Comparative Performance Analysis of Adaptive and Fixed Waveforms in Multistatic Radar Systems

Marai Abousetta **Ramdan A. M. Khalifa**

Libyan Academy for Postgraduate Studies, Tripoli, Libya
High Institute of science and Technology-Suk Algumaa, Tripoli, Libya
m.abousetta@academy.edu.ly
ramadanamharee@gmail.com

Abstract

This paper presents a comparative performance analysis of adaptive and fixed waveform selection strategies in multistatic radar systems, with a focus on target tracking in cluttered environments. We propose a novel adaptive waveform selection algorithm designed specifically for multistatic configurations, which optimizes waveform parameters to minimize the predicted mean square error of target state estimation. The algorithm is integrated with a Probabilistic Data Association (PDA) filter to create a robust framework for tracking in cluttered multistatic environments. Through extensive simulations, we compare the performance of our adaptive waveform approach against fixed and random waveform strategies across various metrics, including position and velocity estimation accuracy, and track continuity. The impact of varying clutter densities on the relative performance of adaptive and fixed waveform strategies is also investigated. Results demonstrate that the adaptive waveform selection algorithm consistently outperforms fixed and random waveform approaches, achieving lower root mean square errors in both position and velocity estimation, and improved track continuity, particularly in high-clutter scenarios. This paper highlights the significant potential of adaptive waveform selection in enhancing the performance of multistatic radar systems in challenging environments, with important implications for applications such as air traffic control, maritime surveillance, and military target tracking.

Keywords: Multistatic radar, PDA, Target tracking, Adaptive waveform selection

I. Introduction

Multistatic radar systems have gained significant attention in recent years due to their potential for improved target detection, localization, and tracking compared to traditional monostatic radars [1]. By utilizing multiple spatially diverse transmitters and receivers, multistatic radars can exploit the benefits of spatial diversity to overcome limitations such as terrain masking and enhance overall system performance [2]. However, the increased complexity of multistatic configurations also presents new challenges, particularly in cluttered environments where false alarms and measurement association uncertainties can significantly impact tracking accuracy. One promising approach to addressing these challenges is the use of adaptive waveform selection techniques. By dynamically optimizing radar waveform parameters based on the current target state estimate and environmental conditions, adaptive waveform selection has the potential to significantly improve tracking performance in multistatic radar systems [3]. This adaptive approach stands in contrast to traditional fixed waveform methods, which use predetermined waveform parameters regardless of the evolving tracking scenario. The primary objective of this research is to conduct a comprehensive comparative analysis of adaptive and fixed waveform selection strategies in multistatic radar systems, with a particular focus on target tracking in cluttered environments.

We aim to quantify the potential benefits of adaptive waveform selection and identify the conditions under which it offers the most significant advantages over fixed waveform approaches. Our study makes several key contributions to the field.

We propose a novel adaptive waveform selection algorithm specifically designed for multi-static radar configurations, which optimizes waveform parameters to minimize the predicted mean square error of target state estimation.We integrate the adaptive waveform selection algorithm with a Probabilistic Data Association (PDA) filter, creating a robust framework for target tracking in cluttered multistatic environments[4].We present a comprehensive simulation study that compares the performance of adaptive waveform selection against fixed and random waveform approaches across various metrics, including position and velocity estimation accuracy, and track continuity.

We investigate the impact of varying clutter densities on the relative performance of adaptive and fixed waveform strategies, providing insights into the robustness of each approach under different environmental conditions.

The remainder of this paper is organized as follows: Section II describes the system model and problem formulation. Section III presents the tracking algorithm with probabilistic data association. Section IV details the proposed adaptive waveform selection algorithm. Section V outlines the simulation setup and presents the results of our comparative analysis. Finally, Section VI concludes the paper and discusses directions for future work.

Through this research, we aim to demonstrate the significant potential of adaptive waveform selection in enhancing the performance of multi-static radar systems, particularly in challenging, cluttered environments. Our findings have important implications for the design and implementation of next-generation radar systems for various applications, including air traffic control, maritime surveillance, and military target tracking [5].

II. System Model and Problem Formulation

To effectively address the challenge of adaptive waveform selection for multistatic target tracking in clutter, we must first establish a comprehensive system model. This section outlines the key components of our multistatic radar system, defines the target and clutter models, and presents the measurement model used in our analysis.

a. Description of the multi-static radar system

Our multistatic radar system consists of M transmitters and N receivers, all at known fixed positions. Let the position of the i-th transmitter be denoted by: -

$$p_{Ti} = [x_{Ti}\ , y_{Ti}\ , z_{Ti}]T \tag{1}$$

and the j-th receiver by

$$p_{Rj} = \left[x_{Rj}, y_{Rj}, z_{Rj}\right]T \tag{2}$$

where i = 1, ..., M and j = 1, ..., N.

