single-pulse signals, thus enhancing the network's adaptability to inter-pulse parameter agility in radar systems. Simulation results demonstrate superior recognition accuracy and generalization capability over four comparative approach, confirming effective adaptation to inter-pulse agility scenarios.

Keywords: jamming recognition; radar waveform parameter agility; adaptive feature-focusing (AFF); mapping relationship; feature scales; 1D-2D feature fusion

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1. Introduction

Waveform parameter agility, as an active anti-jamming measures for radars, provides unparalleled advantages in both anti-jamming and multi-function task operation [1–3]. Conventional, inter-pulse agility in multidimensional radar signal parameters, such as carrier frequency, bandwidth, and pulse width, this operation enables optimized resource allocation based on target quantity and range [4]. Additionally, through randomized or pseudo-randomized inter-pulse parameter switching, such radars significantly enhance low probability of intercept (LPI) and anti-jamming capabilities [5], while improving target detection [6] and angle-tracking accuracy [7].

Effective jamming environment perception is essential for dynamic anti-jamming in radars with multidimensional agile parameters. Although jamming recognition has advanced considerably, the majority of studies have concentrated on non-agile waveforms, paying little attention to parameter agility scenarios. Existing research primarily analyzes jamming signals through transformations across different domains, including the bispectrum [8], frequency [9], time-frequency [10,11], and wavelet domains [12]. After feature extraction and statistical analysis, the discriminative features are preserved and fed into a classifier for recognition. In [13], the proposed method employs Singular Value Decomposition (SVD) on the cyclic spectrum features of signals to identify diverse jamming types. This approach achieves high recognition accuracy even under low Jamming-to-Signal Ratio (JSR) conditions. In [14], discriminative features are extracted from both time-domain and frequency-domain of jamming signals, a multi-model framework combining Decision Trees (DT), backpropagation neural networks (BPNN), and Decision Tree-based Support Vector Machines (DTSVM) is adopted, it achieves robust recognition performance while maintaining computational efficiency. In [15], a radar jamming recognition approach was introduced based on fractal dimension and Rényi entropy features. The fractal dimension characterizes the self-similarity and complexity of signals across time and frequency domains, while Rényi entropy quantifies signal uncertainty and disorderliness. By employing Multi-class Support Vector Machines (MSVM), this approach achieved high-precision classification of active radar jamming signals. These feature-based computation and extraction algorithms once dominated this research field [16–18] and significantly contributed to jamming recognition development. However, such multi-domain feature extraction approaches heavily rely on expert knowledge, and their recognition performance is substantially affected by the quality of manually extracted features.

Recent advances in deep learning have revolutionized radar jamming recognition [19]. Convolutional Neural Networks (CNNs), renowned for their generalization capabilities and automated feature extraction [20], significantly outperform traditional feature-based methods in accuracy [21–25]. In [26], researchers used short-time Fourier transform (STFT) to extract time-frequency feature of jamming signals. These feature underwent simple cropping to eliminate redundancy before being fed into CNNs for recognition and classification. The framework in [27] integrated deep neural networks with probabilistic modeling to explore signal modulation patterns under uncertain noise conditions. For unknown jamming type identification, researchers developed an open-world jamming recognition approach based on siamese neural networks (SNNs) [28]. This approach combined jamming recognition with unsupervised clustering algorithms, enabling simultaneous detection of unknown-class communication jamming and recognition of known-class

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jamming. Numerous CNN-driven automated feature jamming recognition method emerged, gradually replaced manual feature approach.

Recent advances have primarily focused on multi-domain feature fusion for jamming recognition. For deception jamming identification in extended target scenarios, a residual neural network based on Range-Doppler (RD) domain and Time-Frequency (TF) feature fusion was proposed [29]. This approach significantly improved deception jamming classification accuracy by extracting richer jamming features through multi-domain fusion.In [30], researchers developed a transfer learning-based weighted ensemble CNN, processing jamming signals in the TF domain and using the real (R), imaginary (I), magnitude (M), and phase (P) parts of the TF domain instanced signals as separate feature parts. By sharing model parameters of the real part with other sub-classifiers and using transfer learning the four parts of the feature signals, the approach achieved a high-precision jamming recognition. To address the coexistence of single and composite jamming scenarios, [31] introduced a multi-feature fusion network combining Fractional Fourier Transform (FRFT) and STFT transformation. The network demonstrated superior capability in extracting detailed jamming features and achieving accurate recognition by leveraging multi-branch features from the fractional domain of jamming signals.

However, none of the above studies have discussed the impact of parameter agility signals on jamming recognition. How to overcome the adverse effects of jamming feature variations caused by parameter agile signals, and design more efficient network to recognize jamming is important. Therefore, the main contributions and innovations of this paper are listed as follows:

1) Parameter agility jamming recognition problem framework and database: To address adversarial scenarios with radar rapid parameter agility, this paper conducts mathematical modeling of agile-parameter radar signals and their corresponding jamming modulated signals. The constructed dataset captures the time, frequency, and time-frequency domains signal features under parameter agility scenarios, thereby providing a validated data foundation for evaluating other recognition methods.

2) Adaptive feature focusing processing method: To address the impact of agile parameters on signal feature profiles and scales, a functional mapping is established between agile parameters and the scales of feature extraction window. This mapping relationship is implemented via a pre-trained neural network to effectively mitigate feature misalignment caused by parameter agility signals, thereby providing a comparison high-quality feature for multi-feature fusion networks.

3) 1D-2D Multi-Feature Fusion lightweight Network: Based on 1D time-domain high-resolution range profile (HRRP) features and 2D time-frequency domain feature, this framework characterizes electromagnetic scattering and simultaneous time-frequency component features to enhance jamming recognition. Meanwhile, the fusion network was trained and tested using single-pulse received signals, avoiding transformation methods that require multi-pulse information, resulting in stronger adaptation under inter-pulse parameter agility and fast computational efficiency.

The paper is organized as follows: Section II briefly introduces the mathematical models of inter-pulse parameter agility radar and jamming signals; Section III details the 1D-2D fusion recognition network based on adaptive feature focusing; Section IV describes the parameter settings, results, and analysis of simulation experiments; finally, Section V concludes the paper.

2. Signal Model

This study focuses on the efficient modeling and recognition of various jamming types in parameter agility scenarios. On this basis, this section constructs a modeling scheme for multi-dimensional parameter agile radar signals as well as active noise/deception jamming signals. The research scenario is illustrated in Figure 1: the cognitive radar system transmits signals with multi-dimensional parameter agility, which are applied to radar detection or ISAR imaging processing. Key parameters of the signal, including carrier frequency, bandwidth, and pulse width, can achieve dynamic agility between pulses. This paper focuses on investigating the effective cognition of electromagnetic jamming even when agile anti-jamming signals are employed.

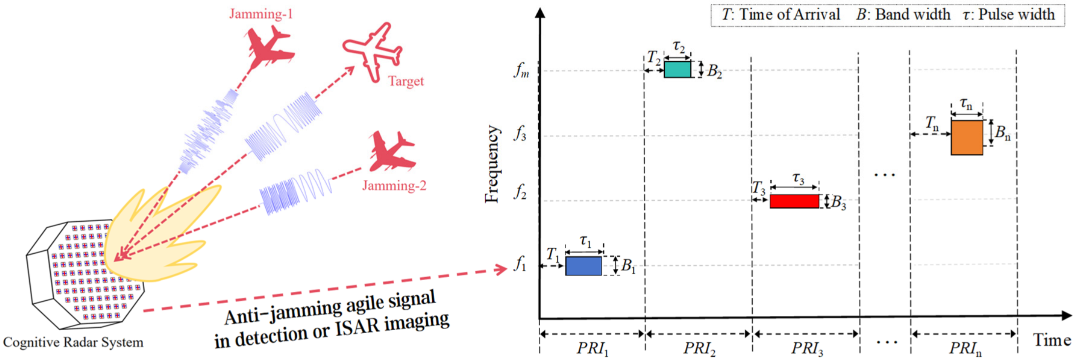

Figure 1. Schematic diagram of multi-dimensional parameter agility radar signal.

The feature fusion recognition Adaptive Feature-Focusing CNN (AFF-CNN) network proposed in this study primarily incorporates two key modalities: 1D HRRP feature in the time domain and 2D STFT feature in time-frequency domain. Consequently, this study specifically investigates the impact of multi-dimensional agile radar signals on HRRP and STFT features in the following.

