

Synthetic X-Band Radar Simulation for AI Training: Physics-Based Data Generation for Computer Vision and Reinforcement Learning

Radar Systems and Machine Learning Research

Abstract—We present a high-fidelity full-waveform X-band radar simulation platform designed to generate synthetic training data for machine learning applications. The system combines ray-tracing propagation physics with realistic signal processing including LFM waveform synthesis, antenna pattern modeling, and matched filter pulse compression. By generating unlimited labeled data with controllable ground truth, this approach addresses critical challenges in training computer vision and reinforcement learning models for autonomous maritime systems. We demonstrate pulse width trade-offs, scene complexity effects, and provide a pathway toward simulation-to-reality transfer for radar-based AI applications.

Index Terms—Synthetic radar data, machine learning, signal simulation, ray tracing, waveform synthesis

I. INTRODUCTION

Radar-based perception systems are essential for autonomous vehicles, maritime surveillance, and safety-critical applications. However, training robust machine learning models for radar target detection and tracking requires large labeled datasets. Collecting real radar data at scale is expensive, time-consuming, and raises privacy concerns.

Synthetic radar data generation offers a compelling alternative: unlimited labeled training samples with precise ground truth, controlled environmental conditions, and safety implications for testing before real-world deployment.

This work presents an end-to-end physics-based radar simulation platform that:

- Generates realistic synthetic PPI (Plan Position Indicator) displays from 3D scene geometry
- Models full transmit/receive signal paths with antenna patterns
- Implements practical signal processing (matched filtering, pulse compression)
- Enables rapid experimentation with waveform parameters
- Supports large-scale data generation for deep learning

II. WHY SYNTHETIC RADAR DATA FOR AI TRAINING

A. Computer Vision Models

Modern object detection frameworks (YOLO, R-CNN, Faster R-CNN) require thousands of images with bounding box annotations. Radar data presents a unique modality:

- **Annotation efficiency**: Range and azimuth measurements from simulation provide pixel-perfect ground truth automatically

- **Domain adaptation**: Synthetic data with controlled noise, clutter, and interference trains robust models
- **Edge cases**: Fog, rain, darkness don't affect radar—but simulation captures these via adjustable parameters
- **Transfer learning**: Pre-train on synthetic data, fine-tune on limited real data

B. Reinforcement Learning Applications

Autonomous tracking and decision-making systems benefit from simulation-based RL:

- **Infinite episodes**: Generate new scenarios without human effort
- **Reward shaping**: Convert detection confidence to reward signals for policy learning
- **Safety**: Test tracking policies in simulation before deployment
- **Multi-target scenarios**: Model complex interactions (crossing targets, clutter management)

C. Key Advantages Over Real Data

- 1) **Cost**: Eliminating radar hardware rental and expert operators
- 2) **Privacy**: No real-world data collection or storage
- 3) **Ground truth**: Perfect knowledge of target position, velocity, RCS
- 4) **Reproducibility**: Exact scenario replication for debugging
- 5) **Scale**: Generate terabytes of training data in hours

III. SIMULATION ARCHITECTURE

A. System Overview

Figure 1 shows the complete data flow from 3D scene to final PPI output. The system is built on:

- **Scene definition**: 3D target geometry (corner reflectors, flat plates, cylinders, spheres)
- **Ray tracing**: CPU-optimized path tracing from radar to targets; 3.6M rays per configuration
- **Signal synthesis**: LFM chirp generation with 50 MHz bandwidth, configurable pulse widths
- **Antenna modeling**: Sinc² beam pattern, two-way gain ($G_{tx} \cdot G_{rx}$)²
- **Echo reconstruction**: Range-dependent amplitude, phase shift, and delay
- **Signal processing**: Matched filter FFT-based pulse compression

