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Simulation and Performance Evaluation of Unscented Kalman Filter in the Line-of-Sight Angle Tracking Problem for Different Maneuvering Targets

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Abstract

This paper presents a simulation study and performance evaluation of the Unscented Kalman Filter (UKF) in the problem of tracking the line-of-sight (LOS) angle for maneuvering targets with different kinematic characteristics. A third-order Singer model is used to describe the target state, including rotation angle, angular velocity, and angular acceleration. The UKF algorithm handles nonlinear and time-varying measurement noise, with the specific condition that only the rotation angle is measured under Gaussian noise. Five typical target motion types are investigated: uniform straight motion, harmonic maneuver (sinusoidal), sudden maneuver, random maneuver, and mixed maneuver. The filter quality is evaluated through plots comparing true values and estimated values for each state parameter, as well as by calculating and illustrating the mean square error (MSE) over time for each parameter. Simulation results show that UKF achieves fast convergence, stable error, and high performance under flexible and complex target maneuver conditions.

Keywords: Unscented Kalman Filter, line-of-sight angle tracking, third-order Singer model, maneuvering target, nonlinear filtering, mean square error, tracking measurement system simulation, angular target tracking.

1. Introduction

In sensor-based target tracking systems, especially infrared guidance or radar systems, the problem of estimating the LOS angle plays a key role in accurately determining the relative position between the sensor and the target. However, in practice, targets often have unpredictable and time-varying maneuvers, which create significant difficulties for filtering and accurately estimating the state. Classical linear filters such as the Kalman Filter (KF) are only suitable for linear systems with linear measurements under stable Gaussian noise. In contrast, for the problem of tracking maneuvering targets with nonlinear models and measurements limited to angular coordinates, linear filters often fail to ensure high accuracy, especially when the target changes state suddenly or exhibits random behavior. The UKF is one of the effective solutions for nonlinear filtering problems, as it does not require model linearization like the Extended Kalman Filter (EKF), but instead uses the sigma point sampling technique to propagate probability distributions through nonlinear functions. This allows the UKF to achieve higher accuracy in estimating the states of nonlinear systems or systems with nonlinear measurements. In this study, the UKF is applied to track the LOS angle of a target using a third-order Singer model a widely used kinematic model to describe maneuvering motion of a target, where the angular acceleration is a Gaussian white noise process with exponential decay over time. The simulation is performed for five typical target motion types to evaluate the adaptability, accuracy, and robustness of the filter under different scenarios.

2. Summary of the Target Line-of-Sight Angle Tracking Algorithm Using the UKF

2.1. Target State Model

Consider a maneuvering target rotating around the line-of-sight axis. The target state at time t is described by the state vector:

$$x(t)=\begin{bmatrix}\theta(t)\\ \omega(t)\\ \alpha(t)\end{bmatrix} \tag{1}$$

Where: $\theta(t)$ - LOS rotation angle (deg);

$\omega(t)=\dot{\theta}(t)$ - Angular velocity (deg/s);

$\alpha(t)=\ddot{\theta}(t)$ - Angular acceleration (deg/s^2).

To describe the target maneuver behavior, the third-order Singer model is used. This is a widely used kinematic model that assumes the angular acceleration is a Gaussian white noise process with exponential decay over time. The continuous-time model is expressed as follows:

$$\dot{x}(t)=\begin{bmatrix}0 & 1 & 0\\ 0 & 0 & 1\\ 0 & 0 & -a_m(t)\end{bmatrix}\begin{bmatrix}\theta\\ \omega\\ \alpha\end{bmatrix}+\begin{bmatrix}0\\ 0\\ 1\end{bmatrix}\xi(t) \tag{2}$$

Where: $\xi(t)$ - is Gaussian white noise, with variance $\sigma_\alpha^2(t)$ (deg^2/s^4);

$a_m(t)$ - is the decay parameter of the Singer model (1/s), representing the diminishing effect of acceleration over time.

$$a_m(t)=a_0+a_1\frac{1+\sin(\omega_a t)}{2} \tag{3}$$

a_0, a_1 - are empirical coefficients;

ω_a - is the oscillation frequency.

By discretizing with sampling step T, the dynamic model is written in Euler difference form as:

$$x_k=x_{k-1}+TA_{k-1}x_{k-1}+T.G.\alpha_t(t_{k-1}) \tag{4}$$

Where:

$$A(t_{k-1}) = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -a_m(t_{k-1}) \end{bmatrix}; G = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \quad (5)$$

$A(t_{k-1})$ - is the system dynamic matrix, describing the state transition in the third-order Singer model;

G - is the angular acceleration control vector;

α_t - is the actual maneuvering acceleration of the target at time t_{k-1}.

