Jamming Waveform Generation Method Based on Generative Adversarial Network Model

Yilin Jiang, Lisong Guan, Wenxuan Liu, and Yuwei Yu

Abstract—**For the issues of unclear jamming effects in traditional intra-pulse jamming waveform generation and the lagging jamming false targets caused by reconnaissance windowing in relay jamming, this paper proposes a jamming waveform generation method based on Generative Adversarial Network (GAN) Models. This model, trained on GAN, generates jamming waveforms driven by jamming effects. Using minimal segments of radar signal headers as input, the jamming waveform generation model reversely predicts and generates complete radar jamming signals based on jamming effects. By reducing the reconnaissance windowing for the jamming side and pre-modulating jamming waveforms based on anticipated jamming effects, this method possesses the capability to achieve transcendental jamming (where the peak value of the jamming false target formed after the pulse compression of jamming waveforms occurs before the peak value of the real target). Experimental results indicate that the radar jamming waveforms generated based on GAN Models can achieve transcendental jamming, increasing the difficulty of radar jamming signal recognition.**

Index Terms—**Generative adversarial network, intra-pulse jamming, jamming effect, transcendental jamming, waveform generation.**

I. Introduction

ADAPTIVE jamming waveform generation technology has consistently been a focal point in the research domain of radar cognitive electronic countermeasures [1], [2], [3]. Generating jamming waveforms based on intercepted radar signals, while ensuring their jamming effects, aims to minimize the duration of reconnaissance windowing as much as possible is advantageous for producing jamming waveforms that yield optimal jamming effects [4]. Conventional fixed jamming waveform generation method, which exhibits lower variability in its jamming waveform, it is susceptible to detection and identification by increasingly transcendental jamming suppression techniques [5], [6]. Therefore, the adaptive jamming waveform generation technique based on sampled radar signals becomes especially crucial.

This paper primarily focuses on the adaptive generation technique of radar jamming waveforms. To achieve coherent jamming for wideband radar, as documented in [7], periodic sampling and retransmission of intercepted radar signals generate coherent jamming signals that, upon reception and processing by the target radar receiver, can create multiple realistic false targets. However, due to its structural limitations, the false targets generated by relay jamming often lag behind the actual targets, so the real target signal typically represents the first peak signal after the compressed echo pulse [8]. With the evolution of intelligent technology, the feature extraction and predictive capabilities of neural networks have offered more solutions for waveform generation techniques [9], [10], [11], [12]. Neural networks can categorize input waveforms into general cases corresponding to output waveforms, and the output waveforms can be pre-calculated as per actual requirements [13], [14], [15]. In the similar domain of waveform design, the approach in [16], utilizing neural networks to generate radar spectrum-notch waveforms, achieves the suppression to jamming. Literature [17] employs GAN to synthesize novel radar waveforms with a desirable Ambiguity Function shape and constant modulus property. Drawing from the research achievements of neural networks in radar waveform design, this paper further proposes network structures and models suited to address the pertinent issues in jamming waveform generation.

This paper employs a Generative Adversarial Network approach to train a model for jamming waveform design. The model predicts and generates complete jamming signals based on small segments of radar signal headers. By modulating the entire jamming waveform according to the expected jamming effects, it addresses the issue of delayed jamming peak values in traditional relay jamming after pulse compression, thereby increasing the difficulty in identifying jamming signals for radar systems. Under conditions of shorter reconnaissance window, the Generative Adversarial-based jamming waveform generation model enables rapid responses to radar detection signal. Moreover, the jamming waveform is generated adaptively according to the requirements of jamming effects. This adaptive approach facilitates jamming waveform generation in complex electromagnetic environments.