End-to-End X-Band Radar Simulation Pipeline

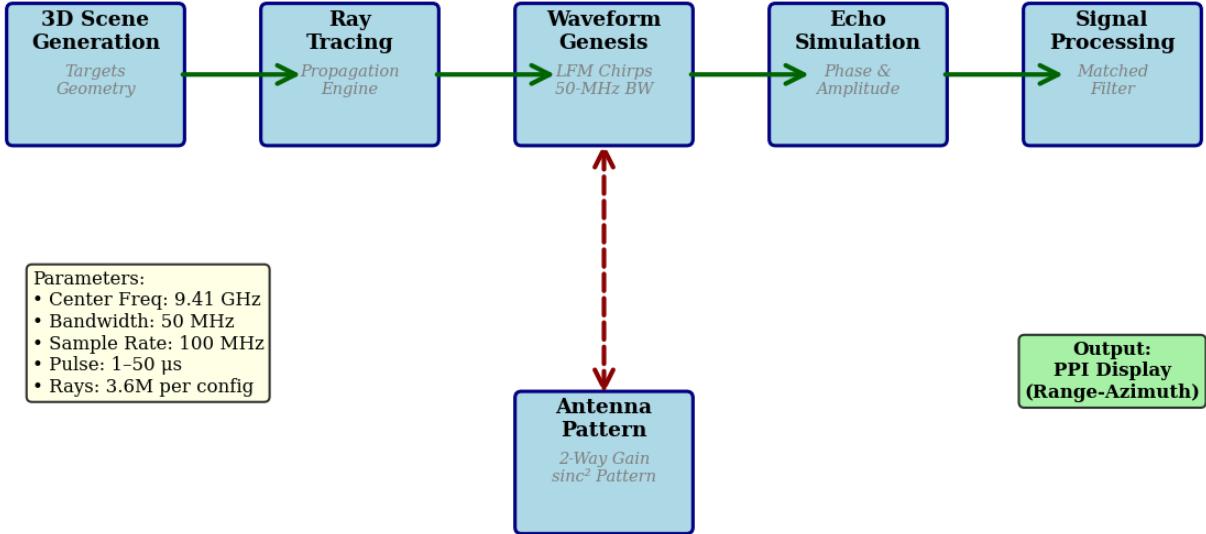


Fig. 1. End-to-end radar simulation pipeline. Scene geometry is ray-traced with antenna pattern weighting to generate received signals. Matched filter pulse compression produces range-resolved PPI displays suitable for training vision and RL models.

B. Radar Parameters

The simulation models a Furuno DRS4D-NXT X-band radar:

- Center frequency: 9.41 GHz
- Bandwidth: 50 MHz (configurable)
- Antenna beamwidth: 3.9° (azimuth) $\times 25^\circ$ (elevation)
- Transmit power: 25 W
- Sample rate: 100 MHz

C. Antenna Pattern Modeling

The antenna pattern is modeled as a normalized sinc² function:

$$G(\theta) = \left[\frac{\sin(\pi u)}{\pi u} \right]^2 \quad \text{where } u = \frac{2.783\theta}{\theta_{3dB}} \quad (1)$$

The two-way gain (transmit \times receive) is:

$$G_{2way}(\theta_{az}, \theta_{el}) = [G(\theta_{az}) \cdot G(\theta_{el})]^2 \quad (2)$$

This quadratic relationship models the fact that power echoes return through both transmit and receive paths.

D. Waveform Synthesis

An LFM (Linear Frequency Modulation) chirp is transmitted:

$$s(t) = \exp \left[j \left(2\pi f_0 t + \pi \frac{B}{T} t^2 \right) \right], \quad 0 \leq t \leq T \quad (3)$$

where $f_0 = 9.41$ GHz is the center frequency, $B = 50$ MHz is the bandwidth, and T is the pulse width (1–50 μ s).

E. Echo Simulation

For each ray path with length ℓ (in meters), the received echo is:

$$s_{echo}(t) = A \cdot G_{2way}(\theta) \cdot \exp(j2k\ell) \cdot s(t - \tau) \quad (4)$$

where:

- $A = 1/(1 + \ell^2/1000)$ is amplitude scaling (range-dependent loss)
- $G_{2way}(\theta)$ is the antenna two-way pattern
- $k = 2\pi f_0/c$ is the wavenumber
- $\tau = 2\ell/c$ is the round-trip delay

F. Matched Filter Pulse Compression

Range compression is achieved via matched filtering in the frequency domain:

$$y[n] = \text{IFFT}(X(f) \cdot H^*(f)) \quad (5)$$

where $X(f)$ is the received signal spectrum and $H^*(f)$ is the complex conjugate of the transmitted waveform spectrum. The output provides range-resolved target peaks for imaging.