2.2. Target Maneuver Types

The target maneuver signal $\alpha_t(t)$ can be expressed in general form for each maneuver type as follows:

- Uniform straight motion (no acceleration):

$$\alpha_t(t) = 0 \quad (6)$$

- Harmonic maneuver (sinusoidal acceleration):

$$\alpha_t(t) = A_\alpha \sin(\omega_\alpha t) \quad (7)$$

Where:

A_α - is the oscillation amplitude (deg/s²);

ω_α - is the oscillation frequency (deg/s).

- Sudden maneuver**:**

$$\alpha_t(t) = \begin{cases} 0, & t < t_0 \\ \alpha_0, & t \geq t_0 \end{cases} \quad (8)$$

t_0 - is the instant when the target starts maneuvering (s);

α_0 - is the acceleration value at the maneuver start (deg/s²).

- Random maneuver**:**

$$\alpha_t(t) = \mu_a + \sigma_a.\eta(t) \quad (9)$$

μ_a - is the mean acceleration (deg/s²);

σ_a - is the standard deviation (deg/s²);

$\eta(t) \sim N(0,1)$ - is a standard Gaussian random variable.

- Mixed maneuver**:**

$$\alpha_t(t)=\begin{cases} 0 & ,t<t_1 \\ A_1\sin(\omega_1 t) & ,t_1\le t<t_2 \\ \alpha_2 & ,t_2\le t<t_3 \\ \mu_3+\sigma_3.\eta(t) & t\ge t_3 \end{cases} \tag{10}$$

t_1, t_2, t_3 - are the switching instants between maneuver phases;

A_1, ω_1 - are the amplitude and frequency in the sinusoidal phase;

α_2 - is the constant acceleration in the third phase;

μ_3, σ_3 - are the mean and standard deviation in the random phase.

2.3. Measurement Model

Assume the sensor measures the target's LOS angle θ, the linear measurement model is:

$$z_k = h(x_k) + \upsilon_k = \theta_k + \upsilon_k \tag{11}$$

z_k - is the measured angle at time k;

$\upsilon_k \sim N(0, R_k)$ - is Gaussian white measurement noise;

R_k - is the measurement noise variance (deg^2).

2.4. UKF for the Three-State System

The UKF uses the Unscented Transform to propagate sigma points through the nonlinear function. For state dimension $n=3$, the UKF algorithm includes the following steps:

Step 1: Initialization

$$\hat{x}_0 = E[x_0], P_0 = E(x_0-\hat{x}_0)(x_0-\hat{x}_0)^T \tag{12}$$

$\hat{x}_0$ - is the initial state estimate vector;

P_0 - is the initial estimation error covariance matrix;

$E[\cdot]$ - is the expectation operator.

Step 2: Determining Unscented Transform Parameters

For n=3, the scaling parameter α_{ut}, the offset parameter κ and the adjustment parameter β are chosen to compute:

$$\lambda = \alpha_{ut}^2(n+\kappa)-n, \quad \gamma=\sqrt{n+\lambda} \tag{13}$$

Where:

α_{ut} - is typically chosen very small (10^{-3}) to ensure convergence;

β - is chosen based on prior knowledge (for Gaussian, $\beta=2$);

κ - is usually chosen as 0;

λ - is the scaling factor to generate sigma points from the covariance matrix.

γ - is also used to generate sigma points from the covariance matrix.

Step 3: Computing the Weights for the Unscented Transform

The weights for the mean and covariance are calculated as:

$$W_m^{(0)} = \frac{\lambda}{\lambda+n}, W_c^{(0)} = \frac{\lambda}{\lambda+n} + (1-\alpha_{ut}^2+\beta) \tag{14}$$

$$W_m^{(i)} = W_c^{(i)} = \frac{1}{2(n+\lambda)}, \quad i = 1,....,2n \tag{15}$$

$W_m^{(i)}$ - is the weighted mean of all sigma points after propagation through the dynamic model;

$W_c^{(i)}$ - is the covariance weight.

