Research and implementation of the Kalman filter in 3D radar target tracking

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ABSTRACT

Tracking a moving target in three-dimensional (3D) space using radar requires the processing system to consistently and accurately update the target's position with minimal delay. The Kalman filter, a powerful tool for target tracking, is utilized to estimate the target's state from noisy measurement data. This paper presents the results of evaluating the effectiveness of the Kalman filter in estimating the altitude and tracking 3D radar targets instead of 2D in existing research. The tests are performed on highly mobile moving target models (UAVs, fighter aircraft, etc.). The evaluation criteria include the accuracy of position and velocity estimation, as well as the computational efficiency of the 3D Kalman filter. Finally, a solution for applying the filter to level 2 processing computers in 3D radar systems is proposed.

Keywords: Kalman filter; Altitude estimation; 3D radar; Noise.

1. INTRODUCTION

Tracking moving targets in three-dimensional (3D) space is not merely a task but an essential aspect of modern radar systems commonly employed in military aviation navigation and automated surveillance systems [1]. In environments with dense target populations (e.g., crowded airspace, cities, or ports), two-dimensional (2D) radar might have difficulty distinguishing targets close to each other but at different heights. This may result in false detections or target merging within the same plane. Compared to earlier radar systems, 3D radar's ability to determine a target's altitude is a game-changer, providing more accurate spatial positioning [2]. This is important for tracking and intercepting fast-moving and agile targets such as fighter jets or missiles. The importance of 3D radars is further underscored by their capability to track and process multiple targets simultaneously, including small, agile ones like cruise missiles or unmanned aerial vehicles (UAVs). Some notable examples of 3D radars globally include Russia's 91N6E radar, a multi-purpose radar used in the S-400 air defense system, capable of tracking numerous targets and accurately identifying missiles, aircraft, and UAVs. The ELM 2084 radar from Israel Aerospace Industries is a multi-purpose 3D radar system capable of detecting threats from UAVs, tactical air weapons, rockets, artillery, mortars, and ballistic and cruise missiles while also providing fire control guidance for intercepting missiles or operating anti-aircraft guns [3].

Several essential methods are used to determine the aircraft's altitude in space, including barometric altimeters, GPS, and radar altimeters. Radar altimeters or 3D radar systems are the most common methods to determine aircraft altitude. These radars employ two main methods: the monopulse method and the electronic scanning method, with antennas characterized by multiple beam patterns [4].

In Vietnam, the four-beam radar (FB) has been in use by the People's Army of Vietnam for over 15 years and is highly regarded for its performance. The FB radar works by dividing the 0-30° space into eight beams (with a maximum of four beams operating in one scanning cycle). Each beam has an independent transceiver system to detect targets, functioning as four 2D radars combined to produce a 3D target (azimuth, range, and altitude). The FB radar has various operating modes with different pulse repetition frequencies (1500 Hz, 750 Hz, 375 Hz) [5]. The system's components have been tested in various geographic regions under continuous operation in Vietnam's hot and humid climate, damaging the components. The systems on the radar station are closely interconnected, from level 1 and level 2 processing to control and synchronization of the entire station. The real-time level 1 point detection computer system has been successfully researched, developed, and tested at the Z119 factory and synchronized on the FB radar station [6]. This computer system has developed a level 1 processing algorithm, and the AI Jetson AGX board has been used. This ensures real-time processing with performance equivalent to or faster than the original 354ПС01 unit of the 3D radar while maintaining a compact size. To meet the requirements for replacing the entire computer system on the radar, research has been conducted to develop the level 2 processing system, synchronize the software, and integrate it into the new generation computer system with equivalent or superior technical specifications compared to the original system on the radar.

The level 2 processing system is a complex task that includes target trajectory detection, tracking, parameter estimation, and extrapolation. Target trajectory detection, for instance, is not a simple process but a series of four intricate steps: gate setting, initial parameter estimation, coordinate extrapolation, and detection standard verification [1, 7]. The development of radar data processing software, particularly for trajectory tracking, parameter estimation, and trajectory extrapolation, requires sophisticated algorithms. Measurement errors are a common issue when determining the target's altitude. Factors such as measurement noise and nonlinear target motion make accurately estimating the target's state in 3D space a significant challenge. The Kalman filter has shown its effectiveness in tracking moving targets by reducing measurement noise and optimizing position estimates, especially for fast-moving, highly mobile targets in 3D space [8-10].

