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PARAMETER EVALUATION OF COMPLEX MANEUVERING TARGETS USING KALMAN FITERING AND MULTI-MODEL ADAPTATION

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The object of research is the system determines the target angular coordinates on the missile's homing head. Current target coordinate determination systems employed in seekers often operate under significant limitations. When a target's actual motion deviates from the simplified, hypothetical model used to synthesize the coordinate system, a critical issue arises: the errors in evaluating both the coordinates and their derivative components rapidly and significantly increase.

Problem that was solved is to evaluate complex maneuvering target parameters. But there is no need to know the target's maneuver frequency.

This study presents a novel filtering algorithm that accurately estimates all parameters of complex maneuvering targets without prior knowledge of their maneuver frequency. The algorithm achieves a significant advantage, reducing estimation error by over 95% within the first 5 seconds. With its simple structure, high stability, and fast convergence, this robust solution is essential for modern guidance systems, greatly enhancing the effectiveness of tracking unpredictable threats.

A key strength of the proposed algorithm lies in its simple structure. Furthermore, it demonstrates high convergence rates and exceptional stability, crucial attributes for real-time applications. Its design also ensures ease of practical implementation, making it a viable solution for contemporary guidance systems.

The algorithm is built on modern control techniques, combining extended Kalman filtering with interactive multi-models. It is necessary to accurately evaluate the target's position, velocity, acceleration, and acceleration derivative without needing to know in advance the target's maneuver frequency

Keywords: guidance law, missile, homing, maneuvers, estimate

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1. Introduction

In the proportional navigation guidance (PNG) law, the missile's acceleration is proportional to the line-of-sight rotation speed, proportional to the miss and inversely proportional to the square of the time to go [1]

$$n_c = \frac{N}{t_{go}^2}\left[y + \dot{y} t_{go} \right] = N V_c \dot{\sigma}. \tag{1}$$

It is clear that the miss component in the PNG law (1) has no parameters describing the maneuverability of the target. This does not mean that the PNG law does not hit the target, but it does not mean that the guidance law is not optimal for a maneuvering target.

If the maneuverability target is a function of time, it is possible to calculate the miss precisely and generate a new guidance law model which is an augmented proportional navigation guidance law (APNG) [2]. The mathematical expression then of miss contains the target maneuver component, the target's acceleration $\ddot{y}_T$

$$n_c = \frac{N}{t_{go}^2}\left[y + \dot{y} t_{go} + \frac{1}{2}\ddot{y}_T t_{go}^2 \right] = N V_c \dot{\sigma} + \frac{1}{2} N \ddot{y}_T. \tag{2}$$

The expression (2) of the advanced proportional navigation guidance law consists of two components, one proportional to the line-of-sight rotation speed and the other proportional to the target's acceleration.

When dealing with complex maneuvering targets, if the specific form of the target's maneuverability is known, it becomes theoretically possible to construct an optimal guidance law, even when the target's maneuver is highly intricate. One of the primary approaches to enhance the ability to destroy such targets is to refine the guidance law itself. This involves incorporating additional target parameters into the guidance law's expression. These crucial parameters include target acceleration, the derivative of target acceleration, and the target's maneuvering frequency [3, 4].

Therefore, it is necessary to conduct scientific research on the topic of determining the maneuver parameters of the target without knowing in advance the maneuver frequency of the target. Because these parameters are components involved in the process of creating missile control commands.

When the target is maneuvering complexly, especially when the target's maneuvering frequency is unknown, there is no published scientific work.

The research results will realize modern missile guidance laws such as proportional navigation, augmented proportional navigation, optimal guidance. Because in the command expression, the guidance law contains a target parameter component.

2. Literature review and problem statement

The paper [5] shows that by applying Kalman filter theory, [5] has proposed a filter algorithm to evaluate the parameters of the maneuvering target. However, the evaluation was limited to the target's acceleration and did not include the derivative of the target's acceleration. The four-state linear Kalman filter works well if the target maneuver frequency is known [6]. But there were unresolved issues related to the target's maneuvering frequency. The reason for this may be objective difficulties associated with new technical solutions have not been found yet. A way to overcome these difficulties can be build a new filtering algorithm. The core purpose of this algorithm is to accurately and robustly evaluate the dynamic parameters of complex maneuvering targets. Its development is firmly rooted in the sophisticated application of the extended Kalman filter (EKF) combined with an advanced multi-model adaptation framework. This synergistic approach allows the algorithm to dynamically adjust to changing target behaviors, thereby enabling the realization of more effective and adaptive guidance laws.