Step 4: Generating the Sigma Points

$$\hat{\chi}_k^{(0)} = \hat{x}_k \tag{16}$$

$$\hat{\chi}_k^{(i)} = \hat{x}_k + \gamma\sqrt{P_k}_{\,i}, i = 1,...,n \tag{17}$$

$$\hat{\chi}_k^{(i)} = \hat{x}_k - \gamma\sqrt{P_k}_{\,(i-n)}, i = n+1,...,2n \tag{18}$$

Where:

$\hat{\chi}_k^{(i)}$ - is the i^{th} sigma point at time k;

$\sqrt{P_k}$ - denotes the Cholesky factor of P_k;

$\left[\sqrt{P_k}\right]_i$ - is the i^{th} column of the matrix $\sqrt{P_k}$.

Step 5: Propagating the Sigma Points Through the Dynamic Model

For each sigma point $\hat{\chi}_k^{(i)} = \left[\theta_k^{(i)}, \omega_k^{(i)}, \alpha_k^{(i)}\right]^T$ the discrete-time Euler model is applied:

$$\hat{\chi}_{k+1|k}^{(i)} = \begin{bmatrix} \theta_k^{(i)} + T.\omega_k^{(i)} \\ \omega_k^{(i)} + T.\alpha_k^{(i)} \\ \alpha_k^{(i)} - T.a_m(t_k)\alpha_k^{(i)} + T.\alpha_{mt}(t_k) \end{bmatrix} + w_k \tag{19}$$

Where: T - is the discrete time step (s);

$a_m(t_k)$ - is the decay parameter of the Singer model at time t_k;

$\alpha_{mt}(t_k)$ - is the actual target maneuvering acceleration;

w_k □ (N, Q_k) - is Gaussian white process noise, with covariance Q_k.

Step 6: Computing the Predicted State and Covariance

$$\hat{x}_{k+1|k} = \sum_{i=0}^{2n} W_m^{(i)} \chi_{k+1|k}^{(i)} \tag{20}$$

$$P_{k+1|k} = Q_k + \sum_{i=0}^{2n} W_c^{(i)} (\chi_{k+1|k}^{(i)} - \hat{x}_{k+1|k})(\chi_{k+1|k}^{(i)} - \hat{x}_{k+1|k})^T \tag{21}$$

Where: $\hat{x}_{k+1|k}$ - is the predicted state;

$P_{k+1|k}$ - is the predicted covariance;

Q_k - is the process noise covariance matrix.

Step 7: Propagating the Predicted Sigma Points Through the Measurement Function

For each predicted sigma point $\chi_{k+1|k}^{(i)}$, compute the sigma point in the measurement space:

$$Z_{k+1|k}^{(i)} = h(\chi_{k+1|k}^{(i)}) = \theta_{k+1|k}^{(i)} \tag{22}$$

The measurement noise $\upsilon_k \sim N(0,R_k)$ is considered in the computation of measurement variance.

Step 8: Computing the Predicted Measurement and Measurement Covariance

$$\hat{z}_{k+1|k} = \sum_{i=0}^{2n} W_m^{(i)} Z_{k+1|k}^{(i)} \tag{23}$$

$$P_{zz} = R_k + \sum_{i=0}^{2n} W_c^{(i)} (Z_{k+1|k}^{(i)} - \hat{z}_{k+1|k})^2 \tag{24}$$

R_k - is the measurement noise variance.

Step 9: Computing the Cross-Covariance Matrix and Kalman Gain

The cross-covariance matrix between the state and the measurement is:

$$P_{xz} = \sum_{i=0}^{2n} W_c^{(i)} (\chi_{k+1|k}^{(i)} - \hat{x}_{k+1|k})(Z_{k+1|k}^{(i)} - \hat{z}_{k+1|k}) \tag{25}$$

Kalman gain:

$$K_{k+1} = P_{xz} P_{zz}^{-1} \tag{26}$$

Step 10: Updating the Estimate and Covariance

When the actual measurement z_{k+1}, is received, update:

$$\hat{x}_{k+1} = \hat{x}_{k+1|k} + K_{k+1}(z_{k+1} - \hat{z}_{k+1|k}) \tag{27}$$

$$P_{k+1} = P_{k+1|k} - K_{k+1} P_{zz} K_{k+1}^T \tag{28}$$

At the update step $(k+1)$:

$$\begin{aligned}
\theta_{k+1|k+1} &= \hat{\theta}_{k+1|k} + K_\theta z_{k+1} - \hat{z}_{k+1|k} \\
\omega_{k+1|k+1} &= \hat{\omega}_{k+1|k} + K_\omega z_{k+1} - \hat{z}_{k+1|k} \\
\alpha_{k+1|k+1} &= \hat{\alpha}_{k+1|k} + K_\alpha z_{k+1} - \hat{z}_{k+1|k}
\end{aligned} \tag{29}$$