II. Generative Adversarial Network

GAN, proposed by Goodfellow et al. [18], is a network framework that estimates the generative model through an adversarial process. At its core, GAN establishes an adversarial training mechanism between the generator (G) and the discriminator (D), aiming to enhance their respective performances through iterative training. The adversarial process between the G and the D can be formulated as a "min-max" optimization problem,

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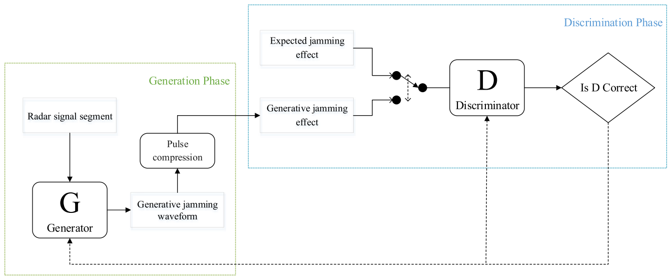


Fig. 1. Training principle diagram for adaptive jamming waveform generation based on GAN.

as shown in (1):

$$\min_{G} \max_{D} V(D, G) = E_{x \sim P_{data}(x)} \left[\ln D(x) \right] + E_{z \sim P_z(z)} \left[\ln \left(1 - D\left(G\left(z \right) \right) \right) \right] \quad (1)$$

where $V(D, G)$ represents the objective function; x denotes the real data; z stands for the input random noise; $P_{data}(x)$ signifies the distribution of real data; and $P_z(z)$ is the prior distribution of the input noise variable.

III. Generation of Jamming Waveform Based on GAN

Fig. 1 illustrates the training principle of the adaptive jamming waveform generation technique based on GAN. Initially, radar signal segments are acquired through reconnaissance windowing. These segments are then input into the generator network to produce generative jamming waveform. Following pulse compression, the generative jamming effects are assessed. The expected and generative jamming effects are separately fed into the discriminator, which learns or evaluates features from its input to discern the data source. Discrepancies between the assessment and the actual results are back-propagated through the network to update the discriminator's weights. The generator learns by attempting to deceive the discriminator, aiming to cause misjudgment. Based on the discriminator's determinations, the generator's network weights are updated through backpropagation.

A. *Jamming Effect Evaluation Based on Pulse Compression*

The radar receiver utilizes a matched filter to perform correlation detection on the received radar signal, thereby achieving pulse compression to enhance the gain and suppress ineffective signals. This paper uses the jamming effect evaluation results based on matched filter to guide the generation of jamming waveform. When the jamming signal enters the matched filter of the radar receiver, the false target jamming peak is formed. The location and peak size of the jamming peak determine the jamming effect against the radar. By judging whether the jamming peak location and peak size formed by the generated jamming signal are consistent with the expected jamming effect, the generator is prompted to generate jamming waveform according to the corresponding jamming strategy.

The input and output of the matched filter are illustrated in Fig. 2, where the input signal $x(t) = s(t) + w(t)$ comprises

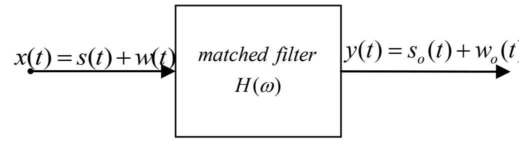


Fig. 2. Schematic diagram of pulse compression.

inputs $s(t)$ (radar signal) and $w(t)$ (noise), and the output signal $y(t) = s_o(t) + w_o(t)$ consists of outputs $s_o(t)$ (radar signal) and $w_o(t)$ (noise) after passing through the matched filter.

The maximum instantaneous signal-to-noise ratio provided at the output end of the matched filter is determined by the input signal energy E and the noise power spectral density N_0, as shown in (2):

$$\left(\frac{S}{N} \right)_{\max} = \frac{2E}{N_0} = \frac{\int_{-\infty}^{\infty} \left| S\left(f \right) \right|^2 df}{\pi N_0} = \frac{2 \cdot \int_{-\infty}^{\infty} \left| S\left(t \right) \right|^2 dt}{N_0} \quad (2)$$

When $x(t) = s(t)$, the output signal $y(t)$ can be represented as (3).

$$y\left(t \right) = s_o(t) = \int_{-\infty}^{\infty} s(\tau) s(\tau + t - t_0) d_\tau = R(t - t_0) \quad (3)$$

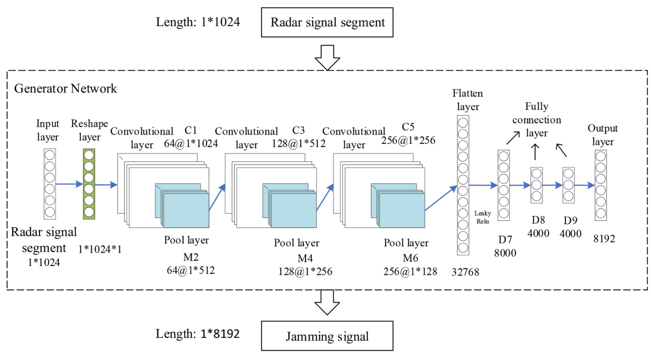
where t_0 denotes the time delay.