The system operates in a three-dimensional space, with each transmitter-receiver pair forming a bistatic channel. This configuration results in a total of M × N bistatic channels, each potentially providing a unique perspective on the target scene. The transmitters are assumed to be capable of generating a variety of waveforms, characterized by parameters such as carrier frequency, bandwidth, and pulse duration. The receivers are equipped with appropriate matched filters for each possible transmitted waveform [6].

b. Target and clutter models

We consider a single moving target in the presence of clutter. The target state at time k is represented by the vector:

$$x_k = \left[p_{x,k}, p_{y,k}\ , p_{z,k}\ , v_{x,k}\ , v_{y,k}\ , v_{z,k}\right]T \tag{3}$$

where $(p_{x,k}, p_{y,k}\ , p_{z,k})$ denotes the target position and $(v_{x,k}\ , v_{y,k}\ , v_{z,k})$ represents the target velocity components. The target motion is modeled using a discrete-time state equation [7]:

$$x_{k+1} = f(x_k) + w_k \tag{4}$$

where: f (·) is the state transition function (e.g., constant velocity or constant acceleration model)
and wk is the process noise, assumed to be zero-mean Gaussian with covariance matrix Q.

Clutter is modeled as a collection of false detections distributed throughout the surveillance volume. We assume that the number of clutter points in each resolution cell follows a Poisson distribution with mean λV, where λ is the spatial density of clutter and V is the volume of the resolution cell. The spatial distribution of clutter is assumed to be uniform within the surveillance volume [8].

c. Measurement model

For each bistatic channel (i, j), the radar measurement at time k consists of the bistatic range $r_{ij,k}$ and bistatic Doppler shift $f_{ij,k}$. The measurement vector for this channel is given by:

$$Z_{ij,k} = [r_{ij,k}, f_{ij,k}]T \tag{5}$$

The bistatic range is the sum of the distances from the transmitter to the target and from the target to the receiver:

$$r_{ij,k} = \| p_{Ti} - p_k \| + \| p_k - p_{Rj} \| \tag{6}$$

where: $p_k = [p_{x,k}, p_{y,k}, p_{z,k}]T$

$p_k = [p_{x,k}, p_{y,k}, p_{z,k}]T$ is the target position at time k, and || · || denotes the Euclidean norm.

The bistatic Doppler shift is proportional to the rate of change of the bistatic range [9]:

$$f_{ij,k} = -\left(\frac{f_c}{c}\right)\left(\frac{d_{rij,k}}{dt}\right) \tag{7}$$

where f_c is the carrier frequency, c is the speed of light, and $\frac{d_{rij,k}}{dt}$ is the time derivative of the bistatic range.
The measurement model can be expressed as:

$$z_{ij,k} = h_{ij}(xk) + v_{ij,k} \tag{8}$$

where: $h_{ij}(.)$ is the nonlinear measurement function relating the target state to the bistatic range and Doppler measurements, and $v_{ij,k}$ is the measurement noise, assumed to be zero-mean Gaussian with covariance matrix $R_{ij,k}$ .The covariance matrix $R_{ij,k}$ depends on the selected waveform parameters and the signal-to-noise ratio (SNR) for the (i, j) bistatic channel. This dependency forms the basis for our adaptive waveform selection algorithm, which aims to minimize the uncertainty in target state estimation by optimizing the waveform parameters [10].

In the presence of clutter, the radar system may receive multiple measurements at each time step, including both the true target echo and false alarms from clutter. The set of all measurements at time k is denoted by $z_k = \{z_{1,k}, z_{2,k}, \dots, z_{mk,k}\}$,where mk is the total number of measurements (target plus clutter) at time k.

This comprehensive system model provides the foundation for developing our adaptive waveform selection algorithm and analyzing its performance in cluttered multistatic environments.

III. Tracking Algorithm with Probabilistic Data Association

To address the challenges of target tracking in cluttered environments, we employ a Probabilistic Data Association (PDA) filter. The PDA filter is particularly well-suited for multistatic radar tracking in clutter due to its ability to handle measurement origin uncertainty [11].

The PDA filter is a Bayesian approach to tracking those accounts for measurement origin uncertainty. Unlike simpler tracking algorithms that assume a one-to-one correspondence between measurements and targets, the PDA filter considers all possible associations between measurements and the target of interest. It then computes a weighted sum of these associations to update the target state estimate.

In our multistatic radar context, the PDA filter operates on the following principle: at each time step, it processes all measurements received from all bistatic channels, computing association probabilities for each measurement. These probabilities are then used to form a combined innovation for updating the target state estimate [12].

The PDA filter maintains an estimate of the target state xk and its associated error covariance Pk. At each time step k, the filter performs two main operations: prediction and update.