$\theta_{k+1|k+1}, \omega_{k+1|k+1}, \alpha_{k+1|k+1}$ - are the updated LOS angle, angular velocity, and angular acceleration at time $(k+1)$;

$\hat{\theta}_{k+1|k}, \hat{\omega}_{k+1|k}, \hat{\alpha}_{k+1|k}$ - is the predicted state before using the measurement;

$K_\theta, K_\omega, K_\alpha$ - is the Kalman gain components corresponding to each state.

$$P_{k+1|k+1} = \begin{bmatrix} p_{\theta\theta} - K_\theta^2 P_{zz} & p_{\theta\omega} - K_\theta K_\omega P_{zz} & p_{\theta\alpha} - K_\theta K_\alpha P_{zz} \\ p_{\theta\omega} - K_\omega K_\theta P_{zz} & p_{\omega\omega} - K_\omega^2 P_{zz} & p_{\omega\alpha} - K_\omega K_\alpha P_{zz} \\ p_{\alpha\theta} - K_\alpha K_\theta P_{zz} & p_{\alpha\omega} - K_\alpha K_\omega P_{zz} & p_{\alpha\alpha} - K_\alpha^2 P_{zz} \end{bmatrix} \tag{30}$$

3. Simulation and Evaluation

The simulation is configured with the following initial parameters:

- Discrete time step: 0.01 (s);

- Simulation duration: 6 (s);

- Covariance matrix: $P_0 = diag(10^{-4}, 10^{-2}, 1)$;

- Process noise is selected according to the characteristics of Gaussian white noise in the Singer model: $Q = diag(10^{-6}, 10^{-4}, 10^{-2})$;

- Measurement noise: $R = (0.01)^2$;

- Unscented Transform parameters:

+ Scaling parameter: $\alpha_{ut} = 10^{-3}$;

+ Offset parameter: κ=0;

+ Adjustment parameter: β=2;

- Singer model parameter: $a_m = 1/20$ (1/s);

- Target maneuver models:

+ Target 1 – Uniform straight motion: $\alpha(t) = 0$;

+ Target 2 – Harmonic maneuver: $\alpha(t) = 3\sin(0.4t)$;

+ Target 3 – Sudden maneuver: $\alpha(t) = \begin{cases} 0, t < 2s \\ 4, t \ge 2s \end{cases}$;

+ Target 4 – Random maneuver: $\alpha(t) = 0.5 + 0.2\eta(t)$, $\eta(t) \sim N(0,1)$;

+ Target 5 – Mixed maneuver

$$\alpha(t)=\begin{cases} 0, & t<1s \\ 2\sin(0.6t), & 1s\le t<2.5s \\ 1.5, & 2.5s\le t<4s \\ 0.5+0.3\eta(t), & t\ge 4s \end{cases}$$

