

An Intelligent Recognition Method for Radar Comb Spectrum Jamming Based on Dual-Channel Deep Convolutional Network

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Abstract: This paper presents a deep learning method to recognize comb spectrum jamming in radar systems. Unlike traditional methods requiring manual feature extraction, our approach learns features directly from signal data. We built a dataset of radar echoes with four comb jamming types and five non-comb interference types. A dual-channel method creates 2D images preserving both magnitude and phase information from the signal spectrum. A CNN classifier with convolutional blocks, batch normalization, and dropout achieves 99.75% accuracy with 1.5% false alarm rate after only 7 training epochs.

Keywords: Comb-spectrum jamming; CNN; Radar interference identification

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1. Introduction

Electronic warfare is critical in modern battlefields. Radar systems face various jamming that degrades performance^[1,2]. Traditional jamming identification methods rely on manual feature extraction and classification, but perform poorly for comb spectrum interference^[3,4]. This paper presents a CNN-based method that automatically learns discriminative features for comb jamming recognition.

2. Radar signal and jamming models

2.1. Radar signal model

The radar transmits a linear frequency-modulated signal with carrier frequency 17GHz, bandwidth 80MHz, and pulse width 2 μ s:

$$x(t) = \text{rect}\left(\frac{t}{T_p}\right) \exp\left(j2\pi f_0 t + j\pi \frac{B}{T_p} t^2\right) \quad (1)$$

The received echo after down-conversion is:

$$x_r(t, t_m) = A \cdot \text{rect}\left(\frac{t - \tau(t_m)}{T_p}\right) \exp(j\pi\gamma(t - \tau(t_m))^2) \cdot \exp(-j2\pi f_0 \tau(t_m)) \quad (2)$$

2.2. Jamming models

2.2.1. Comb-spectrum jamming

Comb-spectrum jamming comes from adding together many single-frequency signals. Its frequency domain has peaks that show up at regular intervals. This jamming puts high power at specific frequencies and works well against frequency-agile and wideband radars. The jamming signal is:

$$J_{comb}(t) = \sum_{j=1}^N U_j \exp(j(2\pi f_j t + \phi_j)) \quad (3)$$

N is the number of spectral lines. U_j is the amplitude of each line. f_j is its frequency. ϕ_j is its starting phase picked from .

Four patterns are generated: symmetric equally-spaced, asymmetric, dense (2MHz spacing), and sparse (4 lines). Jammer-to-signal ratio (JSR) ranges from -15dB to 20dB:

$$JSR = 10 \log_{10} \left(\frac{P_j}{P_s} \right) \quad (4)$$

P_j is the jamming power and P_s is the clean signal power.

JSR values are randomly picked between and when making the data.

2.2.2. Non-comb jamming models

Five types, including broadband Gaussian noise, colored noise, impulsive noise, swept frequency jamming, and strong target signal with noise.

2.3. Composite received signal model

The full received signal has both target echo and jamming:

$$r(t) = x_r(t) + J(t) + n(t) \quad (5)$$

$x_r(t)$ is the target echo. $J(t)$ is either comb-spectrum jamming or non-comb jamming. $n(t)$ is additive white Gaussian noise with power set by the SNR.

This model is used to make training and testing data for the deep learning system.

3. Comb spectrum jamming recognition method based on CNN model

3.1. Overall recognition framework

Figure 1 shows the overall framework. First, we make radar echo signals with different interference types. We use the models from Section II and control JSR and SNR. Secondly, we turn the complex signals into dual-channel feature images. These images keep both magnitude and phase information from the signal spectrum. Thirdly, we put these images into a CNN. The CNN uses many convolutional layers to get features at different levels. Finally, the network gives the classification result. It tells comb spectrum jamming apart from non-comb interference.

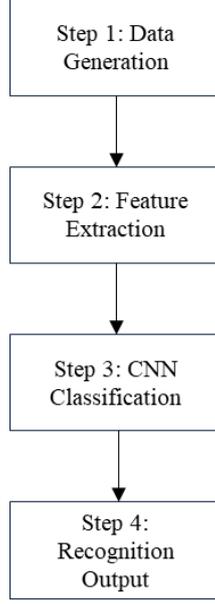


Figure 1. Overall framework of CNN-based comb spectrum jamming recognition.

