

Radar Target Recognition Based on Electromagnetic Scattering Characteristics and Simulated Echo Data

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Abstract—In complex electromagnetic environments, noise, rough-surface scattering, and clutter severely degrade radar target recognition performance. To enhance recognition capability under low Signal-to-Noise Ratio (SNR) conditions, this paper proposes a radar target recognition method that integrates electromagnetic scattering modelling, CST-based Radar Cross Section (RCS) simulation, and an improved one-dimensional Convolutional Neural Network (1D CNN). High-fidelity Linear Frequency-Modulated (LFM) echo signals are constructed from CST-based multi-angle RCS data. A wavelet transform module, a convolutional denoising block, and the Transformer are introduced to strengthen multi-scale feature representation and noise robustness. Experimental results demonstrate that the proposed model outperforms conventional CNN methods in terms of accuracy and F1-score, and maintains a recognition rate of 93% in low-SNR scenarios, indicating strong robustness and practical applicability.

Keywords— Radar Target Recognition, Target Scattering Characteristics, RCS Simulation, CNN, LFM Radar Echo

I. INTRODUCTION

Rapid and reliable target recognition in complex surface environments has become a critical requirement for modern radar systems. In ground or sea clutter environments, target echoes are often submerged by strong interference and noise, which leads to significant performance degradation of conventional radar recognition methods [1]. As a result, they fail to achieve the required anti-interference capability, robustness, and discrimination performance, which has driven increasing research interest in radar target recognition under complex electromagnetic environments.

Radar scattering characteristics, which reflect the geometric structure, material properties, and attitude of a target, have been widely utilized for classification tasks. However, under rough-surface backgrounds, the Radar Cross Section (RCS) is affected not only by the target's physical shape but also by random surface fluctuations, correlation length, incident angle, and other factors. These parameters lead to highly random and non-stationary echo characteristics, posing additional challenges for radar recognition algorithms [2–7]. Consequently, constructing realistic electromagnetic scattering

models and generating high-fidelity echo datasets, is of great importance for advancing radar target recognition research [8].

Deep learning offers new approaches for radar signal interpretation. Convolutional Neural Networks (CNNs) automatically extract discriminative features and have shown strong performance in radar detection, SAR automatic target recognition, and micro-Doppler classification tasks [9–12]. However, most existing radar recognition studies rely on 2-dimension CNNs using time–frequency representations, which involve large parameter sizes and high computational costs [13–18], making them unsuitable for real-time and resource-constrained radar systems. Additionally, conventional CNNs are vulnerable to noise in low-SNR environments and often fail to extract essential scattering features effectively. Therefore, a more lightweight and noise-robust recognition model is needed to address complex clutter and strong interference.

To address these issues, this paper proposes a radar target recognition framework that integrates electromagnetic scattering modelling, CST-based RCS simulation, LFM echo construction, and an improved one-dimensional CNN. A random rough-surface model is generated using a Gaussian power spectral density function, and CST full-wave simulations provide multi-angle RCS data for building a high-fidelity Linear Frequency-Modulated (LFM) echo dataset. A lightweight CNN incorporating multi-scale feature extraction, a denoising module, and channel attention is proposed to enhance recognition under low-SNR conditions. Ablation experiments verify significant improvements in accuracy, robustness, and anti-noise performance.

In summary, this work presents a complete framework from scattering modelling to deep-learning recognition which is designed to meet practical radar target recognition requirements. It offers an engineering-feasible solution for intelligent radar perception under complex surface environments.

II. METHODOLOGY

The proposed radar target recognition framework consists of four core components:

- Stochastic modelling of rough surfaces;

- Acquisition of target RCS through CST simulations;
- Construction of LFM echoes based on the radar equation;
- A improved lightweight one-dimensional CNN.

A. Stochastic Modelling of Rough Surfaces

In this work, a two-dimensional random rough surface is generated using a Gaussian power spectral density function [19]. The main parameters of the rough surface include:

- Root Mean Square (RMS) height h_{rms} ;
- Correlation length (l_x, l_y) ;
- Discrete wave numbers (k_x, k_y) .

For a rough surface whose height follows a Gaussian distribution, the corresponding Power Spectral Density [21] can be expressed as in (1):

$$S(k_x, k_y) = h_{rms}^2 \frac{l_x l_y}{4\pi} \exp\left(-\frac{k_x^2 l_x^2 + k_y^2 l_y^2}{4}\right) \quad (1)$$

In Figure 1, when the correlation length is fixed at 10m and the RMS height increases from 0.25m to 2m, the vertical variations of the random rough surface become more pronounced, with the maximum surface height increasing from approximately 0.5m to 4m. In Figure 2, when the RMS height is kept constant at 5m, decreasing the correlation length from 40m to 5m results in significantly larger horizontal fluctuations. Moreover, the surface exhibits increasingly rapid variations within the same unit area.