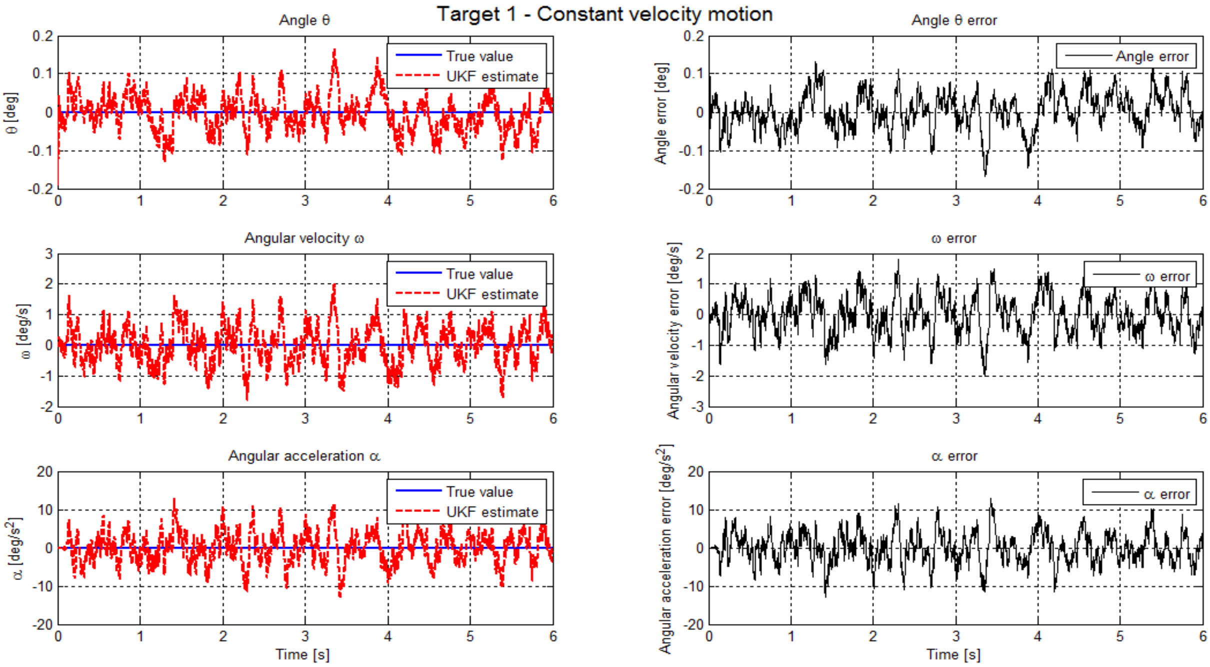

Figure 1: UKF estimation of θ, ω, α and errors for Target 1

Figure 1 shows the simulation results of the UKF in the LOS angle tracking problem, angular velocity and angular acceleration for Target 1- uniform straight motion. In the three plots on the left, the estimated values (red dashed lines) closely follow the true values (blue solid lines) for all three state variables: LOS angle θ, angular velocity ω and angular acceleration α. This demonstrates that the UKF converges quickly and remains stable from the very beginning of the simulation. The three plots on the right show the estimation errors for each state, fluctuating around zero with small amplitudes: LOS angle error within ±0.1 (deg), angular velocity error within ±2 (deg/s) and angular acceleration error within ±11 (deg/s^2). These errors are randomly distributed without noticeable drift (bias), indicating that the UKF works effectively under uniform straight motion and Gaussian measurement noise.

	

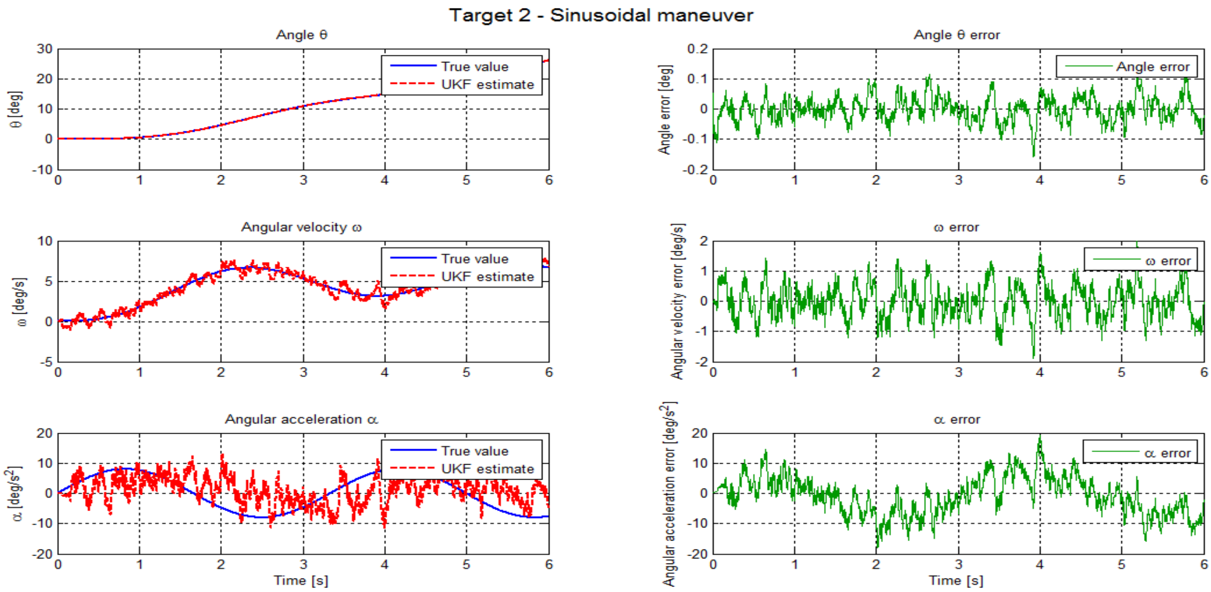

Figure 2: UKF estimation of θ, ω, α and errors for Target 2

Figure 2 shows that for a harmonic maneuvering target, the UKF closely follows the true values of θ, ω and α; errors oscillate slightly around zero (angle ±0.15 (deg), angular velocity ±2 (deg/s), angular acceleration ±19 (deg/s^2)), with no drift tendency and rapid stabilization throughout the sinusoidal motion. This demonstrates that the UKF still maintains high estimation performance under harmonic maneuvering conditions.