This paper aims to evaluate the effectiveness of Kalman filters in estimating target altitude and implementing 3D Kalman filters in target trajectory tracking, assuming the radar tracks highly mobile targets moving in 3D space. The study uses MATLAB simulations to analyze the accuracy and effectiveness of the Kalman filter under Gaussian noise conditions and apply it to level 2 processing computer systems. The paper consists of four main sections: Section 2 discusses the theory of altitude measurement in the FB radar and the use of the Kalman filter for altitude estimation and trajectory tracking in 3D space. Section 3 presents simulation results using the Kalman filter efficiency with a model of a highly mobile target where velocity and acceleration change. The general conclusions and research directions are summarized in section 4.

2. THEORY ON THE METHOD FOR ALTITUDE MEASUREMENT IN THE FOUR-BEAM RADAR AND KALMAN FILTER

2.1. Altitude measurement method in the four-beam radar

In the FB radar, generating four beams in the elevation plane with the required parameters is achieved through a linear antenna array. The elevation angle of the target is estimated by comparing signals received from different beams at varying angles in the elevation plane. The monopulse technique is commonly used in radar systems to determine the elevation angle by simultaneously receiving and processing signals from multiple beams. This method compares the amplitude or phase difference between signals from several beams at different elevation angles.

The beam arrangement in the FB radar is set as follows: two beams above the reference line and two beams below it (see figure 1). Each beam pair is designed to alternate directions, creating a specific feedback pattern when receiving reflected signals from a target. Each beam covers a small portion of the total vertical area, and the alternation of the beams allows for precise determination of the target’s elevation angle by comparing the received power from each beam.

In monopulse systems, signals from the four beams are processed through sum and difference channels:

• The sum channel (Σ) combines signals from all four beams, producing the total received power.

• The difference channel (ΔE) measures the difference in power between the beams above the reference line (radar beam 3 and radar beam 4) and those below it (radar beam 1 and radar beam 2). This power difference (ΔE) is directly related to the target's elevation angle.

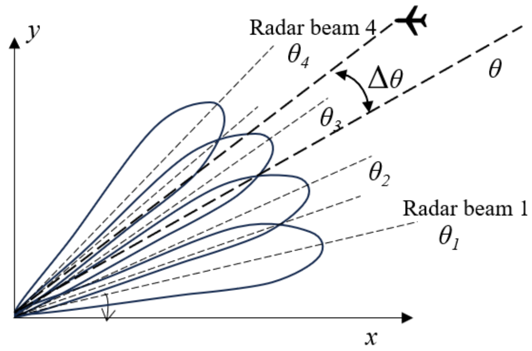

Figure 1. *Four radar beams in the elevation plane for measuring target altitude.*

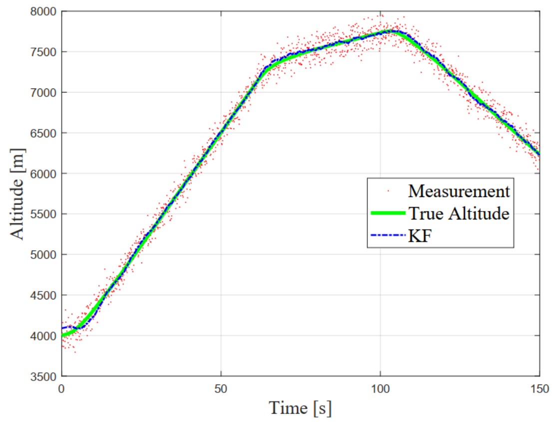

Figure 2. *Results of altitude estimation using the Kalman filter.*

The deviation angle $\Delta\theta$ of the target is estimated by using the ratio of the difference channel (ΔE) to the sum channel (Σ). This ratio is proportional to the angular displacement of the target from the radar's reference line in the elevation plane:

$$\Delta\theta = K\frac{\Delta E}{\Sigma} \tag{1}$$

Where, ΔE is the difference in the signal amplitude received from the upper and lower beams, Σ is the sum of the signal amplitudes from all beams, K is a calibration constant, dependent on the radar's specific beam pattern.