These characteristics manifest in the echoes of LFM signals as follows:

- Increased fluctuations in echo amplitude;
- The appearance of “scattering tails” in the Doppler spectrum;
- An effective reduction in SNR.

Therefore, incorporating rough-surface scattering effects into the echo simulation process helps produce a more robust recognition model.

B. CST-Based Target RCS Simulation

To obtain reliable and realistic scattering characteristics, CST Microwave Studio is employed for full-wave simulations. The simulation scenario is configured as a monostatic RCS scan, where an S-band plane wave is normally incident on the target. The frequency is swept from 2GHz to 4GHz, with far-field observation points sampled at intervals of 0.2GHz. A schematic of the simulation setup is shown in Figure 3.

The RCS scanning angle is configured such that the elevation angle θ increases from 0° to 180° in steps of 5° , while the azimuth angle ϕ is fixed at 0° . Under the same

simulation environment, different targets or target materials are replaced to obtain diverse electromagnetic scattering characteristics. In total, six targets with different material settings are constructed. Among them, Target 1, 2, and 6 represent rough surfaces, Target 3 is a sphere, Target 4 is a cone frustum, and Target 5 is a cube. Table 1 summarizes the simulation configuration in detail, including the materials used for each target.

TABLE 1. SIMULATION PARAMETER CONFIGURATION AND TARGET INFORMATION

Category	Item	Value/Description
Simulation Parameters	Excitation source	Plane wave
	Frequency range	2GHz – 4GHz
	Polarization	Horizontal polarization
	Incident angle	Elevation θ : 0° – 180° Azimuth ϕ : 0°
	Target dimensions	Approximately $2\text{m} \times 2\text{m}$
Target Information	Target 1 (rough surface)	Dry soil
	Target 2 (rough surface)	Cement
	Target 3	Sphere (PEC)
	Target 4	Truncated cone (1008-steel)
	Target 5	Cube (wood)
	Target 6 (rough surface)	Dry sand

By importing the six target models into CST, monostatic RCS simulations are performed to obtain RCS values from 2 GHz to 4 GHz as the elevation angle θ is swept from 0° to 180° . The RCS curves of the six targets at 2–4 GHz with $\theta = 0^\circ$ and $\phi = 0^\circ$ are shown in Figure 4 and Figure 5.

From the Figure 4, it can be observed that even when the target geometry remains the same, variations in material properties—such as conductivity and permittivity—produce noticeable differences in the resulting RCS. Figure 5 illustrates the RCS responses of different objects with different materials. Significant RCS variations are evident across different target types, indicating that RCS can serve as an important feature for distinguishing target echo signals.

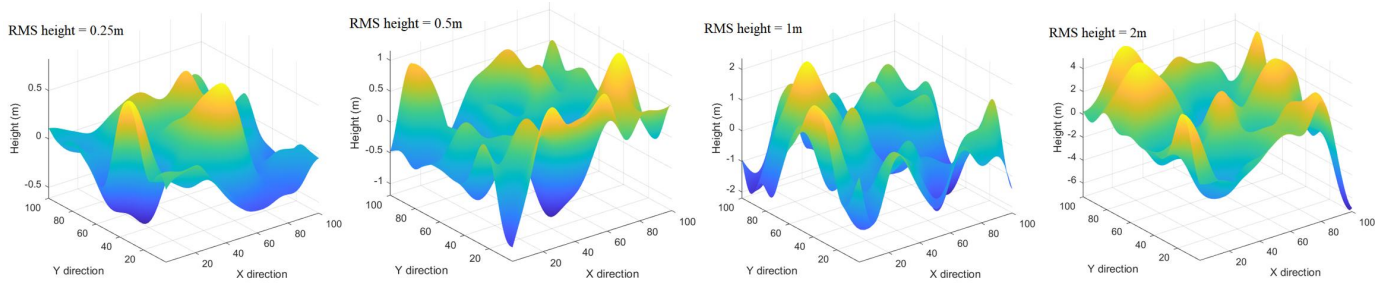


Figure 1. Variations in random rough surface profiles with different RMS heights.