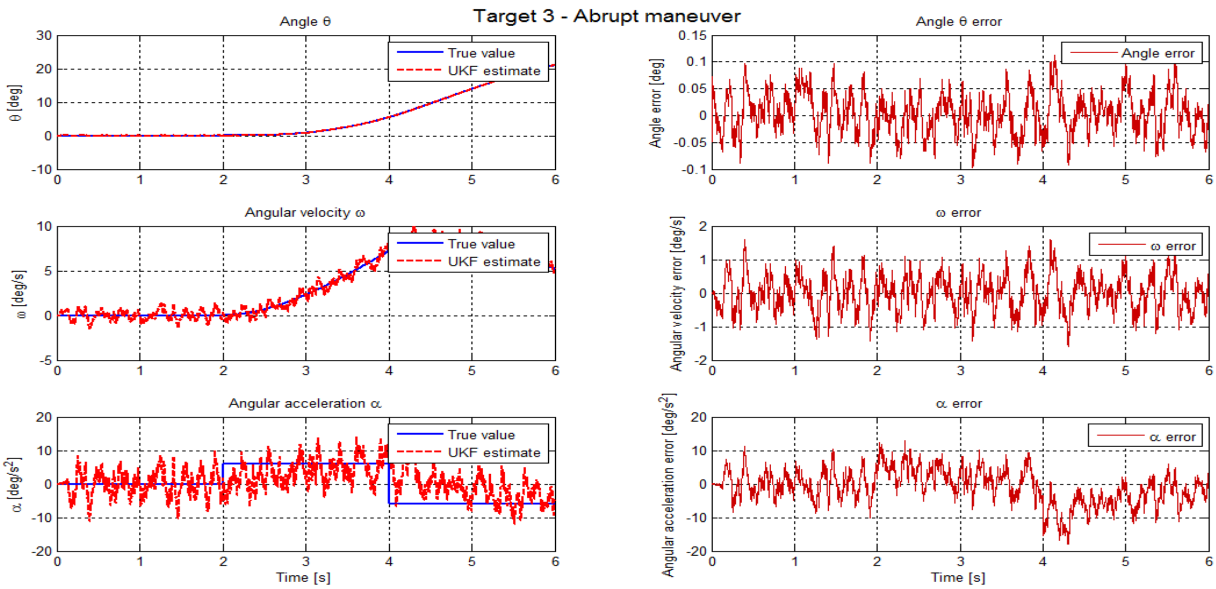

Figure 3: UKF estimation of θ, ω, α and errors for Target 3

Figure 3 shows the simulation results of the UKF for Target 3 with sudden maneuver type. When the target changes acceleration abruptly at maneuver instants, the UKF quickly adjusts, ensuring the estimated trajectory does not lag significantly behind the true value. The errors (angle ±0.11 (deg), angular velocity ±1.4 (deg/s), angular acceleration ±18 (deg/s^2)) are randomly distributed around zero with no drift, indicating that the UKF maintains high performance under sudden state change conditions.