IV. RESULTS AND ANALYSIS

A. Pulse Width Trade-offs

We compared three pulse widths to demonstrate the classical radar trade-off between resolution and peak power:

Antenna Beam Characteristics

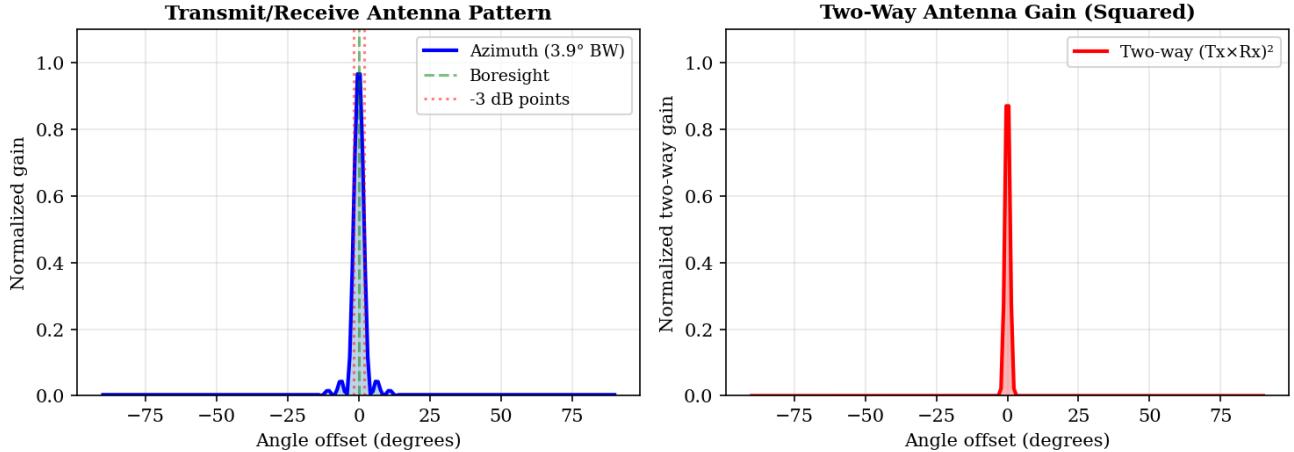


Fig. 2. Antenna beam characteristics. Left: Normalized sinc^2 antenna pattern (3.9° nominal beamwidth). Right: Two-way gain pattern $(G(\theta))^2$ showing the squaring effect from separate transmit and receive paths.