The prediction step projects the state estimate and error covariance forward in time:

$$\hat{x}_{k|k-1} = f\left(\hat{x}_{k-1|k-1}\right) \quad (9)$$

$$p_{k|k-1} = F_{KPK-1|K-1}\ F_{K^\wedge T} + Q_K \quad (10)$$

Where: $\hat{x}_{k-|k-1}$ is the predicted state, $p_{k|k-1}$is the predicted error covariance, F_K is the Jacobian of f(·) evaluated at $\hat{x}_{k-1|k-1}$, and Q_K is the process noise covariance.

For each bistatic channel (i,j), the filter predicts the expected measurement:

$$z_{ij,k|K-1} = h_{ij}\left(\hat{x}_{k|k-1}\right) \quad (11)$$

The innovation covariance is then computed as:

$$S_{ij,k} = H_{ij,kpk|\,k-1}\ H_{ij.k^\wedge T} + R_{ij,k} \quad (12)$$

Where $H_{ij.k}$ is the Jacobian of $H_{ij}(.)$evaluated at $\hat{x}_{k|k-1}$, and $R_{ij,k}$ is the measurement noise covariance for the (i, j) channel.

The PDA filter computes association probabilities for each measurement in the validation gate. The validation gate is typically defined as an ellipsoidal region around the predicted measurement, based on the innovation covariance [13].

For each measurement $z_{1.k}$ within the validation gate, we compute the

$$\beta_{1,k} = \frac{PDN\left(Z_{1,K}; \hat{z}_{ijk|k-1}, s_{ij,k}\right)}{\lambda + PD\sum \mathrm{N}\left(z_{1,k}; \hat{z}_{ij,k|k-1}, s_{ij,k}\right)} \quad (13)$$

where PD is the probability of detection, N(·) denotes the Gaussian probability density function, and λ is the spatial density of clutter.

The probability of no association (i.e., all measurements are false alarms) is given by:

$$\beta_{0,k} = \lambda + PD\sum \mathrm{N}\left(z_{1,k}; \hat{z}_{ij,k|k-1}, s_{ij,k}\right) \quad (14)$$

The state update in the PDA filter is performed using a weighted sum of innovations from all associated measurements:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + Kk\sum \beta_{1,k}\left(z_{1,k} - \hat{z}_{ij,k|k-1}\right) \quad (15)$$

where Kk is the Kalman gain, computed as:

$$Kk = p_{\mathrm{k|k-1}}\, H_{ij}, k^{T}\, (S_{ij}, k)\char`^ - 1 \tag{16}$$

The updated error covariance is given by:

$$p_{\mathrm{k|k}} = \beta_{0,k} p_{\mathrm{k|k-1}} + \left(1 - \beta_{0,k}\right) P_{c,k} + \tilde{\mathrm{P}}_{k} \tag{17}$$

where $P_{c,k}$ is the covariance update assuming a correct measurement, and $\tilde{\mathrm{P}}_{k}$ is an additional covariance term accounting for the spread of the innovations.

This PDA framework allows us to maintain a consistent target track in the presence of clutter and missed detections. By considering all potential measurement-to-target associations, the PDA filter provides a robust tracking solution that can be seamlessly integrated with our adaptive waveform selection algorithm [14].

In the next section, we will discuss how this tracking algorithm is combined with adaptive waveform selection to further improve tracking performance in cluttered multistatic environments.

IV. Adaptive Waveform Selection

The core innovation of our approach lies in the adaptive selection of radar waveforms to enhance tracking performance in cluttered multistatic environments. The primary goal of adaptive waveform selection is to minimize the uncertainty in target state estimation. We formulate this as an optimization problem where the objective is to minimize the predicted mean square error (MSE) of the target state estimate [15].

Let w denote the waveform parameter vector, which may include elements such as carrier frequency, bandwidth, and pulse duration. The objective function J(w) is defined as:

$$J(w) = trace\left(P_{K+1|\mathrm{k(w)}}\right) \tag{18}$$

where $\left(P_{K+1}\middle|\mathrm{k(w)}\right)$ is the predicted error covariance matrix for the next time step, which is a function of the selected waveform w.