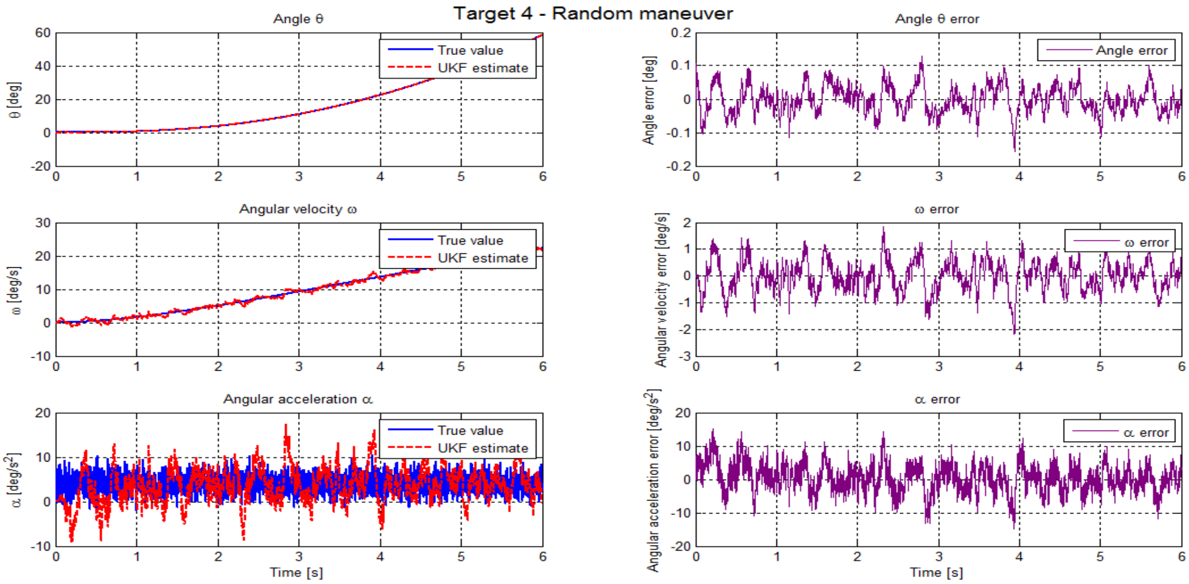

Figure 4: UKF estimation of θ, ω, α and errors for Target 4

Figure 4 illustrates the simulation results of the UKF for Target 4 – random maneuver. The three plots on the left show that the estimated values (red dashed lines) follow the true values (blue solid lines) closely for the LOS angle θ and angular velocity ω, although the angular acceleration α exhibits higher fluctuations due to the random nature of the maneuver. The three plots on the right present the estimation errors for each state: the LOS angle error remains within ±0.15 (deg), the angular velocity error within ±2 (deg/s) and the angular acceleration error within ±15 (deg/s^2).

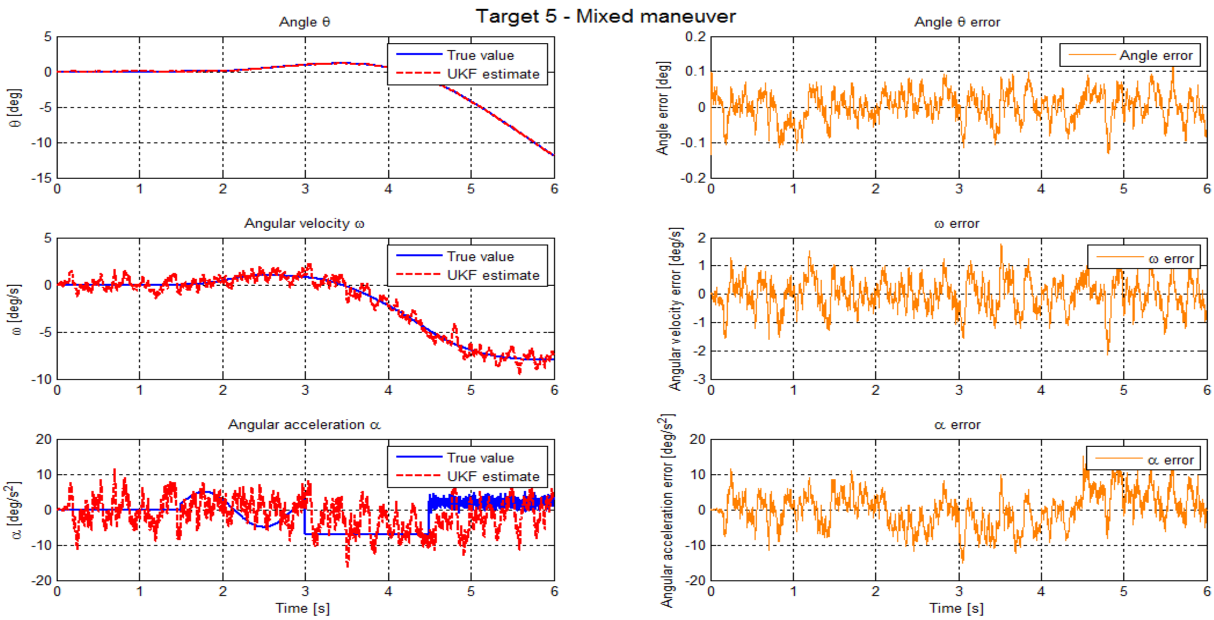

Figure 5: UKF estimation of θ, ω, α and errors for Target 5

Figure 5 shows that for the mixed maneuver target, the UKF still tracks θ, ω and α well in all four motion phases; errors oscillate slightly around zero (angle ±0.12 (deg), angular velocity ±2 (deg/s), angular acceleration ±14 (deg/s^2)) and quickly stabilize after each phase transition.