The constant K is determined during radar calibration and ensures a linear relationship between $\Delta E/\Sigma$ and the angular displacement $\Delta\theta$. Using four beams improves elevation angle estimation compared to systems with two or three beams. The use of multiple beams helps resolve ambiguities in distinguishing elevation angles, especially for targets at large elevation angles. The monopulse technique enables real-time calculation of the target's elevation angle without needing to scan across different elevation angles. This not only saves time but also conserves resources [3].

In practice, the target's altitude is determined by calculating it based on the range R and measured elevation angle $\theta_{elevation}$ using the formula:

$$H = H' + a.H'.R^2 + h_{radar} \tag{2}$$

where, $H' = R.\sin\theta_{elevation} + R^2.b$, R is the range from the radar to the target, $\theta_{elevation}$ is the elevation angle of the target; a, b are the constants used for calculating altitude (a = 4.0001 x 10^{-7}(1/km^2), b = 5.839 x10^{-5}(1/km^2)), h_{radar} is the altitude of the radar station.

2.2. The Kalman filter

2.2.1. Kalman filter for target altitude estimation

Accurately measuring the altitude of a target is crucial in modern radar systems for tracking purposes. However, radar data is often affected by noise from environmental factors, which can distort the signals. The radar's resolution limitations also cause measurement errors, and fast-moving targets with sudden changes can lead to inaccuracies. To mitigate these challenges, the Kalman filter is employed to enhance altitude estimation. It reduces noise by combining multiple measurements and uses the target's dynamic model for better prediction. This improves the overall accuracy of the radar system. In the problem of altitude estimation, the system state can be represented over time as the target's altitude $h(t)$ and its rate of altitude change $\dot{h}(t)$ at time *t*.

The system's state equation can be expressed as:

$$\mathbf{x}(t+1) = \mathbf{F}\mathbf{x}(t) + \mathbf{w}(t) \tag{3}$$

Where, $\mathbf{x}(t) = \begin{bmatrix} h(t) \\ \dot{h}(t) \end{bmatrix}$ is the state vector, $\mathbf{F} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}$ is the state matrix, where Δt time duration between measurements, $\mathbf{w}(t)$ is process noise, assumed to be Gaussian with known variance.

The measurement equation of the system is:

$$\mathbf{z}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{v}(t) \tag{4}$$

Where, ***z****(t)* is the measured altitude, **H** = [1 0] is the measurement matrix, and $\mathbf{v}(t)$ is measurement noise, also assumed to be Gaussian with known variance **R**.

The Kalman filter's implementation process for altitude estimation involves the following steps:

1. Predict the next state based on the system's dynamic model:

$$\hat{\mathbf{x}}(t+1|t) = \mathbf{F}\hat{\mathbf{x}}(t|t) \tag{5}$$

2. Predict the error covariance matrix:

$$\mathbf{P}(t+1|t) = \mathbf{F}\mathbf{P}(t|t)\mathbf{F}^T + \mathbf{Q} \tag{6}$$

where **Q** is the covariance matrix of the process noise.

3. Calculate the Kalman gain:

$$\mathbf{K}(t+1) = \mathbf{P}(t+1|t)\mathbf{H}^T(\mathbf{H}\mathbf{P}(t+1|t)\mathbf{H}^T + \mathbf{R})^{-1} \tag{7}$$

where **R** is the covariance matrix of the measurement noise.

4. Update the estimated state:

$$\hat{\mathbf{x}}(t+1|t+1) = \hat{\mathbf{x}}(t+1|t) + \mathbf{K}(t+1)(\mathbf{z}(t+1) - \mathbf{H}\hat{\mathbf{x}}(t+1|t)) \tag{8}$$

5. Update the error covariance matrix:

$$\mathbf{P}(t+1|t+1) = (\mathbf{I} - \mathbf{K}(t+1)\mathbf{H})\mathbf{P}(t+1|t) \tag{9}$$

2.2.2. 3D Kalman filter

The Kalman filter is an optimal algorithm for estimating the state of a system from noisy observations and is widely used in positioning and tracking systems. It operates in two phases: prediction, where the state is estimated using the system's model, and update, where new data corrects the prediction. Its real-time computational efficiency makes it popular in dynamic systems. In 3D target tracking using radar, the 3D Linear Kalman Filter (LKF) is employed to predict and update the position and velocity of a target in three-dimensional space (x, y, z). Radar measurements provide data on the target's range, azimuth, and elevation angles. The Kalman filter requires a mathematical model to describe the target's state and how this state changes over time, converting the radar measurements into Cartesian coordinates [7].