2.1. Parameter Agility Radar Signal Model

Linear Frequency Modulated (LFM) signals, characterized by a large time - bandwidth product, enable radar to achieve a long detection range and high range resolution simultaneously. Hence, this study adopts the LFM signal as the transmitter signal. Based on its mathematical definition with inter - pulse agility in three parameters, namely carrier frequency, bandwidth, and pulse width, its time - domain expression can be defined as:

$$s(t) = rect\left(\frac{t}{\tau_i}\right)\exp\left[j2\pi\left(f_i t + \frac{B_i t^2}{2\tau_i}\right)\right] \quad (1)$$

In the equation, f_i, τ_i and B_i denote the agile central frequency, pulse width and bandwidth of the i-th pulse in the radar signal, the rectangular function $rect\left(t/\tau_i\right)$ is defined as follows:

$$rect\left(\frac{t}{\tau_i}\right) = \begin{cases} 1, & \left|t-\tau_i\right| \le 1/2 \\ 0\,, & \text{otherwise.} \end{cases} \quad (2)$$

For LFM signals, pulse compression is an effective processing method to maximize the signal-to-noise ratio (SNR) and enhance radar system performance. According to the theory of matched filter design, its mathematical expression is:

$$h(t) = s^*(\tau_i - t) \quad (3)$$

Correspondingly, when the input signal passes through the matched filter, pulse compression is achieved and resulted a narrow pulse output, which significantly improves the radar's range resolution, this mathematical process can be expressed as follows:

$$\begin{aligned} s(t) &= h(t) \otimes s(t) \\ &= \frac{\sin\left[\pi B_i (t-\tau_i)\left(1-\frac{\left|t-\tau_i\right|}{\tau_i}\right)\right]}{\pi B_i (t-\tau_i)\left(1-\frac{\left|t-\tau_i\right|}{\tau_i}\right)} \times \left(1-\frac{\left|t-\tau_i\right|}{\tau_i}\right) \end{aligned} \quad (4)$$

From the above, it can be seen that the HRRP result after pulse compression of the LFM radar signal is a Sinc function. When $t = \tau_i$, the output pulse is at peak; when $t = \tau_i \pm 1/B$, the output pulse is at the first zero crossing, and the pulse width of the main lobe is $2/B$. Furthermore, from the pulse compression mathematical expression of multi-dimensional agile signal, it is evident that the profile and scale of HRRP is only related to the agile pulse width τ_i and bandwidth B_i, and is independent of the agile frequency. The pulse width mainly reflects the displacement of the HRRP after pulse compression in time-domain, while the bandwidth mainly reflects the width and shape differences of the main lobe and each side lobe. Both them affect the network to extract features of the profile and detailed features of the signal.

The Short-Time Fourier Transform (STFT) is an important analysis tool in the field of signal processing, used to analyze the time-frequency characteristics of non-stationary signals, providing both time and frequency information simultaneously. It can serve as an important basis for analyzing and recognizing the intra-pulse features of different types of signals. According to the mathematical definition of STFT, when the input signal is an LFM signal with agile parameters, its mathematical expression is as follows:

$$\begin{aligned} STFT(t,f) = \int_{-\infty}^{\infty} rect\left(\frac{t}{\tau_i}\right)\exp\left[j2\pi\left(f_i t+\frac{B_i t^2}{2\tau_i}\right)\right] \\ \times w(t-\tau)\times e^{-j2\pi ft}dt \end{aligned} \quad (5)$$

In the equation, the first part within the integrand represents the parameter agility LFM signal, and $w(t-\tau)$ is a segmental window function, typically centered at time t, and $e^{-j2\pi ft}$ is a complex exponential function employed for frequency analysis.

From the above, the result of the STFT integral represents the local spectral characteristics of the signal at a specific time and frequency. The scale and profile features of the STFT signal are determined by the pulse width τ_i and bandwidth B_i. The position in frequency-dimension of the STFT signal is determined by the center frequency f_i, however the center frequency does not affect the detailed features of the STFT signal, and has a smaller impact on STFT signal recognition.

2.2. Jamming Signals Model

1) Noise Amplitude Modulation (NAM) Jamming: NAM jamming is a type of noise jamming that modulates Gaussian white noise to the bandwidth of the radar LFM signal. It uses high - energy modulated noise to suppress the radar signal, affecting the signal detection at the receiver. The theoretical mathematical expression for this is as follows:

$$J_{\mathrm{NAM}} = A\left(U_0 + mn(t)\right)\times\exp\left(2\pi f_c t+\phi_0\right) \quad (6)$$

where $n(t)$ represents the zero-mean Gaussian white noise, U_0 is the carrier voltage, m is the noise modulation coefficient, f_c is the carrier frequency of the jamming, and ϕ_0 is the phase uniformly distributed over $[0,2\pi]$.

2) Convolution Noise (CN) Jamming: CN jamming is a convolutional modulation jamming based on Digital Radio Frequency Memory(DRFM) technology. It aims to produce a sophisticated noise jamming effect by convolving the delayed radar signal with Gaussian noise, which can suppress the real target signal in both the time and frequency domains. The theoretical mathematical expression for this is as follows:

$$J_{\mathrm{CN}} = s(t-\tau)\otimes N(t) \quad (7)$$

where “$\otimes$” denotes the convolution operation, and τ is the convolution delay of the radar signal.

3) Multi False-Targets (MFT) Jamming: MFT jamming is created by the jammer through multiple delays,overlap and forwarding of the intercepted radar signals to form multiple false targets, with the purpose of deceiving and consuming radar resources. The theoretical mathematical expression for this is as follows:

$$J_{MFT}(t)=\sum_{n=1}^{N}A_n s\left(t-t_0-\tau_n\right)\times\exp\left[j2\pi\left(f_0 t+K/2t^2\right)\right] \tag{8}$$

where $n(n\geq 5)$ is the number of the jammer forwards false targets, A_n is the modulation amplitude of the i-th forwarding, and τ_n is the time delay of the i-th false target.

4) Interrupted Sampling and Repeating (ISR) Jamming: ISR jamming uses a time - division transceiver system, where the jammer intermittently instances and forwards radar signal. This method has good real - time performance and can obtain a matched filter gain. By sampling and forwarding multiple times within a sampling period, it forms multiple deceptive false targets in the time -frequency domain. The theoretical mathematical expression for this is as follows:

$$\begin{aligned}J_{ISR}(t)=&\sum_{n=1}^{N}A_n rect\left(\left(t-t_{ISR}/2-(n-1)T_s\right)/T\right)\\&\times\exp\left[j2\pi\left(f_0 t+K/2t^2\right)\right]\end{aligned} \tag{9}$$

where T is the radar signal pulse width, t_{ISR} is the pulse width of the jammer's intermittent sampling, T_s is the intermittent sampling period, and A_n is the modulation amplitude of the i-th intermittent sampling and forwarding jamming.

5) Chopping and Interleaving (CI) Jamming: CI jamming involves the jammer capturing the radar signal, mixing and digitally sampling before storing in a digital memory. The signal is then read out and uniformly instanced at equal intervals and segmentally replicated. This type of jamming can significantly obtain a matched filter gain, forming a dense range false target jamming effect against pulse compression radar. The theoretical mathematical expression for this is as follows:

$$J_{\mathrm{CI}}(t)=\sum_{k=0}^{n-1}A_k p\left(t-kT/mn\right) \tag{10}$$

$$p(t)=s(t)\left[rect\left(\left(t-\tau_{CI}\right)/\tau_{CI}\right)\otimes\sum_{l=0}^{m-1}\delta\left(t-lT_a\right)\right] \tag{11}$$

where m is the number of signal pulse sequences instanced by the jammer, n is the number of times each pulse sequence is replicated and forwarded, $\delta(\cdot)$ is the unit impulse function, τ_{CI} is the pulse width of the rectangular pulse sequence, and T_a is the fundamental period of the rectangular pulse sequence.