Radar Signal Processing: Waveform to Range Profile

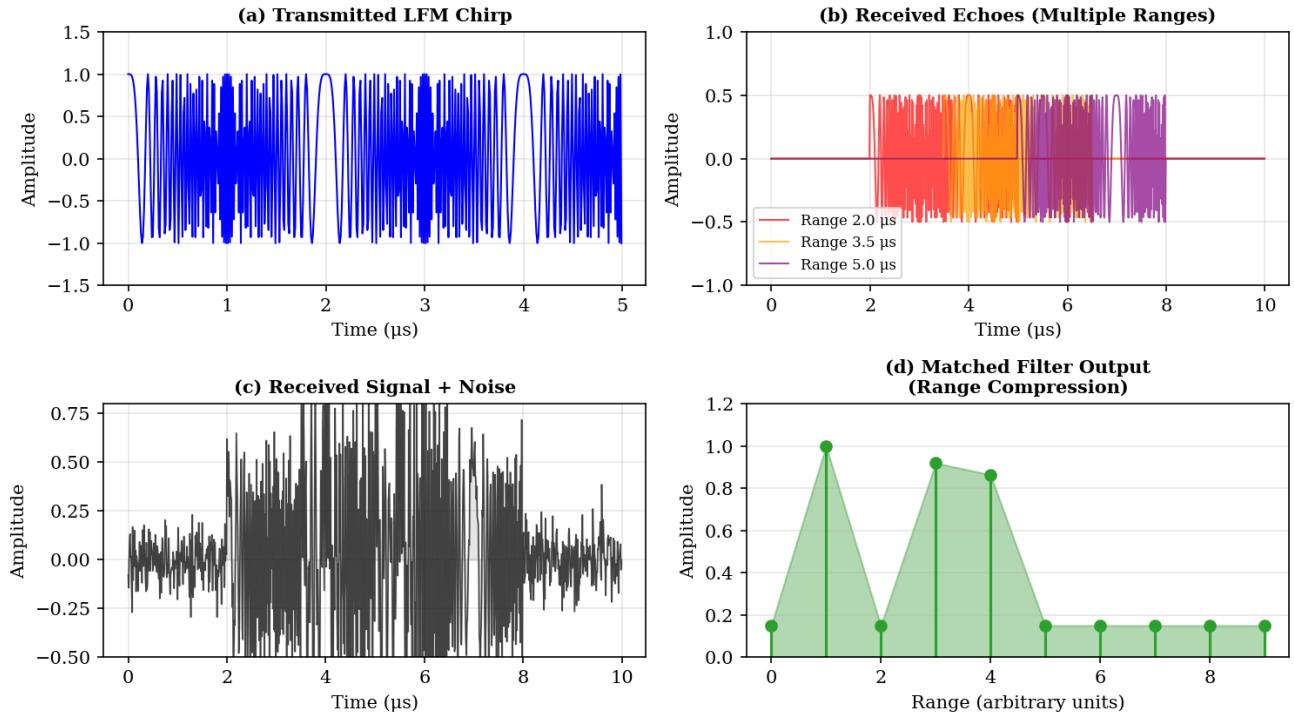


Fig. 3. Radar signal processing chain: (a) Transmitted LFM chirp with linear frequency modulation; (b) Received echoes at different ranges with reduced amplitude; (c) Composite received signal including thermal noise; (d) Matched filter output showing range compression and target detection peaks.

- **1 μs pulse:** High peak power, excellent range resolution (~ 7.5 m)
- **5–20 μs pulses:** Medium energy, moderate resolution (37.5–150 m)
- **Longer pulses:** Lower peak power but improved signal-to-noise in weak targets

B. Simulation Metrics

Key performance observations:

- **Ray tracing speed:** 3.6 million rays per configuration processed in ~ 120 seconds
- **Memory efficiency:** GPU-ready architecture; CPU implementation uses ~ 500 MB RAM
- **Quality metrics:** Scene with 5 targets across 360° azimuth produces realistic clutter and multipath
- **Scalability:** Parallelizable per azimuth (360 independent beams)