The above equation indicates that the output waveform of the matched filter is the autocorrelation function of the input signal $s(t)$. Therefore, the matched filter can be regarded as a correlator that computes the autocorrelation function of the input signal, obtaining the maximum output signal-to-noise ratio at time t_0, where $s_o(t)$ exhibits a peak at time t_0.

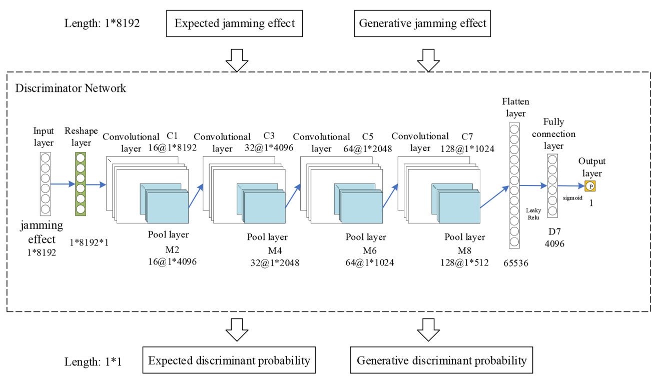
In the process of generating jamming waveforms, when the radar signal is known, the interfering party can apply corresponding jamming modulation to the radar signal, causing the echo signal to generate jamming peaks after pulse compression. However, in practical scenarios where radar signals are unknown, traditional relay jamming relies on reconnaissance windowing to obtain intercepted radar signal segments for modulation and relay jamming. This jamming lags in time compared to the echo radar signal, resulting in jamming peaks lagging behind the real target peaks. This paper leverages the statistical predictive capability of neural networks to generate complete intra-pulse jamming signals using a small segment of radar signal. Through pre-designed modulation, this approach ensures that the jamming peaks precede the real target peaks.

B. *Construction of GAN Model*

1) Generator Network: Fig. 3(a) illustrates the construction method of the jamming waveform generator network. The objective of the generator network is to approximate the desired jamming effects to deceive the discriminator network. During training, a 1∗1024 sampled radar signal segment is used as the network input. The network architecture follows a sequence of convolutional layers followed by fully connected layers (utilizing convolutional layers to extract features from radar signal segments and fully connected layers to predict and generate jamming signals). Ultimately, the network generates 1∗8192

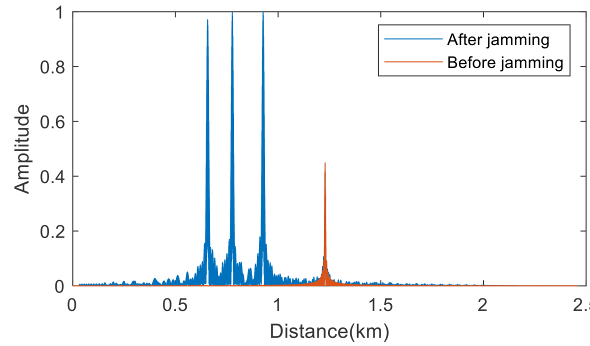


(a) The Generator Network of Jamming Waveform

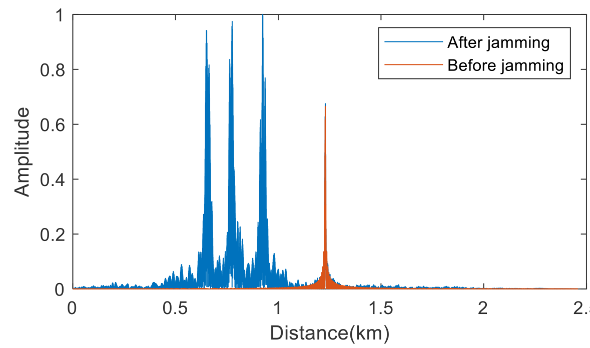


(b) The Discriminator Network of Jamming Effects

Fig. 3. Construction of GAN model.