In 3D space, the target's state includes its position, velocity, and acceleration in three dimensions:

$$\mathbf{x}(t) = \left[x(t)\ y(t)\ z(t)\ \dot{x}(t)\ \dot{y}(t)\ \dot{z}(t)\ \ddot{x}(t)\ \ddot{y}(t)\ \ddot{z}(t) \right]^T \quad (10)$$

Where, **F** is the state transition matrix, **G** is the control matrix, $\mathbf{w}(t)$ is the process noise, assumed to be Gaussian.

The state model is represented in the form of a dynamic equation:

$$\mathbf{x}(t+1) = \mathbf{F}\mathbf{x}(t) + \mathbf{G}\mathbf{w}(t) \quad (11)$$

The observation model relates the radar measurements to the target's state:

$$\mathbf{z}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{v}(t) \quad (12)$$

where **H** is the observation matrix that converts the system's state into measurable quantities, $\mathbf{v}(t)$ is the measurement noise, assumed to be Gaussian.

The Kalman filter is implemented in two steps: prediction and calibration.

1. Prediction:

- State prediction:

$$\hat{\mathbf{x}}(t+1|t) = \mathbf{F}\hat{\mathbf{x}}(t|t) \quad (13)$$

- Error covariance prediction:

$$\mathbf{P}(t+1|t) = \mathbf{F}\mathbf{P}(t|t)\mathbf{F}^T + \mathbf{Q} \quad (14)$$

where $\hat{\mathbf{x}}(t+1|t)$ is state prediction at time t+1 based on the data coming at time t, $\mathbf{P}(t+1|t)$ is the covariance matrix of the prediction error, and **Q** is the process noise covariance matrix.

2. Calibration:

- Kalman gain calculation:

$$\mathbf{K}(t+1) = \mathbf{P}(t+1|t)\mathbf{H}^T[\mathbf{H}\mathbf{P}(t+1|t)\mathbf{H}^T + \mathbf{R}]^{-1} \quad (15)$$

- State calibration:

$$\hat{\mathbf{x}}(t+1|t+1) = \hat{\mathbf{x}}(t+1|t) + \mathbf{K}(t+1)[\mathbf{z}(t+1) - \mathbf{H}\hat{\mathbf{x}}(t+1|t)] \quad (16)$$

- Error covariance update:

$$\mathbf{P}(t+1|t+1) = [\mathbf{I} - \mathbf{K}(t+1)\mathbf{H}]\mathbf{P}(t+1|t) \quad (17)$$

Where, $\mathbf{K}(t+1)$ is the Kalman gain, which determines the weighting of the new measurement in the state update, while **R** is the covariance matrix of the measurement noise.

In this way, the Kalman filter continually refines its estimation of the target's position and velocity by combining prior estimates with new radar measurements, accounting for both the system's dynamics and measurement noise.

3. SIMULATION RESULTS

3.1. Target motion model for altitude estimation

3.1.1. Target motion model for altitude estimation

To evaluate the effectiveness of the Kalman filter in altitude estimation, a target motion model is assumed where the target moves in space with changing velocity and acceleration over time. The state variables include altitude $h(t)$, rate of change of altitude $v_h(t)$, and acceleration $a_h(t)$. In MATLAB, the target motion model is set with the following initial conditions: the radar is located at the origin, and the tracked target starts moving at an altitude (h_0) of 4 km with an initial rate of change of altitude (v_{h0}) of 10 m/s and acceleration, as shown in table 1. The sampling time is set to T = 0.1 seconds, with a standard deviation (σ_h) of 50 meters for altitude measurements.

3.1.2. Kalman filter results for altitude estimation

The Kalman filter was applied to estimate the target's altitude based on the hypothetical motion model described in section 3.1.1. Figure 2 shows the results of altitude estimation using the Kalman filter, comparing it to the actual altitude and the measured altitude over 150 seconds.