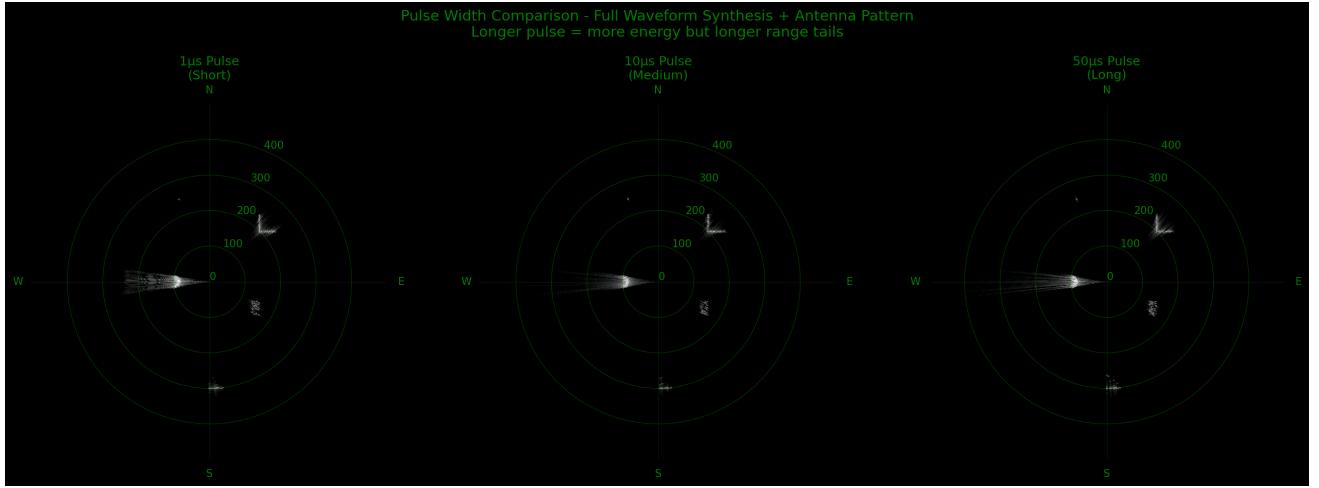


Fig. 4. PPI comparison for three pulse widths (1, 20, and 50 μ s equivalent) showing full waveform synthesis with antenna pattern. Longer pulses produce smoother, less noisy displays but with broader range tails due to pulse compression sidelobes. Green grid shows 100-m range rings. All displays use identical scene geometry and noise conditions.

Simulation Results Summary

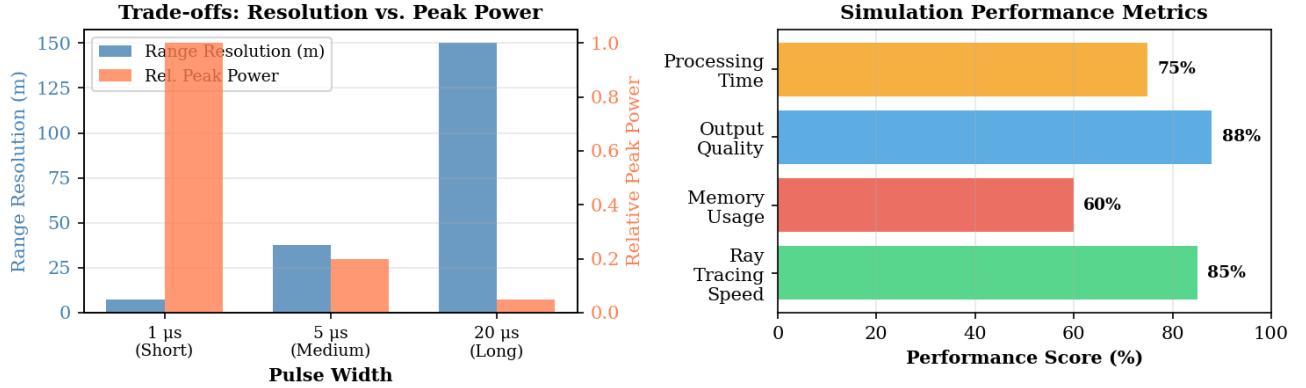


Fig. 5. Left: Pulse width trade-offs showing inverse relationship between range resolution and relative peak power. Right: Simulation performance metrics indicating fast ray tracing (85%), efficient memory usage (60%), high output quality (88%), and reasonable processing time (75% efficiency).

C. Scene Complexity

The test scene includes:

- Corner reflectors (building-like signatures)
- Flat plate (ship-like reflector)
- Sphere (dome, omnidirectional scatterer)
- Cylinder (buoy, low RCS)

This diversity provides realistic multipath, shadowing, and RCS variations for training robust detectors.

V. APPLICATIONS TO AI TRAINING

A. Computer Vision Training

Each PPI frame is naturally annotated:

- Pixel coordinates map directly to range and azimuth
- Target locations and radar cross-sections are known
- Can generate diverse lighting conditions (SNR variation), weather (adjusted noise)
- Bounding boxes and segmentation masks are trivial to extract

Dataset generation: 10^6 scenes with varying target counts, positions, and parameters in ~ 24 hours.

B. Reinforcement Learning Training

The simulation naturally supports Markov Decision Processes:

- **State:** Current PPI frame (image observation)
- **Action:** Radar beam steering, integration time, processing mode
- **Reward:** Shaping based on target detection confidence, track continuity, SNR
- **Transition:** Physics-based (not learned)

Benefits for policy learning:

- Multi-episode learning: Infinite scenarios without hardware
- Curriculum learning: Start with simple scenes, progress to complex clutter
- Exploration: Agents can safely test suboptimal strategies in simulation