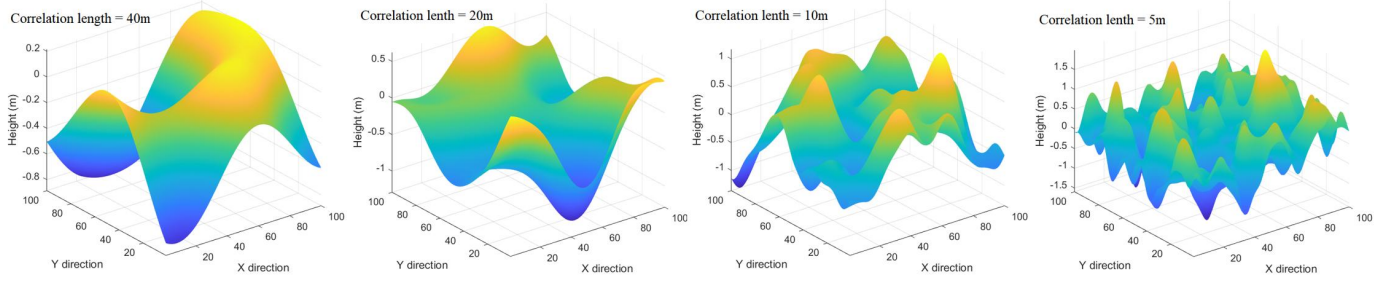


Figure 2. Variations in random rough surface profiles with different correlation lengths.

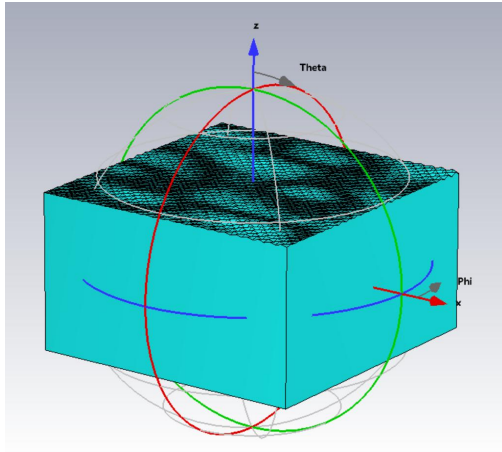


Figure 3. Illustration of the simulation scene and RCS scan angles.

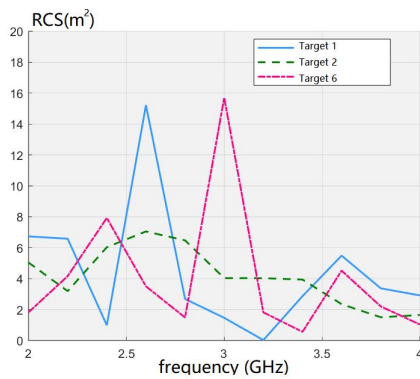


Figure 4. The RCS comparison of Targets 1, 2, and 6.

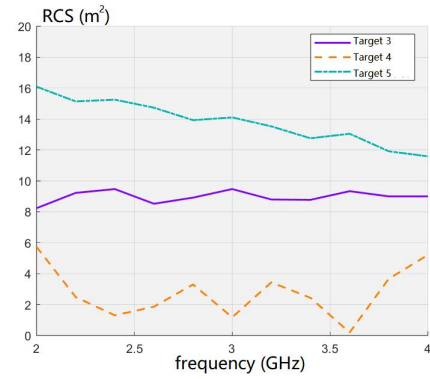


Figure 5. The RCS comparison of Targets 3, 4, and 5.

C. LFM Echo Signal Construction

In practical radar applications, signals with large time duration and wide bandwidth are typically selected to achieve high range resolution and measurement accuracy. Therefore, this work adopts a LFM signal as the transmitted waveform.

Transmitted signals are typically represented as in (2):

$$s(t) = A \text{rect}\left(\frac{t}{T_p}\right) \cdot e^{j2\pi(f_0 t + \frac{k}{2} t^2)} \quad (2)$$

Considering the target RCS and Doppler modulation, the received echo signal can be expressed as in (3):

$$s_{\text{echo}}(t) = \sigma \cdot s(t - \tau) \cdot f_d \quad (3)$$

D. Improved CNN Model

In order to achieve real-time recognition of radar echo signals, this paper designs a lightweight, noise-resistant, and computationally efficient 1D CNN. The improvements to the CNN architecture consist of three components: wavelet

transform, a denoising module, and a transformer attention mechanism. Among them, the wavelet transform and the denoising module operate as preprocessing techniques applied to the input signal, aiming to enhance informative features and suppress noise. However, these two techniques are not applied simultaneously, as cascading wavelet decomposition with additional denoising may excessively remove critical scattering information and degrade recognition performance. Therefore, this work combines wavelet transform and denoising module separately with the Transformer to determine the optimal network configuration.