3.2. Feature extraction and image construction

3.2.1. Spectral feature extraction

FFT converts time-domain signal to frequency domain:

$$R[k] = \sum_{n=0}^{N-1} r[n] e^{-\frac{j2\pi kn}{N}} \quad (6)$$

Magnitude and phase spectra are extracted:

$$M[k] = |R_{shifted}[k]|, \Phi[k] = \angle R_{shifted}[k] \quad (7)$$

3.2.2. Feature enhancement

Log transform enhances weak features:

$$M_{log}[k] = \log_{10}(M[k] + \epsilon) \quad (8)$$

Normalization maps features to [0,1]:

$$M_{norm}[k] = \frac{M_{log}[k] - \min(M_{log})}{\max(M_{log}) - \min(M_{log}) + \epsilon} \quad (9)$$

$$\Phi_{norm}[k] = \frac{\Phi[k] + \pi}{2\pi} \quad (10)$$

3.2.3. Dual-channel image

Normalized magnitude and phase are reshaped to 64×64 and stacked:

$$I \in \mathbb{R}^{64 \times 64 \times 2}, I(:, :, 1) = M_{image}, I(:, :, 2) = \Phi_{image} \quad (11)$$

3.3. CNN architecture

The network comprises four convolutional blocks (32 to 256 filters), batch normalization, ReLU activation, max pooling, and dropout (0.1–0.4). Global average pooling reduces parameters:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W F_c(i, j) \quad (12)$$

Two fully connected layers (128 and 64 neurons) with dropout 0.5/0.4 precede the 2-neuron softmax output:

$$p_c = \frac{\exp(z_c)}{\sum_{j=1}^2 \exp(z_j)} \quad (13)$$

3.4. Training strategy

Cross-entropy loss is minimized:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^2 y_{i,c} \log(p_{i,c}) \quad (14)$$

Adam optimizer ($\eta = 10^{-3}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$) with learning rate halved every 25 epochs. Regularization includes L2 weight decay ($\lambda = 10^{-4}$), dropout, batch normalization, and early stopping.

4. Results and discussion

4.1. Experimental setup and dataset configuration

We ran many simulations to test our CNN-based comb spectrum jamming recognition method. The radar system settings were: carrier frequency 17 GHz, bandwidth 80 MHz, sampling rate 200 MHz, pulse width 2 microseconds, pulse repetition interval 200 microseconds, and 2048 sampling points per pulse.

The training dataset had two classes: comb spectrum jamming and non-comb interference. Each class had 2000 samples so 4000 samples total. The comb spectrum jamming included four patterns: symmetric equally-spaced, asymmetric, dense, and sparse. JSR values were randomly picked from -15 dB to 10 dB. The non-comb interference had five types: strong target signal with noise, broadband Gaussian noise jamming, colored noise jamming, impulsive noise jamming, and swept frequency jamming. We split the dataset randomly with 80% for training and 20% for validation.

4.2. Training process and recognition performance

We trained the CNN with the Adam optimizer. The starting learning rate was . Mini-batch size was 32. We set a maximum of 80 epochs. **Figure 2** shows the training and validation accuracy curves over time.