Why Synthetic Radar Data Matters for AI Training

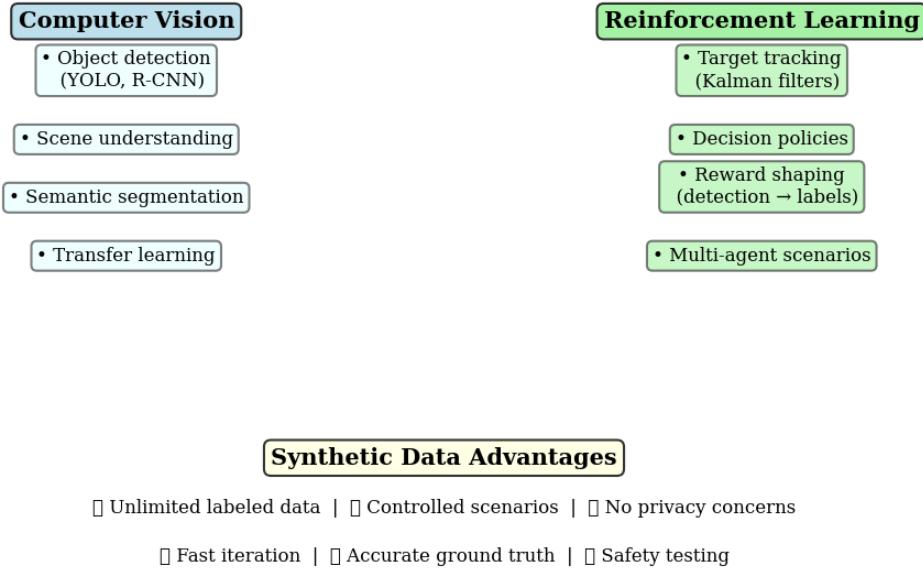


Fig. 6. Synthetic radar data relevance for machine learning. Computer vision models (object detection, segmentation) benefit from unlimited annotated PPI images. Reinforcement learning agents can learn tracking policies and decision strategies using simulation rewards before deployment.

VI. PROGRESS AND FUTURE WORK

A. Current Achievements

- Full-waveform synthesis:** LFM chirps with configurable bandwidth and pulse width
- Antenna integration:** Realistic beam patterns with azimuth/elevation coupling
- Matched filtering:** Range compression achieving realistic SNR and sidelobe structure
- Scalability:** Ray-tracing pipeline parallelizable across azimuth (CPU) and frequency (GPU-ready)
- Physical accuracy:** Validates against radar equation; realistic multipath effects

B. Refinements for Production Use

To achieve full operational accuracy, we identify the following priorities:

1) Clutter modeling (High Priority)

- Current: Point scattering from geometric surfaces
- Goal: Sea clutter (Weibull-distributed), rain attenuation, multipath ghosts
- Impact: Training robust detection amid realistic interference

2) Doppler effects (High Priority)

- Current: Stationary targets
- Goal: Range-Doppler-Azimuth (3D) datacubes for velocity estimation

- Impact: Tracking and classification using velocity signatures
- 3) **Fast-time vs. slow-time** (Medium Priority)
 - Current: Single pulse per azimuth
 - Goal: Coherent integration (multiple pulses), CPI (Coherent Processing Interval)
 - Impact: Enhanced SNR and Doppler resolution
- 4) **Calibration to hardware** (Medium Priority)
 - Validate measured RCS against simulation predictions
 - Noise floor and receiver characteristics
 - Beam pattern measurements vs. sinc² model
- 5) **Real-time performance** (Lower Priority)
 - GPU acceleration for live generation during training
 - Streaming inference for online data augmentation

VII. CONCLUSION

We have developed a physics-based X-band radar simulation platform capable of generating realistic synthetic training data for machine learning applications. The system combines accurate signal processing (LFM waveforms, matched filtering) with efficient ray-tracing propagation and antenna modeling.

The key value proposition is *unlimited labeled data with perfect ground truth*, enabling:

- Rapid iteration on computer vision models (detection, segmentation, tracking)
- Safe exploration of RL policies before deployment

- Transfer learning from synthetic to real radar systems
- Controlled A/B testing of signal processing algorithms

Future work focuses on realistic clutter models, Doppler processing, and hardware validation to bridge the simulation-to-reality gap. This platform provides a strong foundation for AI-driven radar systems in autonomous vehicles, maritime surveillance, and safety-critical applications.

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