The detailed modifications are described as follows:

1) Wavelet Transform: In this work, a wavelet transform is introduced at the input of the CNN, as illustrated in Figure 6. Since conventional CNNs are not inherently sensitive to multi-scale time–frequency variations, the advantages of applying a wavelet transform at the input include:

- Decomposing the signal into sub-bands at different scales;
- Enhancing the CNN’s ability to extract features with different time–frequency resolutions;
- Being suitable for handling local feature variations caused by Doppler spreading and rough-surface scattering.

2) Denoising Block: The CNN architecture with denoising layer as shown in Figure 7. Adding a denoising layer into the CNN enables:

- Convolution-based noise suppression;
- Smoothing operations that mitigate high-frequency interference caused by rough-surface scattering;
- Preservation of essential scattering components.

3) The Transformer: The Transformer module does not alter the underlying CNN architecture. Instead, it enhances overall recognition accuracy in three ways:

- Assigning weights to convolution channels according to their relative importance;
- Strengthening highly discriminative scattering features;
- Suppressing noise-dominated and non-informative features.

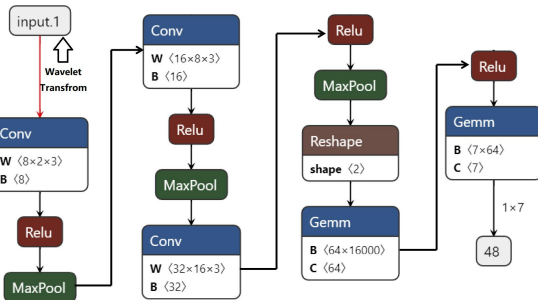


Figure 6. CNN architecture with wavelet transform.

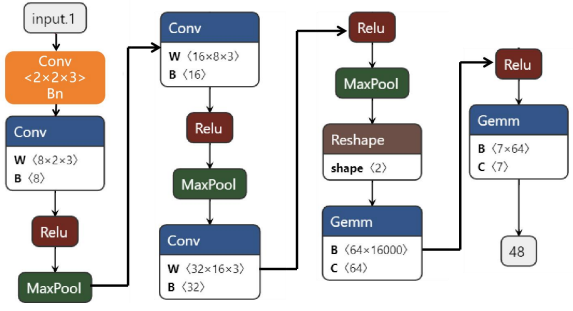


Figure 7. CNN architecture with denoising block.

III. EXPERIMENTS AND ANALYSIS

A. Dataset Construction

The dataset contains six categories of targets, including random rough surfaces and several typical metallic structures (e.g., cylinders and cone frustums). CST is used to perform monostatic backscattering simulations for each target type within the 2–4 GHz frequency range, with an incidence angle step of 5° and a frequency step of 0.2 GHz. A total of 360 RCS samples are obtained for each target category.

B. Experimental Setup

The experiments are conducted on a Windows operating system, and the network is implemented using PyTorch. The hardware platform consists of an NVIDIA GeForce RTX 4060 Ti GPU with 16 GB of RAM.

Table 2 lists the initialization parameters used for training. Since the dataset is relatively small, k-fold cross-validation ($k = 5$) is adopted.

TABLE 2. TRAINING INITIALIZATION PARAMETERS

Parameter	Value
Batch size	32
Epochs	200
Learning rate	1.0×10^{-4}
Dropout	0.3
Optimizer	Adam

To evaluate the effectiveness of the proposed method, the following models are established for comparison:

- Baseline-1: Standard one-dimensional CNN (without wavelet transform, Transformer and denoising block);
- Baseline-2: One-dimensional CNN with wavelet transform added;
- Baseline-3: One-dimensional CNN with denoising layer added;
- Baseline-4: One-dimensional CNN with the Transformer added;
- Proposed-1: Improved model incorporating wavelet transform and attention mechanism;
- Proposed-2: Improved model incorporating denoising block and attention mechanism;

C. Ablation Study

To evaluate the independent contribution of each module and identify the optimal component combination, an ablation study is conducted as shown in Table 3.

According to Table 3, the following observations can be made:

- The wavelet transform effectively captures multi-scale scattering structures, making the model more sensitive to fine-grained differences among targets;
- The denoising module significantly suppresses high-frequency interference caused by noise and rough-surface scattering, enabling the model to extract essential scattering features more reliably and thereby improving recognition performance;
- The attention mechanism does not improve performance independently. When it is combined with the denoising module, which already provides stable and clean feature representations, it can further strengthen the weights of the most discriminative feature channels. As a result, this complementary interaction enhances the model's ability to distinguish multiple target classes and leads to a more robust network configuration.