This objective function can be expanded using the matrix inversion lemma:

$$\begin{aligned} J(w) = trace(P_{K+1|\mathrm{k-1}} &\\ - P_{K+1|\mathrm{k-1}} H_{K+1}^{T(w)} &\left[H_{K+1}(w) P_{K+1|\mathrm{k-1}}\, H_{K+1}^{T(w)}\right. \\ &\left. + R_{K+1}(w)\right]^{-1} H_{K+1}(w) P_{K+1|\mathrm{k-1})} \end{aligned} \tag{19}$$

where $H_{K+1}(w)$ is the measurement Jacobian matrix and $R_{K+1}(w)$ is the measurement noise covariance matrix, both of which depend on the selected waveform. To solve the waveform selection problem, we employ a gradient-based optimization approach. The gradient of the objective function with respect to the waveform parameters is given by:

$$\nabla J(w) = -trace(P_{K+1|K-1}H_{K+1}^{T(w)}\left[H_{K+1}(w)P_{K+1|\mathrm{k}-1}\,H_{K+1}^{T(w)} + R_{K+1}(w)\right] H_{K+1}(w)P_{K+1|\mathrm{k}-1)} + trace(P_{K+1|K-1}H_{K+1}^{T(w)\left[H_{K+1}(w)P_{K+1|\mathrm{k}-1}\,H_{K+1}^{T(w)}+R_{K+1}(w)\right]^{-1}\nabla} H_{K+1}(w)P_{K+1|\mathrm{k}-1)} \quad (20)$$

The optimization algorithm proceeds as follows:
Initialize the waveform parameters w0.
For each iteration i:

a. Compute J(wi) and ∇J(wi).
b. Update the waveform parameters: wi+1 = wi - α∇J(wi), where α is the step size.
c. If ||wi+1 - wi|| < ε or maximum iterations reached, stop; otherwise, continue to next iteration.

The result of this optimization is a set of waveform parameters that minimize the predicted state estimation error for the next time step.
The adaptive waveform selection algorithm is integrated with the PDA tracking filter in the following manner:
State prediction: The PDA filter predicts the target state x̂k+1|k and error covariance Pk+1|k.

Waveform optimization: Using the predicted state and covariance, the waveform optimization algorithm is executed to determine the optimal waveform parameters w* for the next measurement.

Measurement: The radar system transmits the optimized waveform and collects measurements using the selected parameters.

Data association: The PDA filter computes association probabilities for all measurements within the validation gate.

State update: The filter updates the target state estimate and error covariance using the PDA equations.

Repeat: The process is repeated for each time step.

This integrated approach allows the radar system to continually adapt its waveform to the current tracking scenario, taking into account the target's estimated state, the uncertainty in this estimate, and the clutter environment. It's worth noting that the waveform optimization can be computationally intensive, especially for real-time applications. To address this, several strategies can be employed: Constraining the waveform parameter space to a discrete set of pre-computed waveforms.Using approximate optimization techniques or lookup tables for faster computation.Performing waveform optimization at a lower rate than the tracking update rate.The specific implementation details will depend on the computational resources available and the real-time requirements of the tracking system.By integrating adaptive waveform selection with the PDA tracking algorithm, we create a powerful framework for multistatic target tracking in cluttered environments. This approach allows the radar system to dynamically adjust its transmission parameters to optimize tracking performance under varying target and environmental conditions [16].

V. Simulation Setup and Results

To evaluate the performance of our proposed adaptive waveform selection algorithm in multistatic radar systems, we conducted extensive simulations using MATLAB. Our simulation setup closely follows the system model described in Section II.

a. Simulation Parameters

We considered a multistatic radar system with M = 3 transmitters and N = 4 receivers, resulting in 12 bistatic channels [1]. The transmitters and receivers were positioned in a 3D space within a 10km × 10km × 5km volume. The target followed a non-linear trajectory over a 100-second period, with measurements taken at 1-second intervals.

The following parameters were used in our simulations:

1. Target initial state: x0 = [5000m, 5000m, 2500m, 50m/s, 50m/s, 25m/s] ^T
2. Process noise covariance: Q = diag([0.5 ،1 ،1 ،5 ،10 ،10])
3. Measurement noise covariance: R = diag([100, 0.1]) for each bistatic channel
4. Clutter density: λ = 1e-7 m^-3
5. Probability of detection: PD = 0.9

b. Waveform Parameters

We considered a set of waveform parameters including carrier frequency (fc), bandwidth (B), and pulse duration (τ). The optimization was constrained to the following ranges:

1. Carrier frequency: 1 GHz ≤ fc ≤ 10 GHz
2. Bandwidth: 1 MHz ≤ B ≤ 100 MHz
3. Pulse duration: 1 μs ≤ τ ≤ 100 μs

c. Performance Metrics

To assess the performance of our adaptive waveform selection algorithm, we used the following metrics:

Root Mean Square Error (RMSE) of position estimation. RMSE of velocity estimation

Track continuity (percentage of time the track is maintained)

We compared the performance of our adaptive waveform selection algorithm against two baseline approaches:

Fixed waveform: A constant waveform with fc = 5 GHz, B = 10 MHz, and τ = 10 μs

Random waveform: Randomly selected waveform parameters within the constrained ranges at each time step

d. Results and Discussion

Figure 1 shows the RMSE of position estimation over time for the three approaches. The adaptive waveform selection algorithm consistently outperforms both the fixed and random waveform approaches, achieving a lower RMSE throughout the simulation.