(a) The Expected Jamming Effects



(b) The Jamming Effects of The Generative Waveform

Fig. 4. Generate jamming waveform analysis.

jamming signal data. This approach allows for the rapid generation of complete intra-pulse jamming signals based on relatively short radar signal segments, enabling jamming signal generation under shorter reconnaissance window conditions.

2) Discriminator Network: Fig. 3(b) depicts the construction method of the jamming effects discriminator network. The discriminator network aims to effectively differentiate between the expected jamming effects and the generative jamming waveform effects. During training, $1*8192$ jamming effect data is utilized as the network input. Eventually, the network utilizes a sigmoid function to transform the output into a binary classification probability.

IV. Experimental Simulation Analysis

A. Experimental Data

The experimental parameters for jamming waveform generation based on the GAN Model are as follows: Radar signal center frequency: $144\,\text{MHz}$, Pulse width: $8.192\,\mu\text{s}$, Signal bandwidth: $30\,\text{MHz}$, Sampling frequency: $1\,\text{GHz}$, Reconnaissance windowing time for the jamming aircraft: $1.024\,\mu\text{s}$, Signal to noise ratio of intercepted radar signal: $10\,\text{dB}$, Power of the jamming signal: $15\,\text{dB}$.

For the GAN training: Number of training rounds: 300, Learning rate: 10^{-5}. Both the generator and discriminator utilize the Adam optimizer for optimization.

For the comparative experiment of intermittent sampling relay jamming: Sampling time for intermittent sampling relay jamming: $1.024\,\mu\text{s}$, Sampling relay period: $2.048\,\mu\text{s}$. All other conditions remain the same as mentioned above.

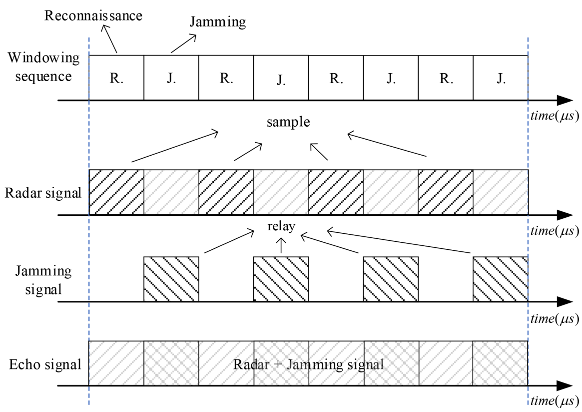
B. Analysis of Jamming Effect of Generative Waveform

Based on the network architecture model described in Section III-B, separate generator and discriminator networks were constructed. The generator network predicts jamming signals based on input radar signal segments, and after pulse compression, the discriminator network distinguishes between the jamming effects of the generative waveform and the expected jamming effects. Following 300 rounds of adversarial training, the effectiveness of the generative jamming waveform by the generator is depicted in Fig. 4.

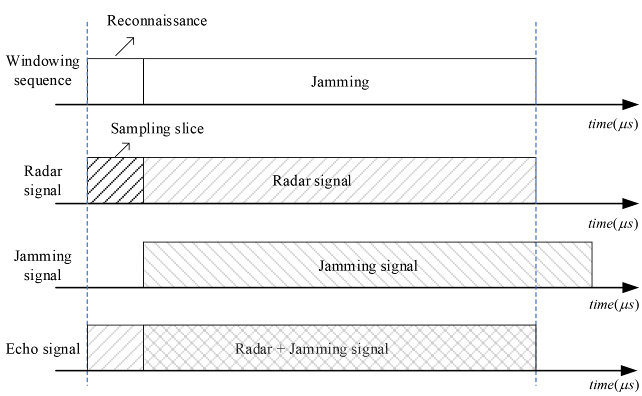
Through comparison, it can be observed that the jamming effects generated by the generator closely match the expected jamming effects. After pulse compression, the generative jamming waveform can produce false target peaks at the anticipated jamming positions. Based on the above experiments, a reasonable judgment can be made: Based on the preset and perfect training set, the neural network can learn the probability distribution of radar signal through reconnaissance window. In the process of using, the neural network can generate the corresponding jamming waveform according to the radar signal segment intercepted by the reconnaissance window.