6) Smeared Spectrum (SMSP) Jamming: SMSP jamming involves the jammer capturing the radar signal, mixing it, and digitally sampling it before storing it in a digital memory. Subsequently, through the shifting of register groups and modulation of the clock frequency, the original radar LFM signal's frequency modulation rate is altered by a factor of N, and the signal is repeatedly concatenated N times to form an jamming signal with unchanged pulse width. This type of jamming can create false targets in the range dimension and a smeared spectrum in the frequency dimension. The theoretical mathematical expression for this is as follows:

$$J_{\mathrm{SMSP}}(t)=J_0\left(t-t_d\right)e^{j2\pi f_d t}\otimes\sum_{i=1}^{N-1}\delta\left(t-iT_p/N\right) \tag{12}$$

where N denotes the number of sub-pulse shifts and replications in the SMSP jamming, and t_d and f_d represent the time delay and Doppler frequency modulation of the SMSP jamming, respectively. According to the principle of SMSP jamming signal generation, the clock frequency is adjusted to N times the original frequency to obtain the first sub-pulse signal modulated by the radar signal. The $J_0(t)$ mathematical expression is as follows:

$$J_0(t)=\exp\left(j\pi N\frac{B}{T_p}t^2\right)\quad 0\leq t\leq\frac{T_p}{n} \tag{13}$$

2.3. Effects of Agile Parameter Modulation

To analyze the impact of parameter agility on the HRRP and STFT features, three groups of signal feature with different agile parameters are plotted in Figure 2. It can be seen that due to the influence of parameter agility, although three pulses are both CI jamming sampling instances from LFM signal, some significant differences manifested as follows:

In the HRRP feature, the peak of the forwarded target shape becomes sharper with the increase of signal bandwidth, and the resolution in the distance dimension is more clear. In the STFT feature, with the increase of signal bandwidth and pulse width, the feature profile and scale in the distance and frequency dimensions increase significantly. However, for a same type of jamming, the characteristic differences brought by the agile parameters will have a mismatch effect on the feature extraction. Especially after the variable waveform signal is modulated by different jamming mode, the influence of inaccurate characteristics of the jamming signal will be more obvious.

Therefore, designing an adaptive scale feature module to process the received signal features, when the pulse width τ_i and bandwidth B_i agiled rapidly, algorithm can still maintain a good correlation similarity for the HRRP and STFT features of the same type of signal, it is the key to improving the jamming recognition performance for parameter agility radar system.

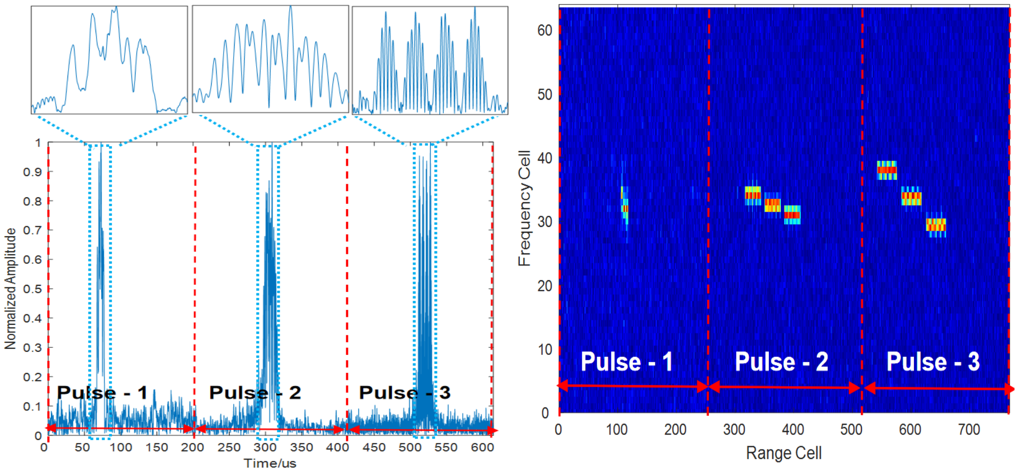

Figure 2. HRRP and STFT features of CI Jamming (parameter agility in three pulses).

3. Adaptive Feature Focusing CNN Algorithm

Based on the analysis in Section II, the HRRP and STFT feature change with agile parameters consequently, which increase the recognition difficulty to network. To address this challenge, this paper proposes an adaptive feature focusing CNN network, the network implementation framework illustrated in Figure 3.

In the application scenarios of network, for radar systems with multidimensional parameter agility, the transmitted signal ***S*** varies in waveform parameters such as bandwidth, pulse width, frequency during target detection. Simultaneously, the jammer intercepts the radar signal and generates modulated jamming signals ***J***, whose characteristics also vary due to transmitted waveform parameters.

In the adaptive feature focusing processing module, the processing of the transmitted signal ***S*** mainly relies on the adaptive parameter mapping network, which is a multi-layer feedforward neural network, it maps the agile parameters of ***S*** into the scale factors of feature window. Meanwhile, the received jamming signal ***J*** executes pulse compression and STFT processing to generate original HRRP and STFT transform signals, these transformed signals then execute salient point detection, and then execute adaptive feature focusing operation using the scale factors, ultimately forming AFF-HRRP and AFF-STFT feature signals.

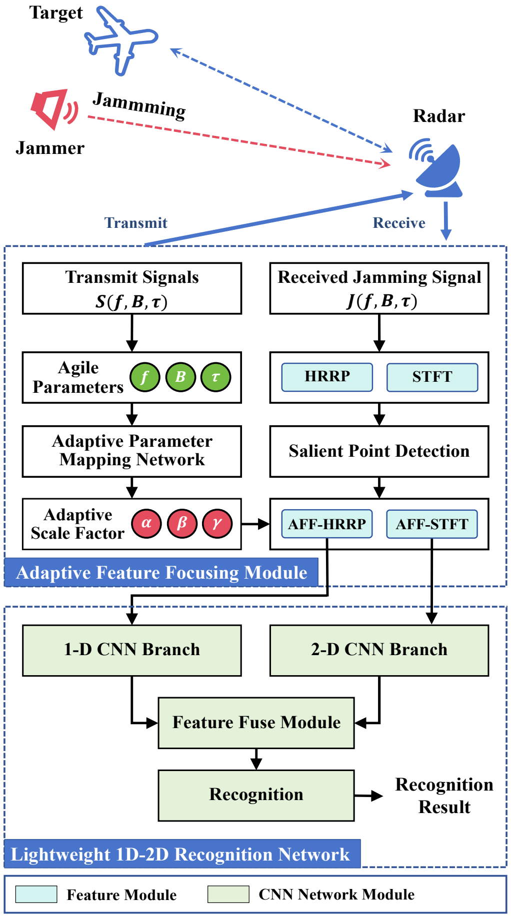

Figure 3. Flowchart of adaptive feature focusing convolutional neural network algorithm.

In the lightweight 1D-2D feature fusion recognition network, the features from both time domain and time-frequency domain are processed through 1D and 2D CNN branches respectively, and are fused to achieve jamming recognition in parameter agility scenarios.

Following of this section, the specific implementation details of the AFF processing module and the lightweight fusion CNN will be introduced.

3.1. Adaptive Feature Focusing(AFF) Module

The AFF module establishes a mapping relationship between signal agile parameters and feature extraction scale factors through the pre-trained AFF network. After the detection of salient point on original HRRP and STFT features, it performs adaptive-scale window extraction for each salient point, subsequently integrating these extractions to generate focused feature. The implementation framework of the AFF module is illustrated in Figure 4.

During the network training, several jamming pulses with different agile parameters can be received and collected to pre-train the parameter mapping network, and then the parameters of network are fixed. In network applications, since the parameters of signal S are known when the radar is transmitted, and there is a certain time delay between transmission and reception, the pre-trained network can be used to calculate the feature scale factor in this time delay. After the radar receives the incoming jamming pulse, adaptive feature focusing processing can be carried out immediately.

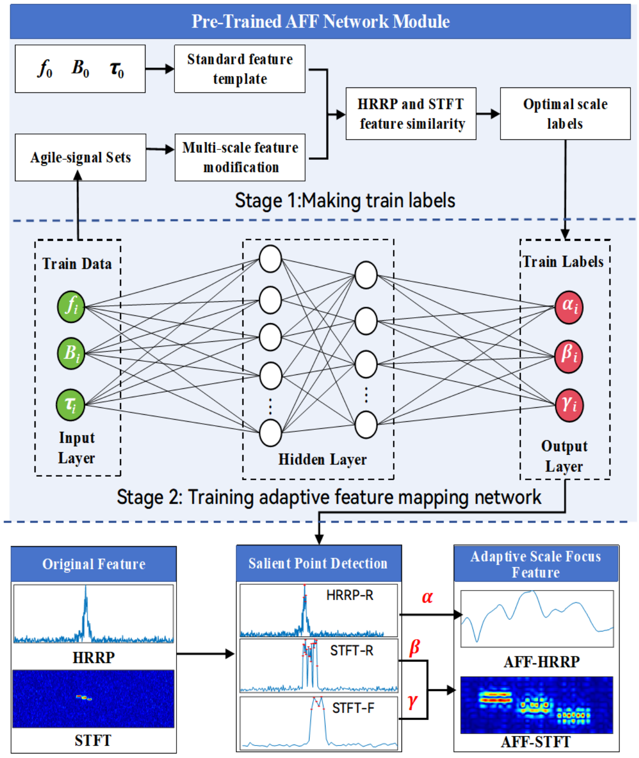

Figure 4. Block diagram of adaptive feature focusing module.