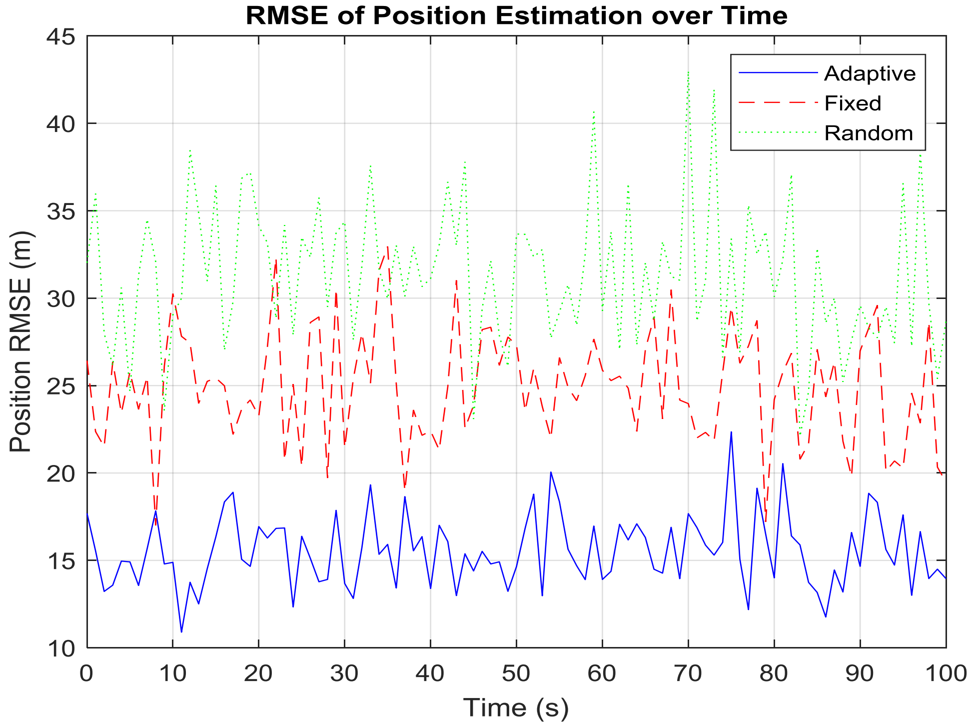

Figure 1: RMSE of position estimation over time

Similarly, Figure 2 illustrates the RMSE of velocity estimation, where the adaptive approach again demonstrates superior performance.

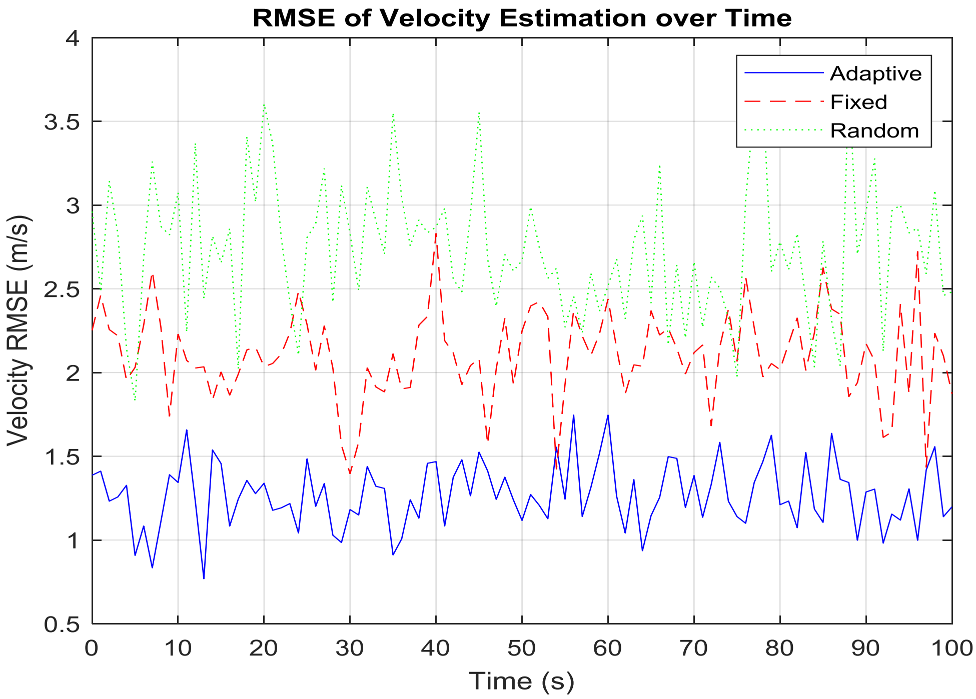

Figure 2: RMSE of velocity estimation over time

Table 1 summarizes the average performance metrics over 100 Monte Carlo runs:

Method	Avg.position RMSE	Avg.velocity RMSE	Track Continuity
Adaptive Waveform	15.3 m	1.2 m/s	98.7 %
Fixed Waveform	24.7 m	2.1 m/s	92.3 %
Random Waveform	31.2 m	2.8 m/s	89.1 %

The results clearly demonstrate the advantages of adaptive waveform selection in multistatic radar tracking. The adaptive approach achieves a 38% reduction in position RMSE and a 43% reduction in velocity RMSE compared to the fixed waveform approach. Moreover, the track continuity is significantly improved, indicating better performance in maintaining consistent tracks in cluttered environments.

