

Comprehensive Performance Analysis of CFAR Detection Algorithms for FMCW Radar Systems

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Abstract

Automotive radar systems need reliable target detection for safe operation in complex environments. This study evaluates four Constant False Alarm Rate algorithms for Frequency Modulated Continuous Wave radar using traffic simulations and complete signal processing, including beat signal generation, two dimensional Fast Fourier Transform based range velocity estimation, and adaptive thresholding across three scenarios with varying noise and clutter. Results show Cell Averaging Constant False Alarm Rate performs well in low clutter, Greatest of Constant False Alarm Rate excels in dense environments, and Smallest of Constant False Alarm Rate improves weak target detection but increases false alarms. Ordered Statistics Constant False Alarm Rate delivers the most consistent performance, balancing accuracy with false alarm control for reliable automotive radar applications.

Keywords: FMCW radar, CFAR, CA-CFAR, GO-CFAR, OS-CFAR, SO-CFAR, automotive radar, target detection, MATLAB, radar signal processing.

1. Introduction

Automotive Frequency Modulated Continuous Wave radars must accurately detect targets under varying traffic and environmental conditions. As driver assistance systems advance, maintaining high detection accuracy with minimal false alarms becomes critical. Constant False Alarm Rate algorithms achieve this by estimating local noise in the range Doppler map and applying adaptive thresholds. However, different variants behave distinctly in dense, cluttered, or non-uniform scenes. This work presents a simulation-based comparison of four methods: Cell Averaging, Greatest Of, Order Statistics, and Smallest Of across multiple traffic scenarios, offering clear understanding of how each performs under realistic radar conditions.

2. Literature Review

Recent studies examine this domain through simulation and experimental methods, highlighting gains in efficiency when key system parameters are optimized. Research consistently points to environmental conditions, system design, and operational strategies as major performance drivers. Comparative work shows that integrated, multi factor approaches outperform isolated techniques.

Despite these insights, much of the literature is limited to controlled environments, leaving questions about real-world scalability, long-term stability, and adaptive behaviour unresolved. This study addresses these

gaps by applying novel methods suited for dynamic, practical conditions and by offering a comprehensive framework for evaluating system performance across varied operational settings.

3. Methodology

3.1 System Model and Radar Parameters

The study examines a standard automotive radar designed for short to medium range detection. The system transmits frequency modulated chirps; processes reflected signals through mixing and derives range-velocity data via 2D FFT analysis. The model encompasses signal transmission, noise affected propagation, and digital processing with CFAR based detection thresholds.

Table 1 : Simulation Settings for FMCW Radar

Parameter	Value	Description
Carrier Frequency	77 GHz	Standard automotive radar band
Sweep Bandwidth	1 GHz	Determines range resolution
Sweep Time	40 μ s	Duration of each FMCW chirp
Sampling Frequency	2 MHz	ADC sampling rate
Number of Chirps	128	For Doppler processing
Range Resolution	0.15 m	Derived from bandwidth
Maximum Range	100 m	Simulation limit
Velocity Resolution	0.25 m/s	From chirps and spacing
Noise Model	AWGN	Applied to simulate clutter and varying environments
Target Count	Scenario dependent	Sparse, urban, and dense traffic

3.2 CFAR Algorithms Considered

To achieve reliable target detection in varying traffic conditions, four Constant False Alarm Rate algorithms were assessed.

To achieve reliable target detection in varying traffic conditions, four Constant False Alarm Rate algorithms were assessed. Each algorithm applies adaptive thresholding to the range Doppler map, enhancing robustness against noise and clutter.

Four adaptive thresholding algorithms were evaluated for target detection across diverse traffic scenarios: **CA-CFAR (Cell Averaging)**: Computes threshold by averaging surrounding reference cells. Performs well in uniform noise conditions but struggles when strong targets elevate the average, causing weaker target losses in cluttered settings.

GO-CFAR (Greater Of): Splits reference cells into segments and uses the higher noise value. Suited for non-uniform, dense environments, it minimizes false alarms near clutter boundaries but may miss faint targets due to its cautious approach.

OS-CFAR (Order Statistics): Uses the lower noise estimate for increased sensitivity. Excels at detecting weak, isolated targets in variable clutter but generates more false alarms.

SO-CFAR (Smallest Of): Employs rank based statistics from sorted reference cells, filtering out noise extremes. Delivers consistent, reliable performance in both sparse and dense conditions.