Table 1. *Changes in target acceleration and initial value for altitude estimation.*

Samples	Value a_h (m/s²)
1 to 50	(1:50)/5
51 to 100	3
101 to 200	(0.1: 0.1:10)/10
201 to 600	0
601 to 1000	- a_h (1:400)
1001 to 1500	- a_h (1:500)
Initialization	
h_0	4 km
v_{h0}	10 m/s
σ_h	50 m
Q	*diag*{1, 1}
R	σ_h^2
T	0.1 s

Table 2. *Changes in target acceleration during the maneuver and initial value for target state estimation.*

Acceleration axis	Samples	Acceleration (m/s²)
a_x	1 to 20	(1:20)/5
	21 to 60	1
	61 to 70	(10: -1:1)/5
	71 to 600	0
	601 to 1200	-a_x (1:600)
	1201 to 1500	-a_x (1:300)
a_y	1 to 300	0
	301 to 1500	a_x (1:1200)
a_z	1 to 60	(1:60)/50
	61 to 600	*0*
	601 to 1500	-a_x (1:900)/10
Initialization		
(x_0, y_0, z_0)	(40 km, 60 km, 2 km)	
$(\sigma_x, \sigma_y, \sigma_z)$	(10 m, 10 m, 10 m)	
Q	*diag*{0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1}	
R	*diag*$\{\sigma_x^2, \sigma_y^2, \sigma_z^2\}$	
T	0.5 s	

In figure 2, the estimated altitude using the Kalman filter (dash-dotted line) closely matches the actual altitude of the target (solid line), with the most significant error occurring when the target's altitude changes abruptly. To assess the accuracy of the Kalman filter, the root mean square error (*RMSE*) parameter is used, as defined in equation (18). With an initial assumption of a standard deviation of 60 meters for altitude measurements, the measured altitude is represented by dots in figure 2. The *RMSE* for altitude estimation is 14.13 meters.

3.2. Target motion model in 3D space

3.2.1. Target motion model in 3D space

To evaluate the effectiveness of the Kalman filter in 3D target tracking, the author set up a target motion model in MATLAB. The radar measurement system uses 3D radar, typically represented in spherical coordinates, where the radar station is the origin. The target information received from the radar includes range r, elevation θ, and azimuth φ. It is assumed that the target data from the 3D radar system has been converted from polar to Cartesian coordinates (x, y, z). The target is assumed to move in 3D space along both linear and nonlinear trajectories, exhibiting high mobility with potential velocity changes and abrupt directional shifts. Noise affecting the system includes process noise (related to the target's movement) and measurement noise (related to the radar system). Process noise represents the accelerations affecting the target's motion, while measurement noise represents the errors inherent in the radar system.

In our MATLAB simulation of the Kalman filter, we set the initial values as follows: the radar is placed at the origin (0, 0, 0), and the tracked target starts moving from position (40 km, 60 km, 2 km) with an initial velocity of (20 m/s, 50 m/s, 40 m/s), and the acceleration values change according to table 2. The sampling time is T = 0.5 seconds (or the radar scan cycle), and the standard deviation for distance measurements $(\sigma_x, \sigma_y, \sigma_z)$ is (10 m, 10 m, 10 m). These initial values provide a clear starting point for our evaluation.

3.2.2. Results of applying the 3D Kalman filter

The 3D Linear Kalman Filter (LKF) was applied to estimate the target's state based on the assumed 3D radar target trajectory model presented in section 3.2.1. The state transition, noise, and measurement matrix were set based on the system and target characteristics described in table 1. Figure 3 shows the results of the 3D LKF state estimation compared to the actual trajectory and measured data for N = 1500 samples.