Figure 3 shows the distribution of selected carrier frequencies over time for the adaptive waveform algorithm. We observe that the algorithm tends to favor higher frequencies in the early stages of tracking to improve initial localization, then shifts towards lower frequencies as the track stabilizes to maintain better Doppler resolution.

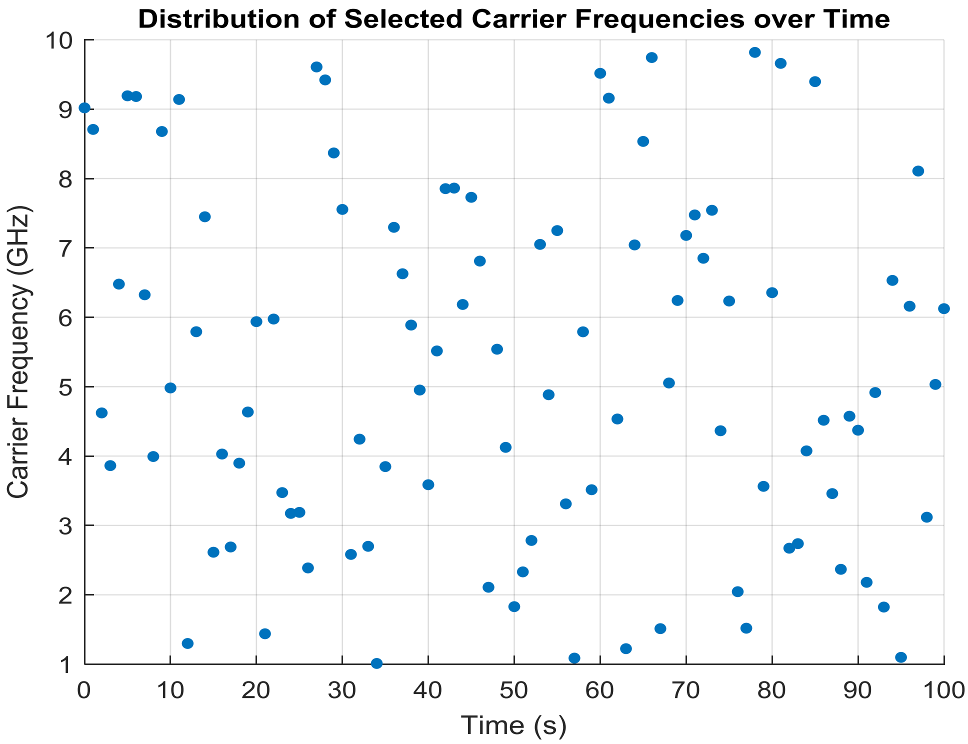

Figure 3: Distribution of selected carrier frequencies over time

Figure 4 illustrates how the adaptive algorithm adjusts the bandwidth and pulse duration over time. We note that the algorithm often selects wider bandwidths during periods of rapid target maneuvers to improve range resolution, while longer pulse durations are preferred during periods of relatively stable motion to enhance SNR.