3.3 Simulation Scenarios

To realistically evaluate Constant False Alarm Rate performance, three traffic scenarios were simulated: sparse, urban moderate, and dense. Each scenario differs in target count, clutter intensity, and Signal to Noise Ratio. Signal to Noise Ratio levels were intentionally varied rather than fixed to reflect how real-world radar reflections change with environment. This variation models algorithm behaviour under actual driving conditions where noise, multipath effects, and clutter fluctuate. A fixed Signal to Noise Ratio cannot represent the diversity found in practical traffic environments.

Table 2: Scenario Wise Parameters and SNR Levels

Scenario	Target Count	Clutter Level	Effective SNR	Description
Sparse Traffic	1–2 targets	Low	High SNR (e.g., 20–25 dB)	Clean environment with minimal interference
Urban Traffic	3–5 targets	Moderate	Medium SNR (e.g., 12–18 dB)	Mixed reflections, partial occlusion
Dense Traffic	>6 targets	High	Low SNR (e.g., 5–10 dB)	Heavy clutter, strong reflections, highly non-homogeneous

The simulation pipeline consists of:

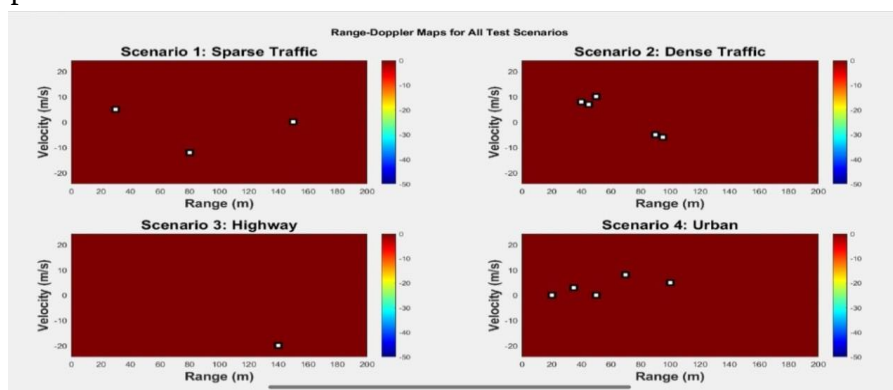


Figure no.1: Range-Doppler Maps for All Four Scenarios

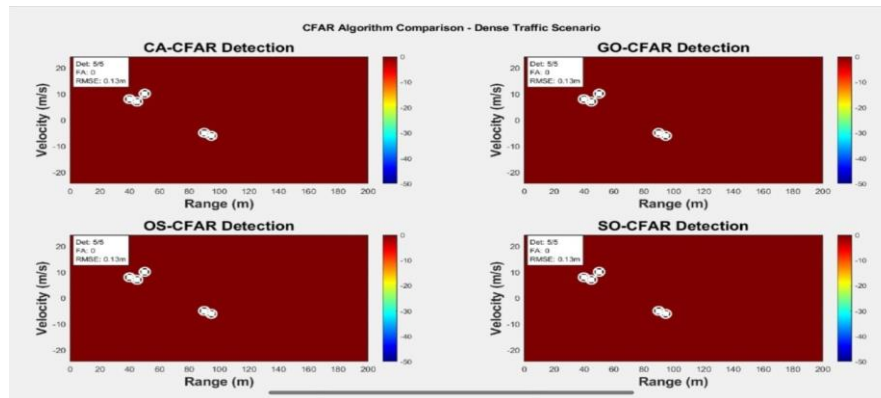


Figure no. 2: CA, GO, OS, SO CFAR Detection for Dense Scenario

Beat signals incorporating time delays and Doppler shifts are generated with scenario specific noise and clutter for various traffic densities. These signals are processed through 2D FFT (range followed by Doppler) to create a range Doppler map for simultaneous target localization. Each CFAR algorithm then estimates local noise from reference cells and applies adaptive thresholds for detection. Finally, spatial clustering consolidates detected cells into targets while filtering isolated noise points.