In the pre-trained AFF mapping network, the mapping relationship can be mathematically expressed as follows:

$$\psi:\mathbb{R}_S^3\left(f,B,\tau\right)\rightarrow\mathbb{R}_L^3\left(\alpha,\beta,\gamma\right) \tag{14}$$

In the above formula, $\mathbb{R}_S^3$ is the multi-dimensional agile parameter set, $\mathbb{R}_L^3$ is the scale label set, representing the adaptive scale factor in the transform domain, its value represents the size of the window scale for feature extraction, $\mathbb{R}_L^3$ and $\mathbb{R}_L^3$ correspond through the mapping network. Among them, α is the scale factor of range dimension in HRRP feature, and β,γ is the scale factor of range and frequency dimensions in STFT feature.

The training process of this mapping network consists of two stages. The stage one is to make the network training labels, based on the generated set of agile signals and template signal, extract the multi-scale HRRP and STFT features and calculate feature similarity between the agile signals and the standard template signal, finally select the scale factor corresponding to the maximum coefficient as the mapping label. In Stage two, the AFF network is trained using the agile signal parameter set as input data and the optimal scale factor as the label, jointly establish the mapping relationship of AFF network.

In stage one, taking the agile parameters for signal frequency f, bandwidth B and pulse width τ, and generating the agile signal sets according to equation (1) correspondingly. Taking frequency f as an example, the mathematical expression for the set of agile frequency parameters is as follows:

$$A(f)=\left\{f^{(i)}\middle|f^{(i)}=f^{\min}+i\cdot\Delta f,i=0,1,\cdots,N_f-1\right\} \tag{15}$$

In the equation, $f^{(i)}$ represents the i-th agile value of the frequency, $f^{\min}$ is the minimum value of the frequency jump range, Δf is the minimum interval of the frequency jump, and Δf is the total number of agile values of the frequency parameter. Similarly, the sets of agile parameters for bandwidth and pulse width can be obtained, and all combinations of single agile parameters form the union set of agile parameters.

For comparative purposes, f_0, B_0, τ_0 as the standard template signal parameters, are taken as the center values of the frequency, bandwidth, and pulse width agility ranges. The design takes into account the agile range of each parameter, so that when the template signal is matched with the signals of different agile parameters, the template signal features can be used as a standard to balance the feature differences brought by agile parameter. The expression for the values is as follows:

$$(f_0, B_0, \tau_0) = \mathrm{Md}\left(f, B, \tau\right) \tag{16}$$

where $\mathrm{Md}\left(\cdot\right)$ denotes the operation of taking the median. Then, based on the template parameters and the set of agile parameters, the template signal $\boldsymbol{S}_0$ and the set of agile signals $\boldsymbol{S}_{i(i\geq 1)}$ are generated under the LFM signal model. The mathematical expressions are as follows:

$$\boldsymbol{S}_i = LFM_i(f_i, B_i, \tau_i),\ \ i = 0, 1, \ldots, N \tag{17}$$

It should be noted that the template signal $\boldsymbol{S}_0$ is a single signal, while the agile signal sets $\boldsymbol{S}_{i(i\geq 1)}$ can taken as N signals corresponding to a set of parameters. After performing PC and STFT operation on $\boldsymbol{S}_i$, respectively, can obtain the HRRP features $\boldsymbol{HR}_i$, as well as the time-frequency features $\boldsymbol{TF}_i$. And then, making projections respectively and generating the distance dimension projection sequence $\mathcal{I}_i^1$ of $\boldsymbol{HR}_i$, as well as the distance and frequency dimension projection sequences $\mathcal{I}_i^2$ and $\mathcal{I}_i^3$ of $\boldsymbol{TF}_i$. Among them, the projection sequences of the HRRP and STFT features of the signal can be expressed as $\left\{\mathcal{I}_i^k, k = 1, 2, 3\right\}$.

The salient point detection processing is carried out on the projected sequence, and the detected point sequence is obtained as $\mathcal{P}$. The mathematical expression for saliency point detection is:

$$\mathcal{P}_i^k = \left\{m \in \{1, 2, \ldots, M^k\} \mid a_m > A_{th} \times \mu_k, a_m \in \mathcal{I}_i^k\right\} \tag{18}$$

where M^k represents the number of elements of $\mathcal{I}_i^k$, μ_k is the sequence mean of the projected sequence $\mathcal{I}_i^k$, and A_{th} is the threshold coefficient, which is generally taken as $A_{th} = 1.5$.

Furthermore, based on the value α, β, γ of the scale factor in different dimensions, the sequence of AFF module of the extracted signal features corresponding to the window sizes of the scale factor in different dimensions can be obtained as:

$$\mathcal{K}_i^k = W\left(\mathcal{P}_i^{k,1} \middle| \mathcal{F}^k\right) \cup \cdots \cup W\left(\mathcal{P}_i^{k,M} \middle| \mathcal{F}^k\right) \tag{19}$$

$$W\left(\mathcal{P}_i^{k,m} \middle| \mathcal{F}^k\right) = \left[\mathcal{P}_i^{k,m} - \mathcal{F}^k / 2, \mathcal{P}_i^{k,m} + \mathcal{F}^k / 2\right] \tag{20}$$

where $W\left(\mathcal{P}_i^{k,m} \middle| \mathcal{F}^k\right)$ represents the rounding operation of the sequence with $\mathcal{P}_i^{k,m}$ as the center and factor $\mathcal{F}^k$ as the window width within the sequence window. Among them, the factor takes the value of $\mathcal{F}^k \in \left\{\alpha, \beta, \gamma,\ \ when\ k = 1, 2, 3\right\}$.

And then, according to the sequence $\mathcal{K}_i^k$, After adaptive scale feature focusing processing, the feature can be defined as AFF-HRRP and AFF-STFT, their expression are:

$$\widehat{\boldsymbol{HR}}_i = sq\left(\boldsymbol{HR}_i \middle| \mathcal{K}_i^1\right) \tag{21}$$

$$\widehat{\boldsymbol{TF}}_i = sq\left(\boldsymbol{TF}_i \middle| \mathcal{K}_i^2, \mathcal{K}_i^3\right) \tag{22}$$

where $sq\left(Q|\mathcal{K}\right)$ represents a new matrix composed of the elements selected from matrix Q whose subscripts are sequence $\mathcal{K}$. To ensure the feature similarity calculations can be implemented, it need to adjust the size of feature, the size of the HRRP feature is adjusted to 1×512, and the STFT feature is adjusted to 64×256.

Next, based on the HRRP and STFT feature of multiple sets of agile signals cropped at different scale factors, feature similarity matching is performed with the standard template $\widehat{\boldsymbol{HR}}_0$ and $\widehat{\boldsymbol{TF}}_0$. The purpose is to compare different agile parameters and select the optimal scale factor to extract the feature, which can better match the standard template feature, thereby improving the recognition ability of similar signals. The method for selecting the optimal scale window factor is based on the principle of maximum similarity matching, and its mathematical expression is as follows:

$$l_i^\alpha = \arg\max_{1\le j\le L}\left(corr\left(\widehat{\boldsymbol{HR}}_0, \widehat{\boldsymbol{HR}}_{i,j}\right)\right) \quad (23)$$

$$\left\{l_i^\beta, l_i^\gamma\right\} = \arg\max_{1\le p,q\le L}\left(corr\left(\widehat{\boldsymbol{TF}}_0, \widehat{\boldsymbol{TF}}_{i,p,q}\right)\right) \quad (24)$$

In the equation, $corr\left(\boldsymbol{a},\boldsymbol{b}\right)$ denotes the correlation calculation between the data matrices $\boldsymbol{a}$ and $\boldsymbol{b}$. $\arg\max_{j}\left(R_j\right)$ represents the traversal of all values of j to return the maximized parameter R_j. The return values are stored in l_i^α 、 l_i^β and l_i^γ as label. These label correspond to the optimal scale extract windows under the calculation criterion, namely, the optimal extract window α for the HRRP feature and the optimal extract window β,γ for the STFT feature.