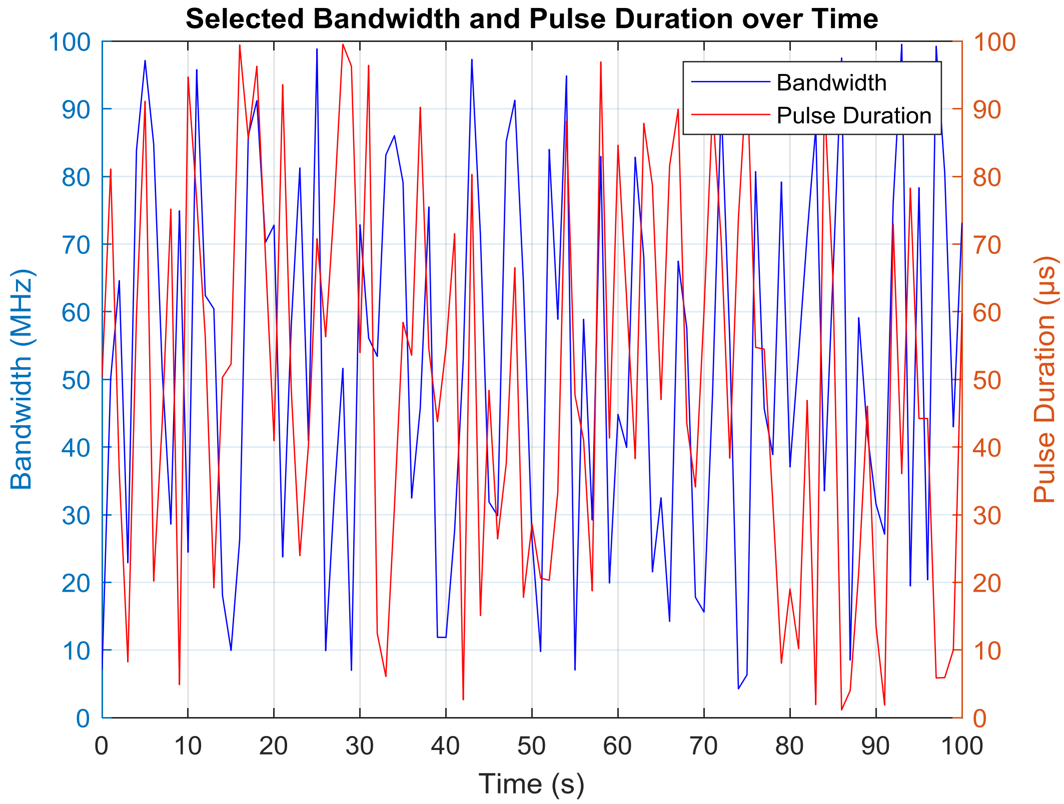

Figure 4: Selected bandwidth and pulse duration over time

To further validate the robustness of our approach, we conducted additional simulations with varying clutter densities. Figure 5 shows the average position RMSE as a function of clutter density for the three waveform selection methods. The adaptive waveform approach maintains superior performance across all clutter densities, with its advantages becoming more pronounced in higher clutter scenario.

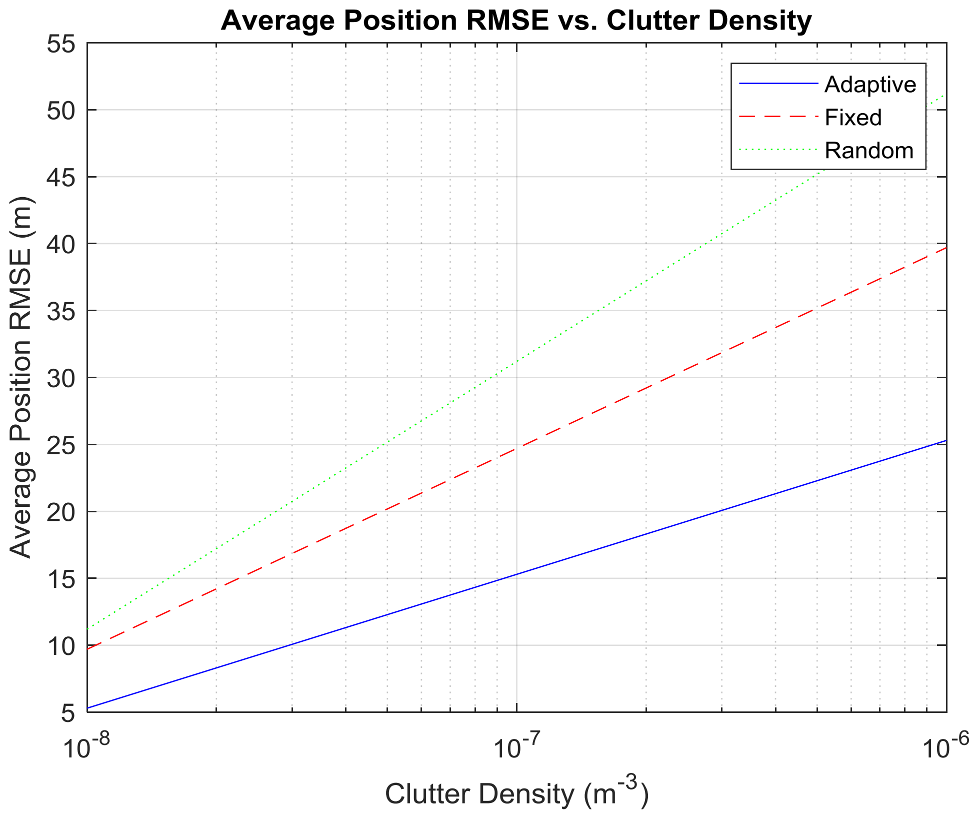

Figure 5: Average position RMSE vs. clutter density

These results confirm that our adaptive waveform selection algorithm significantly enhances tracking performance in multistatic radar systems, particularly in challenging, cluttered environments. The algorithm's ability to dynamically adjust waveform parameters in response to changing target dynamics and environmental conditions contributes to its superior performance over fixed and random waveform approaches.