TABLE 3. ABLATION STUDY RESULTS

Model	Accuracy	Precision	Recall	F1 score
Baseline-1	0.82	0.67	0.67	0.65
Baseline-2	0.89	0.75	0.75	0.75
Baseline-3	0.93	0.82	0.86	0.82
Baseline-4	0.91	0.85	0.85	0.83
Proposed-1	0.86	0.73	0.73	0.73
Proposed-2	0.93	0.88	0.90	0.88

D. Results analysis

Based on the ablation study results shown in Table 3, after adding the wavelet transform to the baseline-1 model, the accuracy increased from 0.82 to 0.89. This demonstrates that the wavelet transform effectively extracts signal features through multi-scale time-frequency analysis, particularly enhancing the model's ability to recognize complex patterns due to its high-resolution analysis in the low-frequency range. After adding the denoising convolutional layer, the accuracy increased to 0.93, with all other metrics significantly outperforming the baseline model, indicating that the denoising layer effectively suppresses noise and improves feature purity.

Baseline-3 performed the best among all single-module improvements, suggesting that rough surface scattering, clutter, and multi-source interference, commonly found in complex environments, tend to severely disrupt the structural features of radar echoes. The denoising layer, with its ability

to suppress high-frequency noise and enhance structural scattering, provides the model with cleaner and more stable input, making its contribution the most significant among all modules. Baseline-4, which performs slightly worse than Baseline-3, shows that the attention mechanism is effective in reallocating channel weights, amplifying useful features and suppressing ineffective ones. However, when the input still contains significant noise (i.e., without prior denoising), the attention mechanism's resources are distracted by noise and pseudo-features, limiting its potential for improvement.

Interestingly, Proposed-1 performs worse than Baseline-2 and Baseline-4. This is due to the wavelet transform preserving high-frequency structures at multiple scales, while the attention mechanism tends to treat some high-frequency noise as important features. Without the denoising layer, the combination of these two modules reinforces certain noise patterns, leading to performance degradation. In contrast, Proposed-2 outperforms all other model combinations, indicating that the denoising module first purifies the input, enabling the attention mechanism to perform "channel selection and weight allocation" on high-quality features. The attention mechanism then further strengthens the stable scattering components preserved by the denoising module. This complementary interaction improves the model's ability to differentiate between various scattering patterns, which is the key to achieving the optimal performance of the proposed model.

IV. CONCLUSIONS

This paper presents a complete radar target recognition framework designed for complex operational environments. The framework integrates electromagnetic scattering modelling, CST simulation, LFM echo construction, and an improved one-dimensional convolutional neural network. By thoroughly modelling rough-surface scattering characteristics and multi-angle backscattering RCS patterns, a high-fidelity radar echo dataset with diverse noise and scene conditions is constructed, providing a reliable foundation for recognition based on deep learning.

Based on this dataset, a lightweight one-dimensional CNN incorporating the wavelet transform, a denoising module, and a Transformer mechanism is developed. Experimental results show that:

- The wavelet transform enhances multi-scale feature extraction and improves sensitivity to subtle scattering differences;
- The denoising layer effectively suppresses interference caused by rough surfaces and clutter, serving as a key component for robustness;
- The Transformer further optimizes channel weights when provided with high-quality input features, enabling more stable discrimination among multiple target types.

The ablation experiments demonstrate that the proposed model 2 outperforms traditional one-dimensional CNN and other baseline models in Accuracy, F1-score, Recall, Precision, exhibiting strong robustness. The final model (Proposed-2)

achieves the best balance between recognition accuracy and computational efficiency, making it suitable for real-time deployment on embedded radar systems.

Future work may be extended in several directions:

- Incorporating more real-measured RCS and radar echo data to further improve generalization in real-world scenarios;
- Investigating the effects of rough surfaces, atmospheric turbulence, and other external factors on echo statistics to refine scattering models;
- Exploring lightweight Transformers, graph neural networks, and other emerging architectures under complex electromagnetic environments;
- Deploying the model on operational radar hardware for real-time processing tests and flight experiments.

In conclusion, the proposed approach provides a theoretically sound and engineering-feasible solution for radar target recognition, and contributes to improving the adaptability and reliability of modern intelligent radar systems in complex environments.

ACKNOWLEDGMENT

This research was supported in part by the National Natural Science Foundation of China (Grant No.62472037, Grant No.62073040, Grant No. 62402045 and Grant No. 62203048). And it was supported by Science and Technology on Electromechanical Dynamic Control Laboratory, China (No. 614260124040210, No. 614260125020105).

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