By searching and calculating the label values, we can establish the optimal feature corresponding to a set of agile parameters. The frequency, bandwidth, and pulse width parameters of the agile waveform are used as the input for network training, and the corresponding optimal scale label are used as the output for network training, thereby training a supervised parameter mapping neural network. The expression is as follows:

$$L\left\{l_i^\alpha, l_i^\beta, l_i^\gamma\right\} = Net\left(f_i, B_i, \tau_i\right) \quad (25)$$

After the network training is completed, the optimal scale factor parameters for any set of agile signal parameters can be calculated through the network, and the adaptive scale feature extraction can be performed.

3.2. 1D-2D Feature Fusion Network for Single Pulse

This section primarily introduce the construction of the feature fusion network based on AFF module. In the feature extraction and recognition network, the purpose is to obtain feature vectors of the HRRP and STFT and train them. Given the information dimensions differences in the two domains, 1D-2D feature fusion neural network is trained and applied using single-pulse received signals, effectively adapting to the inter-pulse agile parameter of radar waveforms, the network diagram is shown in Figure 5. The network mainly consists of three parts: the one-dimensional CNN branch, the two-dimensional CNN branch with attention module, and the feature information fusion module. After AFF processing, the single-pulse adaptive feature AFF-HRRP and AFF-STFT are obtained and fed into the 1D and 2D feature extraction branch, respectively.

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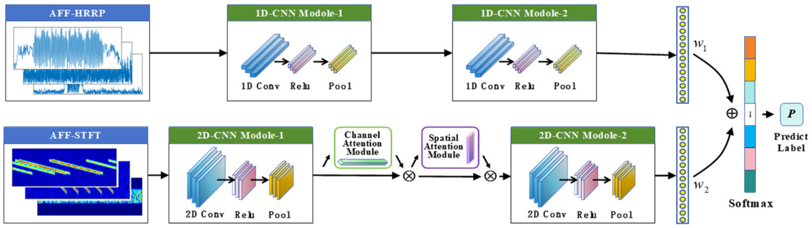

Figure 5. Block Diagram of the Single-Pulse 1D-2D Feature Fusion Jamming Recognition Network.

In the upper branch for HRRP feature extraction, two cascaded 1D convolutional modules process the jamming signal to extract its temporal features. These modules map the low-dimensional jamming characteristics inherent in the HRRP into a higher-dimensional feature space. Each module comprises a convolutional layer, a rectified linear unit (ReLU) nonlinear activation layer, and a downsampling pooling layer. The two convolutional modules utilize a combination of average pooling and max pooling layers. Average pooling better captures the overall information in the feature map and smooths out noise distortions caused by rapid fluctuations in the temporal waveform. The subsequent max pooling layer retains the salient features of the target after size transformation, further extracting the effective information from the signal. The mathematical expressions are as follows:

$$\boldsymbol{I}_{\text{hr-1}} = \underset{pool}{\text{aver}}\left(\sigma\left(\boldsymbol{W}_1 \cdot \boldsymbol{X}_{\text{hr}} + b_1\right)\right) \tag{26}$$

$$\boldsymbol{I}_{\text{hr-2}} = \underset{pool}{\max}\left(\sigma\left(\boldsymbol{W}_2 \cdot \boldsymbol{I}_{\text{hr-1}} + b_2\right)\right) \tag{27}$$

In the equations, $\boldsymbol{X}_{\text{hr}}$ represents the input data of the AFF-HRRP feature in time domain. $\boldsymbol{I}_{\text{hr-1}}$ and $\boldsymbol{I}_{\text{hr-2}}$ correspond to the first and second level jamming features extracted after downsampling. $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ are the training weight vectors, while b_1 and b_2 are the biases used to enhance the network's fitting capability, $\sigma(\cdot)$ denotes the rectified linear unit activation function ReLU, $\underset{pool}{\text{aver}}(\cdot)$ and $\underset{pool}{\max}(\cdot)$ represent the average pooling and max pooling operations, respectively.

In the lower branch for time-frequency domain feature extraction, two cascaded 2D convolutional modules are employed to extract the time - frequency domain features of the jamming. These modules can cover different - sized receptive fields in the STFT feature, thereby effectively extracting jamming information while considering both local and global signal features. Both cascaded 2D convolutional modules utilize rectified linear unit (ReLU) nonlinear activation layers and downsampling pooling layers. The mathematical expressions are as follows:

$$\boldsymbol{I}_{\text{tf-1}} = \underset{pool}{\max}\left(\sigma\left(\boldsymbol{W}_3 \cdot \boldsymbol{X}_{\text{tf}} + b_3\right)\right) \tag{28}$$

$$\boldsymbol{I}_{\text{tf-2}} = \underset{pool}{\max}\left(\sigma\left(\boldsymbol{W}_4 \cdot \boldsymbol{I}_{\text{tf-CBAM}} + b_4\right)\right) \tag{29}$$

In the equations, $\boldsymbol{X}_{\text{tf}}$ represents the input data of the AFF-STFT feature in the time-frequency domain. $\boldsymbol{I}_{\text{tf}}$ corresponds to the jamming features extracted after downsampling by the convolutional module. The definitions of weights, biases, activation functions, and the max pooling layer are the same as mentioned earlier.

Since the recognition of different types of signals mainly relies on the differences in the profiles and detailed features, and the STFT features of signal contain richer feature information, it proves

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more conducive for the network to extract discriminative features. To enhance the perception of jamming feature within this two-dimensional feature extraction process, a lightweight Convolutional Block Attention Module (CBAM) module is inserted in the two-dimensional feature extraction to further perceive the jamming features. Specifically, the channel attention mechanism in CBAM can effectively capture the regions where jamming exists, while the spatial attention mechanism in CBAM is used to extract the spatial distribution and shift features of the jamming in the signal image. The overall attention mechanism process in the second part can be expressed as follows:

$$\boldsymbol{I}_{\mathrm{tf-CBAM}} = M_s\left(M_c(\boldsymbol{I}_{tf-1}) \otimes \boldsymbol{I}_{tf-1}\right) \otimes \left(M_c(\boldsymbol{I}_{tf-1}) \otimes \boldsymbol{I}_{tf-1}\right) \tag{30}$$

In the equations, $M_c(H)$ and $M_s(H)$ represent the operations of the channel attention mechanism and the spatial attention mechanism, respectively, and $\otimes$ denotes element-wise multiplication. The calculation expressions for the channel attention mechanism and the spatial attention mechanism are as follows:

$$M_c(\boldsymbol{I}) = \sigma\left(W_{c_2}\left(W_{c_1}\left(P^c_{\mathrm{avg}}(\boldsymbol{I})\right)\right) + W_{c_2}\left(W_{c_1}\left(P^c_{\mathrm{max}}(\boldsymbol{I})\right)\right)\right) \tag{31}$$

$$M_s(\boldsymbol{I}) = \sigma\left(W_s\left(\left[P^s_{\mathrm{avg}}(\boldsymbol{I}); P^s_{\mathrm{max}}(\boldsymbol{I})\right]\right)\right) \tag{32}$$

where W_{c_1} and W_{c_2} are the trainable weight vectors of the first and second convolutional layers in the channel attention mechanism module, and W_s is the trainable weight vector of the convolutional layer in the spatial attention mechanism module. P^c_{avg} 、 P^c_{max} and P^s_{avg} 、 P^s_{max} represent the global average pooling and global max pooling of the channel attention mechanism module and the spatial attention mechanism module respectively. $[\cdot]$ denotes the concatenation operation of $P^s_{\mathrm{avg}}(\boldsymbol{I})$ and $P^s_{\mathrm{max}}(\boldsymbol{I})$, and $\sigma(\cdot)$ represents the Sigmoid activation function.

The information fusion architecture is designed to integrate multi-domain features for jamming recognition, yielding robust and discriminative feature representations. Specifically, the time-domain HRRP feature characterizes the electromagnetic scattering properties of jamming signals from a high-resolution perspective, whereas the time-frequency STFT feature depicts the signal's frequency components at different time instants via joint temporal and spectral analysis. Since each domain captures unique characteristics of radar jamming signals, feature fusion can capitalize on their complementary advantages to enhance recognition accuracy.