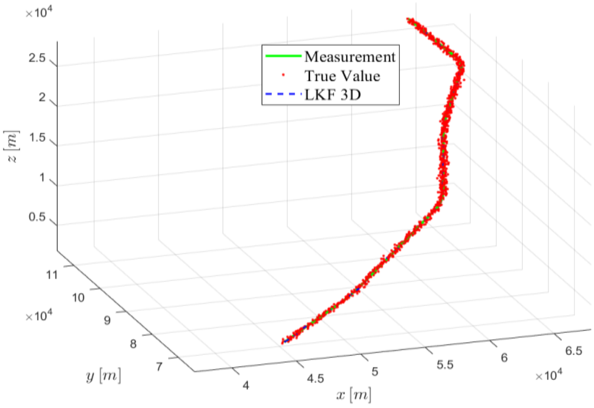

Figure 3. *Results of target state estimation using the 3D LKF.*

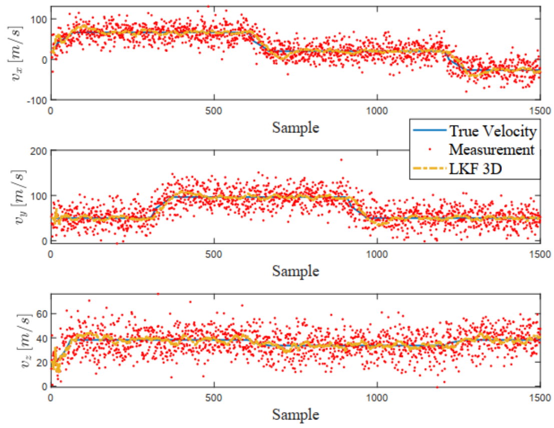

Figure 4. *Comparison of target velocity estimation using the 3D LKF.*

In figure 3, the estimated trajectory (dash-dotted line) closely follows the actual target trajectory (solid line), while dots represent the measured data. However, to better analyze the effectiveness of the 3D LKF, the estimated velocity is examined in figure 4, which compares the estimated velocity using the 3D LKF to the actual velocity and the measured velocity (affected by noise). The most significant estimation errors occur during sudden changes in the target's acceleration and movement, but these errors are minimal.

The 3D Kalman filter's performance was evaluated based on criteria such as position and velocity estimation errors and computational complexity. *RMSE* (equation 18) and prediction time were used to assess the results accurately based on MATLAB simulations.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2 + (\hat{z}_i - z_i)^2\right]} \quad (18)$$

Where, ($\hat{x}_i$, $\hat{y}_i$, $\hat{z}_i$) is the estimated value for the *i-th* sample, (x_i,y_i,z_i) is the actual value for the *i-th* sample over a total of N samples. Figure 3 shows that for the assumed target motion model, the *RMSE* in position estimation is 40.15 meters, and the *RMSE* in velocity estimation is 5.39 m/s.

4. CONCLUSIONS

This paper presents a study evaluating the effectiveness of Kalman filters in estimating target altitude and the applicability of 3D Kalman filters in tracking target trajectories, assuming that the tracked targets in the radar system are highly mobile and moving in three-dimensional space, using MATLAB. The authors developed a target data model for altitude measurement and a motion model for targets in space with varying speeds and accelerations. The results of applying the

Kalman filter demonstrate its effectiveness in altitude estimation with an *RMSE* of 14.13 meters (while assuming a standard deviation of 60 meters in altitude measurement). The accuracy of position and velocity estimation in three-dimensional space is relatively high, with an *RMSE* of 40.15 meters (assuming a standard deviation of 100 meters in horizontal space measurements). These results indicate that the Kalman filter significantly supports the implementation of research to build level 2 processing software on modern 3D radar systems. In future research, the authors aim to improve and test various Kalman filters to enhance accuracy and reduce processing time for direct testing on radar system computers.

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TÓM TẮT

Nghiên cứu, ứng dụng bộ lọc Kalman trong theo dõi mục tiêu rađa 3D

Theo dõi mục tiêu chuyển động trong không gian ba chiều (3D) bằng rađa là một nhiệm vụ phức tạp, đòi hỏi hệ thống xử lý phải có khả năng cập nhật vị trí của mục tiêu một cách liên tục, chính xác và không có độ trễ quá lớn. Một trong những thuật toán tiêu biểu cho lọc bám mục tiêu đó là sử dụng bộ lọc Kalman. Bộ lọc Kalman là công cụ mạnh mẽ được sử dụng để ước lượng trạng thái của mục tiêu từ dữ liệu đo lường có nhiễu tác động. Nhưng hiện nay, các nghiên cứu chỉ tập trung ứng dụng bộ lọc Kalman ở trong không gian hai chiều (2D), chính vì vậy, bài báo này trình bày kết quả đánh giá hiệu quả của bộ lọc Kalman trong ước lượng độ cao và theo dõi chuyển động mục tiêu rađa 3D. Các thử nghiệm được thực hiện trên mô hình mục tiêu chuyển động có tính cơ động cao (UAV, máy bay chiến đấu,...). Các tiêu chí đánh giá bao gồm độ chính xác trong ước lượng vị trí và vận tốc, sự phức tạp trong tính toán ước lượng của bộ lọc Kalman 3D. Sau đó đưa ra phướng án khả năng áp dụng trên các máy tính xử lý cấp 2 trên các đài rađa 3D.

Từ khoá: Bộ lọc Kalman; Ước lượng độ cao; Rađa 3D; Nhiễu.