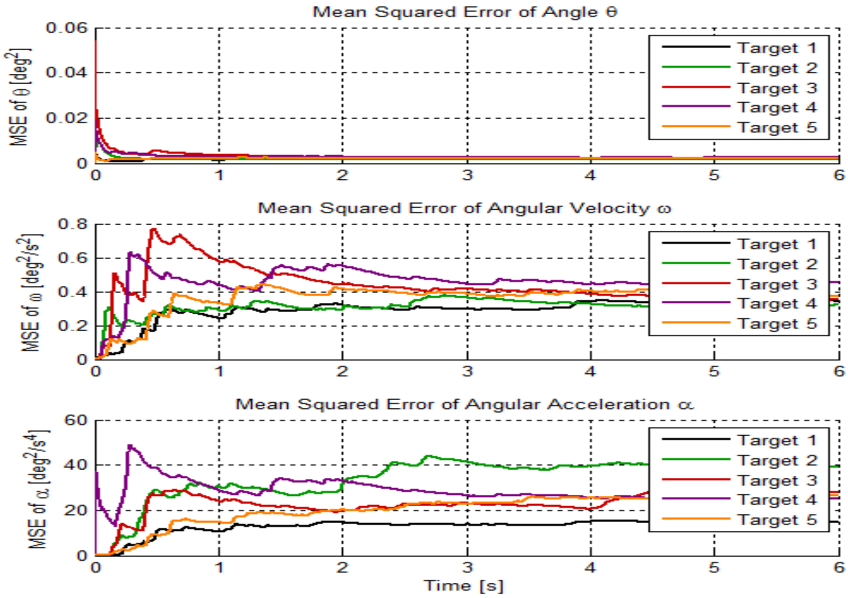

Figure 6: MSE of θ, ω, α over time

The chart shows the mean square error (MSE) of the three angular quantities: LOS angle θ, angular velocity ω and angular acceleration α over time for five different targets. Across the three charts, it can be seen that the LOS angle θ is estimated with the highest accuracy. Specifically, the MSE of θ quickly decreases to near zero within the initial period (under 1 second) and remains almost zero for the rest of the time for all targets, indicating highly effective angle estimation.

In contrast, angular velocity ω has significantly larger errors. After an initial oscillation phase (0 to about 0.5 seconds), the MSE of ω stabilizes at about 0.2–0.5 (deg^2/s^2), depending on the target. Target 1 shows the best estimation performance with the lowest error, while Targets 4 and 5 have higher errors, indicating differences in performance depending on the maneuver type. Angular acceleration α has the largest and most fluctuating errors. In the initial phase, the MSE of α spikes, particularly for Target 4 with values near 60 (deg^2/s^4). Although the curves tend to stabilize afterward, the error remains relatively high, especially for Targets 2 and 4. In summary, Target 1 has the lowest errors and highest accuracy across all three variables, while Target 4 shows the lowest performance, particularly in angular acceleration estimation.

4. Conclusion

The simulation and evaluation results show that the UKF is capable of accurately tracking and estimating LOS angle, angular velocity, and angular acceleration of maneuvering targets with diverse kinematic characteristics. The filter achieves fast convergence, stable errors, and no drift tendency in most scenarios, including cases where the target changes state abruptly or performs complex maneuvers. The LOS angle is estimated with the highest accuracy, followed by the angular velocity, while the angular acceleration is more difficult to estimate accurately due to its rapid variations. These results confirm that the UKF is an effective and reliable nonlinear filtering solution for target tracking systems based solely on angular measurements, especially in environments with Gaussian noise.

In the future, this research can be extended in several directions: integrating the UKF with multi-sensor fusion to improve accuracy and reliability in complex environments; investigating UKF variants such as the Square-Root UKF or Adaptive UKF to optimize estimation performance under non-Gaussian or correlated noise conditions; combining the UKF with advanced trajectory prediction algorithms to enhance performance for targets with strong nonlinear and unpredictable maneuvers; and testing and evaluating the proposed approach using real-world data from radar or infrared systems to verify its effectiveness in operational conditions.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship and publication of this article.

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