In the information fusion module, the features from the two domains are instanced with adaptive weights to represent their importance. The mathematical expressions for the trainable weight-based feature information fusion are as follows:

$$\boldsymbol{F}_{\mathrm{fuse}} = \omega_1 \cdot \boldsymbol{I}_{\mathrm{hr}} + \omega_2 \cdot \boldsymbol{I}_{\mathrm{tf}} \tag{33}$$

$$\boldsymbol{P} = \mathrm{softmax}\left(\boldsymbol{F}_{\mathrm{fuse}}\right) \tag{34}$$

where $\boldsymbol{I}_{\mathrm{hr}}$ and $\boldsymbol{I}_{\mathrm{tf}}$ are the fully connected layer outputs for the HRRP and STFT features, respectively. ω_1 and ω_2 are the trainable weight scores for the two domains. $\boldsymbol{F}_{\mathrm{fuse}}$ is the result of feature information fusion, and $\boldsymbol{P}$ is the score for signal type recognition after feature fusion.

4. Experimental Results

In this section, the settings of the agile signal dataset and the corresponding radar jamming dataset are introduced firstly, and then, the experimental parameter settings of AFF-CNN algorithm and the comparison algorithms are described. Finally, we simulated and analysed the effects of adaptive feature focusing extraction and the algorithm performance analysis under multiple evaluation aspects.

4.1. Datasets

To evaluate the recognition performance of the proposed approach, the paper conducts experiments based on the radar agile signal model and jamming signal model introduced in Section II. The LFM waveform is selected as the probing signal, and the detailed settings for the signal waveform parameters and jamming parameters are shown in Table 1. The center frequency of the signal is $f_0 = 3$GHz, and the sampling rate is $f_s = 40$ MHz.

For each instance in the radar received signal S_t, pulse compression is performed to obtain the time-domain HRRP dataset S_{hr}, where each instance is resized to 1×512. The STFT is applied to S_t to obtain the time-frequency domain dataset S_{tf}, where the input time-domain instances are divided into 256 segments with 64 points of overlap between adjacent segments. A 16-point Hamming window is selected as the window function for the STFT, and the number of Fourier transform points is 64, resulting in a size of 64×256 for each time-frequency instance.

The dataset comprises six jamming types and target signals (detailed in Table 1), with 1000 instances per type yielding N = 7000 total samples. The data was partitioned using an 80% to 20% proportion for training and testing sets respectively.

Table 1. Signal Parameters Setting.

Signal Type	parameters	Range of value
TARGET	Agile Bandwidth	2-20Mhz
	Agile Pulse width	5-100us
	Agile Frequency	0-300Mhz
	Relative Delay of each pulse	0-30us
NAM	Bandwidth	100Mhz
CN	Bandwidth	2-20Mhz
	Noise Bandwidth	100Mhz
MFT	Number of false target	3~6
	Interval of false target	0-60us
	Bandwidth	2-20Mhz
	Pulse width	5-100us
ISR	Width of slices	2-5us
	Number of slices	4
	Relative delay of each pulse	0-36us
CI	Width of slices	3-10us
	Number of slices	3
	Relative delay of each pulse	0-36us
SMSP	Number of jamming sub-pulse	5
	Relative delay of each pulse	0-36us

4.2. Experiment Settings

The AFF-CNN algorithm designed in this paper consists of three branch modules, each structure and parameter as shown in Table 2. These modules primarily include convolutional layers, pooling layers, CBAM attention mechanism modules, regularization layers, and fully connected layers. Additionally, the model is trained for 40 epochs.

Simulations incorporated agile waveform parameters and jamming models from Section II, signal types are conducted for six typical jammings and target signals, namely TARGET and NAM, MFT, ISR, CI, CN, SMSP jamming. The 1D-CNN and 2D-CNN use time-domain and time-frequency domain jamming data, respectively, with parameters as shown in Table 1. The proposed algorithm is compared with the time-frequency domain 2D convolutional network [25], the multi-domain feature fusion convolutional neural network with attention mechanism (MDFRCNN) [29], the multi-feature fusion network based on time-frequency domain and fractional Fourier transform domain (MFF-Net)

[31], and the multi-weight ensemble convolutional network based on TF amplitude and phase data (WECNN-TL) [30]. In addition, To verify the effectiveness of integrating the AFF module with lightweight networks , we compared the performance of the 1D-2D fusion network proposed in this algorithm with that of MobileNet [32], which is also a lightweight network. All experiments are conducted on a computer equipped with a 2.20-GHz CPU, 32.0-GB RAM, and a Quadro RTX 4900 GPU card, using Python 3.7 (64-bit). The simulations employ the Monte Carlo method, with all presented results averaged over 10 independent runs of the algorithm to ensure reliability.

Table 2. AFF-CNN Network Setting.

Branch	Layer	Conv.Kernel	Activation	Pool
1-D Convolution Branch	input		1×512	
	Conv.1	(32×1)×16	ReLU	Maxpool(2×1)
	Conv.2	(32×1)×10	ReLU	Averpool(2×1)
	Flatten		1×1040	
	Linear		1040×10	
2-D Convolution Branch	input		64×256	
	Conv.1	(3×3)×32	ReLU	Maxpool(2×1)
	CBAM		32	
	Conv.2	(3×3)×10	ReLU	Maxpool(2×1)
	Flatten		1×8680	
	Linear		8680×10	
Fuse Module	Linear		10×7	
	output		7×1	

4.3. Experiment Results

To compare the performance of different algorithms, the paper mainly analyzes the results from four aspects:

1) **Adaptive Feature Focusing Processing Effectiveness Analysis:** To address the impact of multi-dimensional parameter agility on the feature perturbation of jamming signals, the algorithm firstly employs the adaptive feature focusing module to ensure feature consistency and uniformity across varying agile parameters. To evaluate the effectiveness of the AFF module, there selected three distinct parameter agility pulses for both MFT and SMSP jamming types. Figure 6 visualizes STFT features before and after AFF processing, it can be seen from the original STFT before AFF processing, due to the effects of bandwidth and pulse width agility, significant variations in STFT features are observed even for the same type of jamming signal. Conventional CNNs perform regional feature extraction using fixed-scale windows, resulting in inconsistent feature representations for identical jamming types that degrade recognition accuracy. From the AFF-STFT features after AFF pocessing, the same type of signals can effectively adapt to the influence of parameter variability due to the matching of the adaptive window, and the signal features maintain good consistency among different groups of variability parameters.

Further quantitative analysis examined the AFF module’s performance under the agile parameters. Table 1 details the signal variation ranges. For each parameter, 100 variation values spanning these ranges were selected to form distinct parameter groups. The feature similarity for HRRP and STFT features of various signals after AFF processing is calculated in Table 3. For the 7 different types of signals, after AFF processing of HRRP features, the similarity of 6 jamming signal types is improved and the SMSP jamming features is decreased. After AFF processing of STFT features, the similarity of 6 jamming signal types is improved and the CI jamming features is decreased. The statistical average of the similarity of various signal features before and after AFF processing is conducted, the similarity of HRRP signal features increased from 0.15 to 0.28, and the similarity of STFT features increased from 0.13 to 0.25. This demonstrates the AFF module approximately doubles feature similarity for identical signal types. Such enhancement will contribute to the recognition of agile parameter signals from the perspective of feature learning.