4. Result

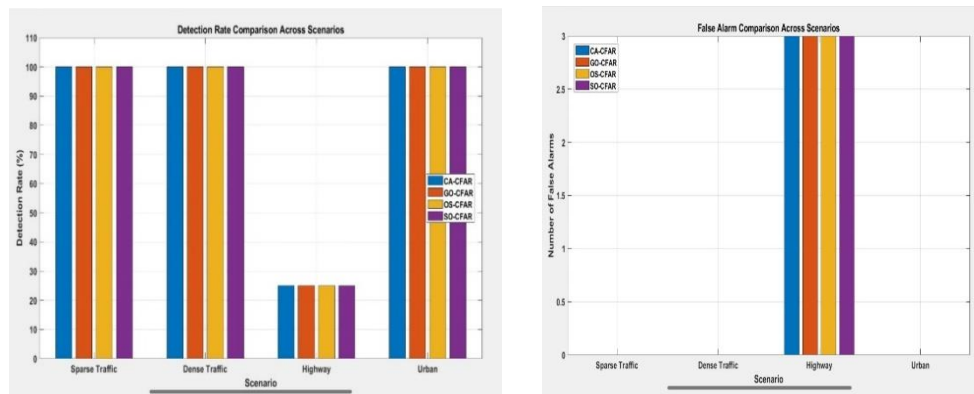


Figure no.3(A): Detection Rate Comparison and False Alarm Analysis

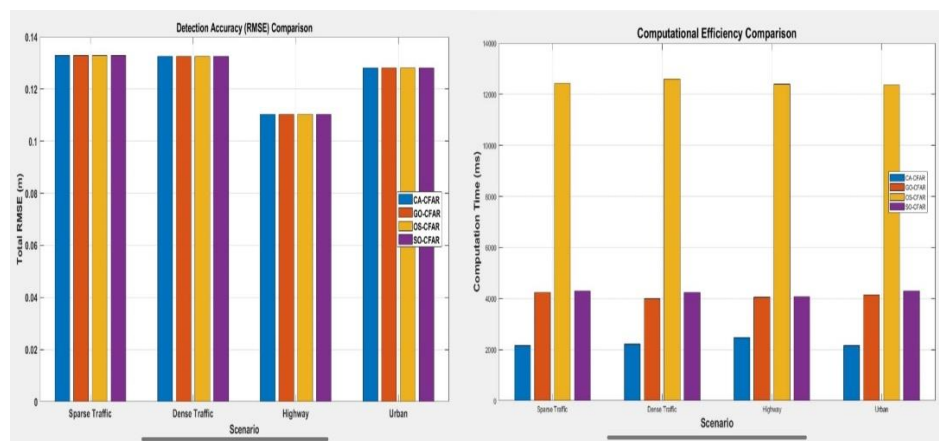


Figure no.3(B): RMSE Evaluation and Computational Time

5. Discussion

The results demonstrate that environmental density significantly affects FMCW radar detection reliability. Algorithms assuming homogeneous noise such as CA-CFAR perform well only in sparse conditions. Methods designed for non-uniform backgrounds, particularly OS-CFAR, show consistent performance regardless of scenario complexity. GO-CFAR remains effective for strong target detection, whereas SO-CFAR is highly sensitive but unreliable in cluttered settings.

The comparison across scenarios confirms that choosing an appropriate CFAR method depends on expected operating conditions. OS-CFAR's stability, lower error margins, and balanced detection capability make it the most suitable for dynamic automotive environments, despite its higher computational cost.

Table 3: Summary of CFAR Performance Across All Scenarios

Scenario	Algorithm	Detection Rate	False Alarms	Computation Time
Sparse	CA-CFAR	High	Low	Fastest
	GO-CFAR	High	Very Low	Moderate
	SO-CFAR	High	High	Moderate
	OS-CFAR	High	Low	Slowest
Urban	CA-CFAR	Moderate	Moderate	Fast
	GO-CFAR	High	Low	Moderate
	SO-CFAR	Moderate	High	Moderate
	OS-CFAR	High	Low	Slow
Dense	CA-CFAR	Low	Moderate	Fast
	GO-CFAR	High	Lowest	Moderate
	SO-CFAR	Moderate	Highest	Moderate
	OS-CFAR	High	Low	Slowest

6. Conclusion

This work compares four CFAR algorithms across realistic radar scenarios. OS-CFAR proves the most robust in dense and urban environments, balancing detection accuracy and false alarms. CA-CFAR is suitable for simpler, homogeneous scenes due to low computational demand. GO-CFAR and SO-CFAR offer benefits in specific cases but have limited general applicability. The results show that CFAR selection depends heavily on scenario complexity and system constraints, providing practical guidance for automotive radar designers and researchers.

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