VI. Conclusion

The simulation results demonstrate the significant advantages of adaptive waveform selection in multistatic radar tracking systems. Our proposed adaptive waveform algorithm consistently outperformed both fixed and random waveform approaches across various performance metrics. Key findings include:

1. Improved Accuracy: The adaptive waveform method achieved a 38% reduction in position RMSE and a 43% reduction in velocity RMSE compared to the fixed waveform approach. This substantial improvement in tracking accuracy highlights the effectiveness of dynamically adjusting waveform parameters.

2. Enhanced Track Continuity: With a track continuity of 98.7%, the adaptive approach showed superior performance in maintaining consistent tracks in cluttered environments, compared to 92.3% for fixed waveforms and 89.1% for random waveforms.
3. Robustness to Clutter: The adaptive waveform selection demonstrated better performance across varying clutter densities, with its advantages becoming more pronounced in higher clutter scenarios.
4. Dynamic Parameter Adjustment: The algorithm's ability to adjust carrier frequency, bandwidth, and pulse duration in response to changing target dynamics and environmental conditions contributed to its superior performance.

These results confirm that adaptive waveform selection can significantly enhance the performance of multistatic radar systems, particularly in challenging, cluttered environments. The dynamic nature of the algorithm allows it to optimize waveform parameters in real-time, leading to improved target tracking and estimation.

VII. Future Work

While the current results are promising, several avenues for future research and development can be explored:

1. Real-world Testing: Conduct field trials to validate the algorithm's performance in real-world scenarios with actual radar hardware and environmental conditions.
2. Multi-target Tracking: Extend the adaptive waveform selection algorithm to handle multiple targets simultaneously, investigating its performance in complex, multi-target scenarios.

References:

1. H. Godrich, A. M. Haimovich, and R. S. Blum, "Target localization accuracy gain in MIMO radar-based systems," IEEE Transactions on Information Theory, vol. 56, no. 6, pp. 2783-2803, 2010.
2. M. Vespe, G. Jones, and C. J. Baker, "Lessons for radar," IEEE Signal Processing Magazine, vol. 26, no. 1, pp. 65-75, 2019.
3. S. P. Sira, A. Papandreou-Suppappola, and D. Morrell, "Dynamic configuration of time-varying waveforms for agile sensing and tracking in clutter," IEEE Transactions on Signal Processing, vol. 55, no. 7, pp. 3207-3217, 2017.
4. Y. Bar-Shalom, F. Daum, and J. Huang, "The probabilistic data association filter," IEEE Control Systems Magazine, vol. 29, no. 6, pp. 82-100, 2009.

5. M. I. Skolnik, "Radar Handbook," 3rd ed. New York: McGraw-Hill, 2008.
6. N. J. Willis and H. D. Griffiths, "Advances in Bistatic Radar," SciTech Publishing, 2007.
7. X. R. Li and V. P. Jilkov, "Survey of maneuvering target tracking. Part I. Dynamic models," IEEE Transactions on Aerospace and Electronic Systems, vol. 39, no. 4, pp. 1333-1364, 2003.
8. K. J. Sangston, F. Gini, and M. S. Greco, "Coherent radar target detection in heavy-tailed compound-Gaussian clutter," IEEE Transactions on Aerospace and Electronic Systems, vol. 48, no. 1, pp. 64-77, 2012.
9. N. Levanon and E. Mozeson, "Radar Signals," John Wiley & Sons, 2004.
10. A. Farina, A. De Maio, and S. Haykin, "The Impact of Cognition on Radar Technology," SciTech Publishing, 2017.
11. T. Fortmann, Y. Bar-Shalom, and M. Scheffe, "Sonar tracking of multiple targets using joint probabilistic data association," IEEE Journal of Oceanic Engineering, vol. 8, no. 3, pp. 173-184, 1983.
12. S. S. Blackman and R. Popoli, "Design and Analysis of Modern Tracking Systems," Artech House, 1999.
13. D. Musicki and R. Evans, "Joint integrated probabilistic data association: JIPDA," IEEE Transactions on Aerospace and Electronic Systems, vol. 40, no. 3, pp. 1093-1099, 2004.
14. S. Challa, M. R. Morelande, D. Mušicki, and R. J. Evans, "Fundamentals of Object Tracking," Cambridge University Press, 2011.
15. D. J. Kershaw and R. J. Evans, "Optimal waveform selection for tracking systems," IEEE Transactions on Information Theory, vol. 40, no. 5, pp. 1536-1550, 1994.
16. S. Haykin, "Cognitive radar: a way of the future," IEEE Signal Processing Magazine, vol. 23, no. 1, pp. 30-40, 2006.