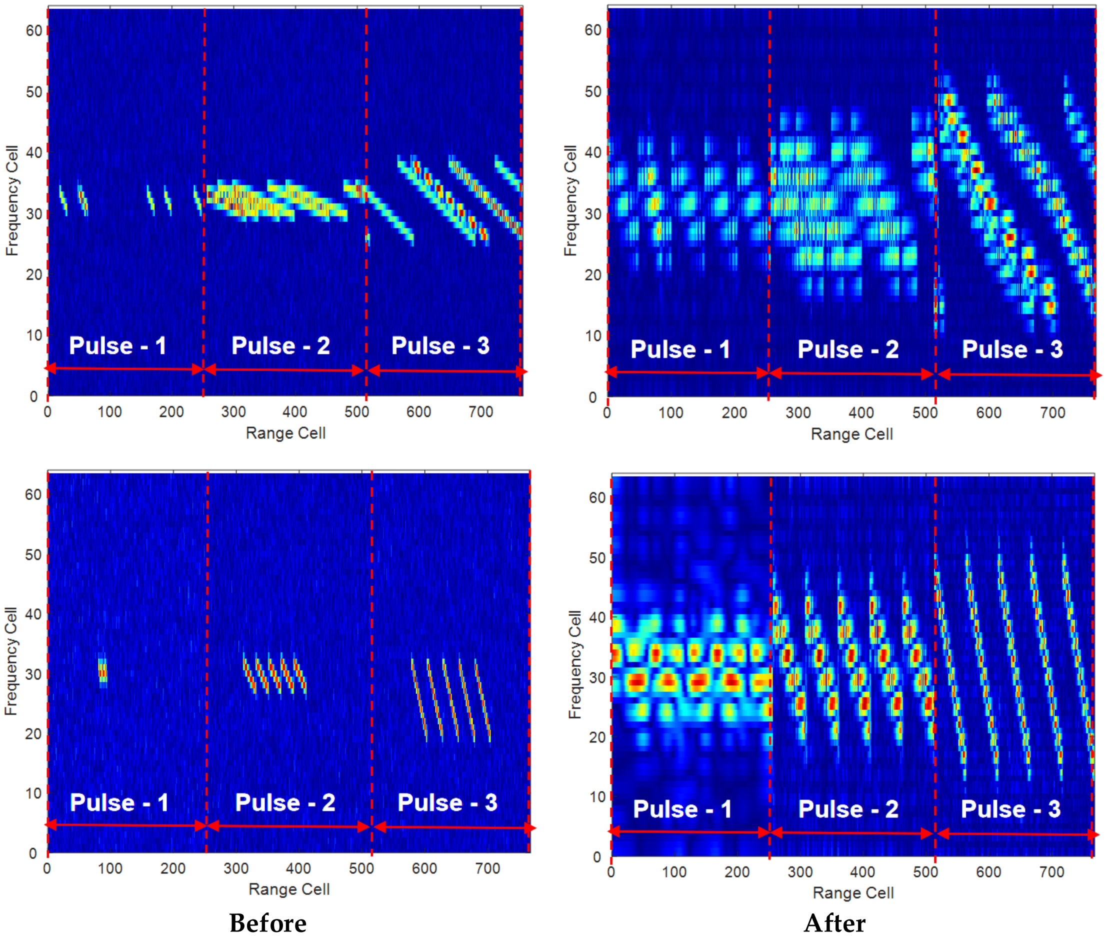


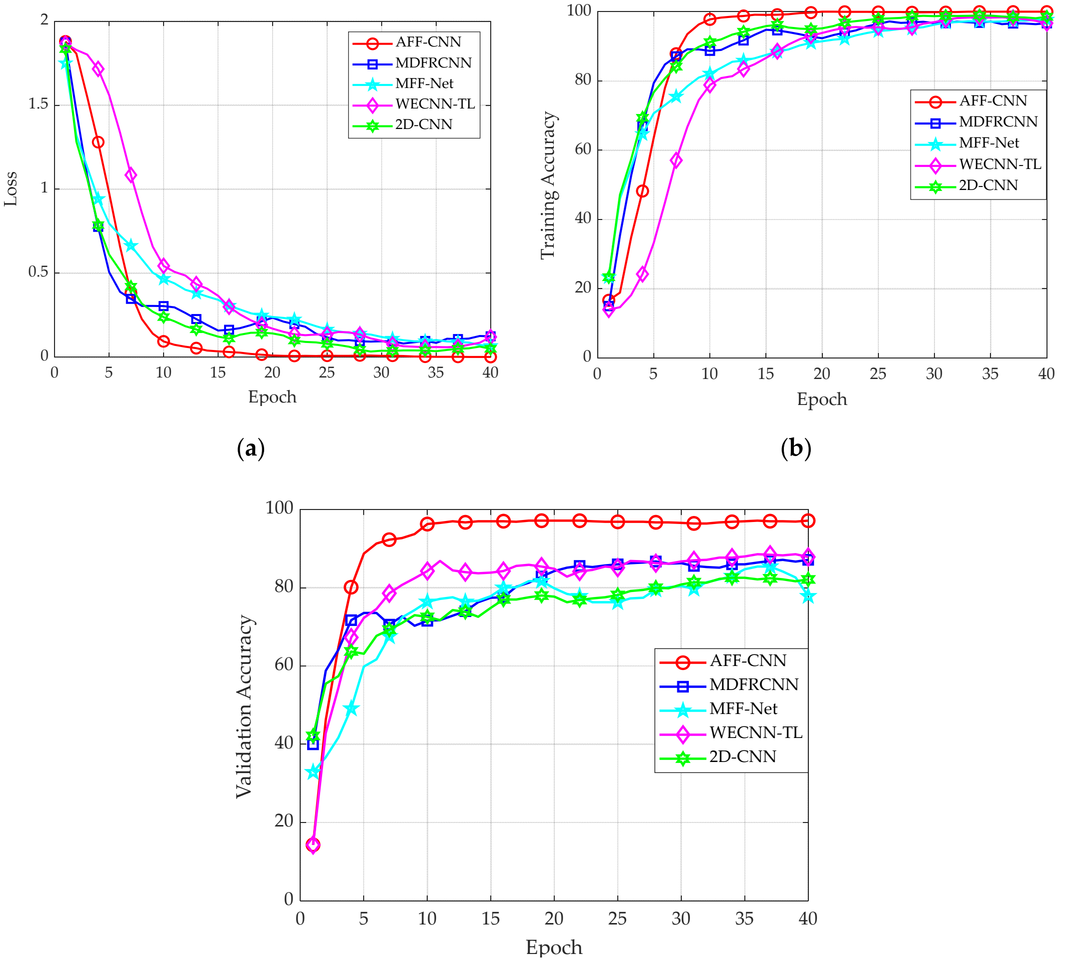
Figure 6. Block Diagram of the Single-Pulse 1D-2D Feature Fusion Jamming Recognition Network (Columns 1–2 correspond to MFT and SMSP jamming, and the left and right show the STFT feature before and after AFF module).

Table 3. Feature Similarity Improvement among Different Parameter Groups.

Domain Type	Adaptive scaling	TARGET	NAM	MFT	ISR	CI	CN	SMSP	Average
HRRP	Before	0.0387	0.0365	0.1904	0.1925	0.0361	0.0390	**0.4750**	0.1457
	After	**0.8326**	**0.0375**	**0.3668**	**0.2431**	**0.0370**	**0.3100**	0.0964	**0.2757**
TF	Before	0.0858	0.0198	0.0983	0.1170	**0.3361**	0.0778	0.1333	0.1257
	After	**0.3098**	**0.0426**	**0.3092**	**0.3107**	0.3319	**0.0998**	**0.3492**	**0.2500**

2) **Agile Signal Recognition Capability Analysis:** After AFF processing of the signals, the recognition performance of the proposed AFF-CNN network is compared with other networks. The average accuracy for six jamming types and target signals is statistically evaluated at JNR/SNR = 0 dB. Training loss and accuracy curves are visualized in Figure 7. Of these, Figure 7a depicts the

training loss curves, The training loss of AFF-NET converges to 0.02, and exhibits superior convergence. Other algorithms stagnate near 0.1 loss, indicating limited feature extraction capability without adaptive processing, making it difficult to extract deeper features. Figure 7b shows the training set recognition accuracy curves, other all algorithms such as MDFRCNN, MFF-Net, WECNN-TL and 2D-CNN exceed 95% accuracy after convergence, AFF-CNN achieves a better performance with the accuracy at 99.76%. Figure 7c illustrates the validation set recognition accuracy curves, Due to signal agile differences, MDFRCNN, MFF-Net, WECNN-TL, and 2D-CNN show signs of overfitting, with accuracy dropping to 82%-87%, AFF-CNN demonstrates stronger adaptability in the validation set and achieves 96.85% accuracy, improves 10% in recognition rate over others.



(**a**) (**b**)

(**c**)

Figure 7. Algorithm comparison experiments curves: (**a**) Loss curves of the algorithms; (**b**) Accuracy curves in training datasets; (**c**) Accuracy curves in validation datasets.

3) **Scene Generalization Capability Analysis:** During the process of radar anti-jamming, signal strength varies significantly across scenarios due to factors like radar-target distance, radar-jammer distance, and jamming power modulation. Once the jamming recognition network is trained and its parameters are fixed, the jamming recognition network must generalize across scenarios to handle real-world dynamics.To evaluate algorithm adaptability to signal strength variations, all algorithms were trained at JNR = 0 dB with fixed parameters. Recognition accuracy was then validated using a dataset spanning JNR form -10 to 20 dB, and simulation results are visualized in Figure 8. It can be seen that recognition accuracy improves significantly with higher JNR for all five algorithms, confirming stronger signals aid jamming feature extraction. Four comparison algorithms suffer degraded performance with an average recognition accuracy of less than 80%, due to JNR mismatch

between training and validation. The proposed AFF-CNN exhibits superior generalization, maintaining more than 90.67% accuracy when JNR > 10 dB and demonstrating strong practicality.