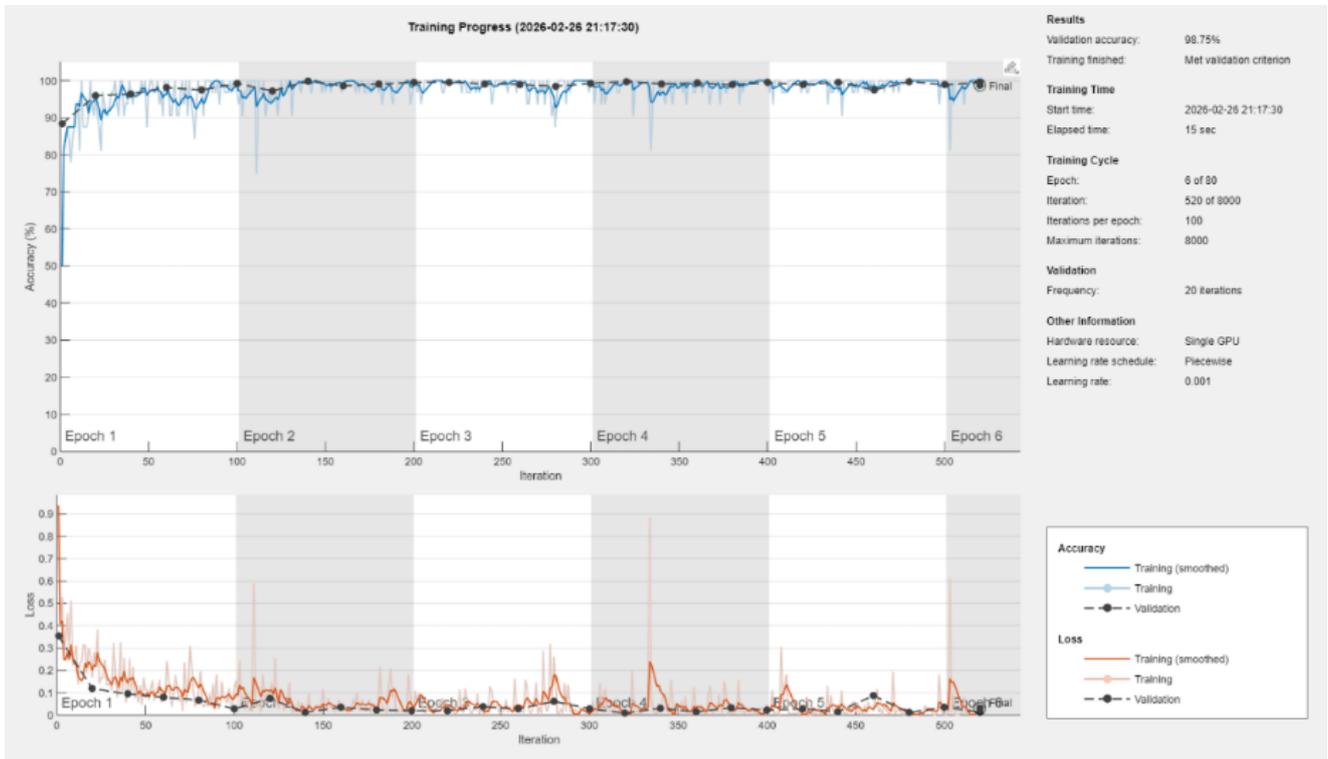


Figure 2. Training and validation accuracy curves.

The experimental results are shown in **Figure 2**. The training process converged very fast. Validation accuracy hit after only 7 epochs. Total training time was just 15 seconds on one GPU. The training and validation curves stayed close to each other the whole time. This means regularization worked well and there was no big overfitting problem.

4.3. Recognition performance analysis

Table 1 presents the confusion matrix for the proposed CNN method evaluated on the validation set.

Table 1. Confusion matrix

Actual/predicted	Comb	Non-Comb
Comb	400	0
Non-Comb	6	394

From the confusion matrix, the following performance metrics are derived as follows:

- (1) Overall accuracy: 99.25%
- (2) Comb class recognition rate:
- (3) Non-comb class recognition rate:
- (4) Precision:
- (5) Recall:
- (6) F1-Score: 99.26%

The results show the CNN method worked very well. The overall accuracy of means it could reliably tell

comb and non-comb interference apart. The false alarm rate was only . This is when non-comb was wrongly called comb. The miss detection rate was . This is when comb was wrongly called non-comb. These low error rates meet the tough needs of real radar anti-jamming systems.

5. Conclusion

This paper presented a deep learning method to recognize comb spectrum jamming in radar systems. We made a dual-channel feature image method that keeps both magnitude and phase information from the signal spectrum. These images go into a CNN we built. Test results showed the method worked very well. Overall accuracy was . The comb class recognition rate was . The false alarm rate was only . Training was fast and reached high accuracy after just 7 epochs.

Disclosure statement

The author declares no conflict of interest.

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