C. Comparative Experiment With Intermittent Sampling Relay Jamming

The designed comparative experiment between generative jamming and traditional intermittent sampling relay jamming

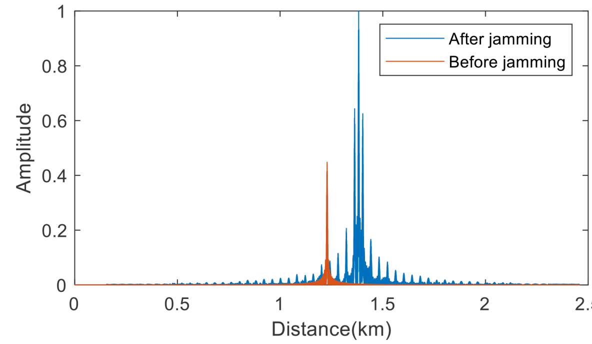


(a) Reconnaissance Jamming Sequence of Intermittent Sampling Relay Jamming

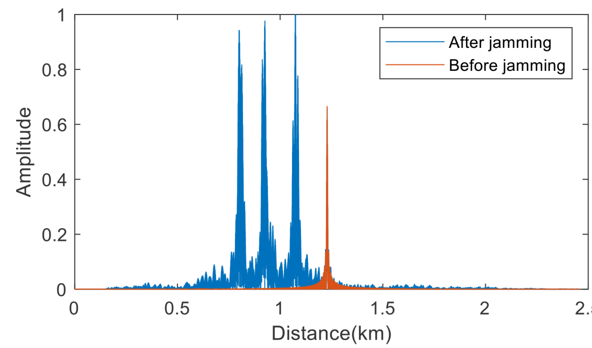


(b) Reconnaissance Jamming Sequence of Generative Jamming

Fig. 5. Reconnaissance jamming sequence.



(a) Jamming Effect of Intermittent Sampling Relay Jamming



(b) Jamming Effect of Generative Jamming

Fig. 6. Comparison diagram of jamming effect.

aims to validate the transcendental jamming capabilities of generative jamming. In practical electronic warfare scenarios where radar waveform information of the jamming aircraft is unknown, the jamming aircraft needs to intercept radar signals through reconnaissance windowing. The traditional intermittent sampling relay jamming conducts "capture-delay-relay" operations within the pulse: upon capturing the radar signal, the jamming aircraft samples and stores a small segment of the signal, then modulates, amplifies, and immediately relays it. This process continues for subsequent signal segments in a loop until the entire pulse ends, as depicted in Fig. 5(a). In contrast, the Generative Adversarial-based jamming waveform design method predicts and generates the entire jamming signal using a small number of radar signal segments through neural networks for reconnaissance jamming, as illustrated in Fig. 5(b).

After undergoing matched filtering, the jamming effects of both jamming methods are depicted in Fig. 6. The intermittent sampling relay jamming necessitates continuous reconnaissance windowing and subsequently designing jamming waveforms based on the detected radar signals during these windows. This inevitably results in the delayed jamming peak after compression of the echo pulse, lagging behind the actual target. In contrast, the generative jamming waveform, after pulse compression, exhibits a jamming peak before the actual target, achieving transcendental jamming. This occurs because the generative jamming predicts and generates jamming signals using segments of radar signals. The neural network within the generator effectively categorizes input radar signal segments to correspond to specific output jamming waveforms. These output jamming waveforms can be calculated in advance based on anticipated jamming effects, enabling the capability to modulate jamming peaks forward under relatively shorter reconnaissance window conditions.

V. Conclusion

This paper proposed a jamming waveform generation method based on GAN Models. The model predicted and generative jamming waveforms based on a small number of radar signal header segments, reducing the reconnaissance windowing delay of the jamming aircraft. The training involved an adversarial interaction between the jamming waveform generator network and the jamming effects discriminator network. Simulation results demonstrated that this method enabled the reverse prediction of jamming waveforms based on jamming effects, allowing for the pre-modulation of generative jamming waveforms, hence possessing the capability to achieve transcendental jamming. The theoretical insights and simulation analyses of the proposed jamming waveform generation adversarial model in this paper could serve as a theoretical reference for the engineering application of jamming waveform generation.

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