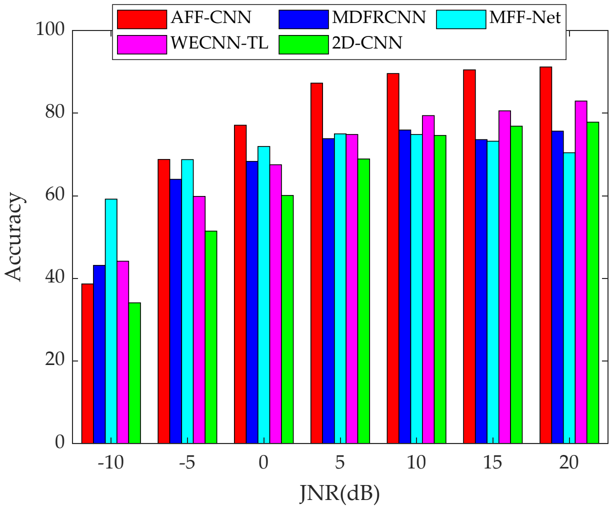
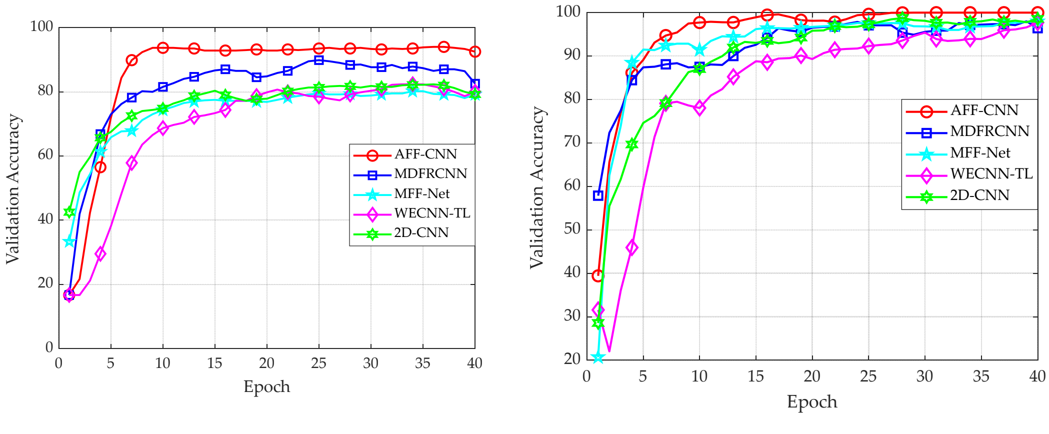


Figure 8. Recognition accuracy in different JNR.

The other two generalized scenarios are the unequal-signal-power scenario and the non-agile parameter scenario, with the algorithm comparison curves illustrated in Figure 9. Specifically, Figure 9(a) corresponds to the unequal-signal-power scenario, where the signal SNR = 0 dB and the jamming JNR = 10 dB. This setup is common and meaningful for scenarios where jamming is stronger than the target echo. It can be found that compared to the equal-power signal scenario in Figure 7c, the algorithm performance declined overall. The recognition accuracy of MFF-Net, WECNN-TL, and 2D-CNN averaged approximately 80%, while MDFRCNN achieved roughly 85%, the proposed AFFCNN reached 92.16%, demonstrating remarkable superiority.



(**a**) (**b**)

Figure 9. Algorithm comparison experiments curves in generalization scene: (**a**) Accuracy curves in unequal power signals situation. (**b**) Accuracy curves in non-agile parameter signals situation.

Figure 9b corresponds to the non-agile parameter scenario, Compared with the agile parameter in Figure 7c, the recognition performance of all algorithms is significantly improved. This indicates that fixed waveform parameters are more conducive to the feature extraction and recognition, the recognition accuracy of all five algorithms exceeds 97%, and the proposed AFF-CNN outperforms its counterparts by an average margin of 1.5%. These results verify that the proposed algorithm remains effective in the non-agile parameter scenario.

4) **Computational Agility Analysis:** As shown in Table 4, the average iteration time across 100 simulation training runs was compared for five algorithms, every training runs 100 samples for each type of signal. AFF-CNN and 2D-CNN exhibited the shortest computation times at 2.85 seconds and 2.97 seconds, respectively. Although 2D-CNN processes only the STFT features, the proposed AFFCNN fuses both 1D HRRP and 2D STFT features. The low computational burden of 1D HRRP effectively enhances recognition capability and convergence, resulting in AFFCNN being slightly faster even than the single-domain 2D-CNN. Compared with the MDFRCNN method fusing STFT and RD features, the MFF-Net method fusing STFT and FRFT features, and the WECNN-TL method fusing the real and imaginary parts of STFT feature, the runtime efficiency of the proposed algorithm is increased by 98.45%, 55.96%, and 179.49% respectively. Additionally, this comparison only accounts for network recognition time, excludes the time for signal processing and feature generation. Algorithms relying on RD or FRPT features require accumulating multiple pulses or complex transforms, addin extra computation time. In contrast, the HRRP and STFT features in the proposed algorithm can be obtained from a single pulse signal, making it more computationally efficient and better adapted to scenarios with rapid, multi-dimensional parameter agility between pulses.

Table 4. Running Time of Algorithm.

Method	AFFCNN	MDFRCNN	MFF-Net	WECNN-TL	2D-CNN
Time(s)	2.8522	5.6601	4.4483	7.9717	2.9742

In terms of balancing network lightweighting and algorithm recognition performance, Figure 10 shows the recognition accuracy of the proposed 1D-2D feature fusion CNN network and the MobileNet network on signal types. Before integrating the AFF feature focusing module, the recognition accuracy of both the feature fusion CNN and MobileNet networks reached approximately 82%. After the integration of the AFF module, their recognition accuracy was improved to around 95%. As a widely adopted lightweight recognition network, MobileNet has a computational parameter size of 1.56 MB, while the parameter size of the 1D-2D feature fusion CNN network proposed in this algorithm is only 427.7 KB. These results demonstrate that integrating the AFF module with a lightweight network enables the achievement of excellent jamming recognition performance with a network of smaller parameter size.

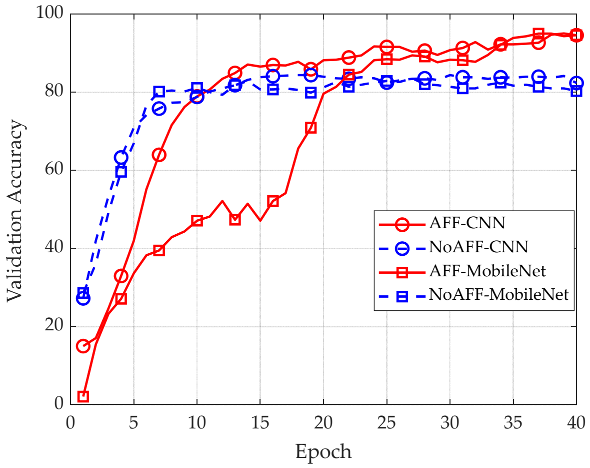


Figure 10. Accuracy curves comparison with typical lightweight networks.

5. Conclusions

The multi-dimensional parameter agility of radar waveforms is a crucial approach for anti-jamming in cognitive radar. This paper proposes a novel AFF-CNN algorithm to address the issues of feature misalignment and reduced recognition effectiveness under parameter agility scenarios. The purpose of the AFF-CNN method is to eliminate and balance the impacts of agility on HRRP and STFT features, fuse 1D and 2D features, and recognize jamming via a lightweight network. Simulation results demonstrate that, compared with four typical multi-domain fusion algorithms, The AFF-CNN maintains a recognition accuracy of at least 93% across diverse scenarios, achieves a statistically averaged performance improvement of 5–7% over competing methods, and demonstrates superior recognition and generalization capabilities under scenarios with varying JNR levels or unequal signal power. Moreover, the proposed recognition network remains effective in non-agile parameter scenarios.

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