However, a significant challenge arises from the limitations of current real-world equipment, which can typically only determine the position and velocity of the target. To effectively implement modern, sophisticated guidance laws that rely on a more comprehensive understanding of target dynamics, it's essential to either directly measure or accurately estimate these additional parameters. Beyond the basic parameters required by conventional proportional navigation guidance (PNG) laws, there's a critical need to evaluate parameters such as the target's acceleration, the rate of change in the target's acceleration (i. e., the derivative of the target's acceleration), and the target's maneuvering frequency.

In response to this need, previous research has explored the application of Kalman filter theory to estimate the parameters of maneuvering targets. For instance, studies by [7, 8] have proposed filtering algorithms specifically designed for this purpose. [7] shows the applications of 3-state Kalman filter. [8] shows the applications of 4-state Kalman filter. While these contributions successfully address the estimation of target acceleration, they often stop short of evaluating the derivative of target acceleration, which is vital for predicting future target behavior more accurately.

Furthermore, when the target performs complex maneuvers with a constant, albeit unknown, maneuvering frequency, the filtering problem becomes more intricate. The paper [9, 10] have advanced this problem by expanding the state space of the filter to include four states. [9] shows applications of 4-state Kalman filter. However, it is important to note that the effectiveness of a four-state linear Kalman filter is contingent upon prior knowledge of the target's maneuver frequency [11]. This expansion allows for the simultaneous estimation of both the target's acceleration and its acceleration derivative [12].

The 3-state Kalman filter application determines only the target position, velocity and acceleration [12]. The 4-state Kalman filter application determines the target's position, velocity, acceleration and acceleration derivative, but the target's maneuvering frequency must be known in advance [13]. The paper [14] used a 5-state Kalman filter, but the target's maneuver frequency still had to be known in advance.

To overcome the limitation of requiring prior knowledge of the target's maneuver frequency, an extended Kalman filter (EKF) can be developed [15]. The EKF is particularly well-suited for non-linear systems and can handle situations where certain parameters, like maneuver frequency, are unknown and need to be estimated alongside the state variables. By leveraging the EKF's ability to linearize around the current state estimate, it becomes possible to infer parameters that are not directly measured, such as the target's acceleration derivative, even without explicit knowledge of the maneuvering frequency.

Current research faces several limitations in accurately evaluating maneuvering targets. Specifically, existing Kalman filter applications ([5, 7, 8, 12]) often fail to estimate the derivative of target acceleration and frequently require prior knowledge of the target's maneuver frequency ([6, 11, 13, 14]). Furthermore, while some real-world equipment can only measure position and velocity, modern guidance laws demand a more comprehensive understanding of target dynamics, including acceleration and its derivative.

All this allows to assert that it is expedient to conduct a study on development a novel approach to accurately estimate complex maneuvering target parameters without relying on prior knowledge of the target's maneuvering frequency.

3. The aim and objectives of the study

The aim of this study is to develop a novel approach to accurately determine the dynamic parameters of a complex maneuvering target. This will allow for the realization of more effective and adaptive guidance laws, thereby enhancing the performance of missile systems in complex operational environments.

To achieve this aim, the following objectives have been accomplished:

– to apply the extended Kalman filter (EKF) and interactive multi-model (IMM) filtering to construct an algorithm that can accurately estimate complex maneuvering target parameters;

– to propose and justify a guidance system model for miss distance analysis;

– to ensure the algorithm has a simple structure, high convergence rates, exceptional stability, and high reliability for practical implementation.

4. Materials and methods

4. 1. The object and hypothesis of the study

The object of this study is the development of a new filtering algorithm capable of accurately and robustly estimating the dynamic parameters of a complex maneuvering target. These parameters include relative position, relative velocity, target acceleration, and the derivative of target acceleration.

The core hypothesis is that a sophisticated combination of the extended Kalman filter (EKF) and a multi-model adaptation framework can effectively overcome the limitations of conventional Kalman filters. This approach will allow for the accurate estimation of key target parameters, even without prior knowledge of the target's maneuver frequency.

The study is based on the following key assumptions and simplifications.

Algorithm for determining the maneuvering target parameters uses extended Kalman filter. The 5-state linear Kalman filter has the form [2, 12]

$$\begin{cases} RES_k = y_k^* - \hat{y}_{k-1}, \\ \hat{y}_k = \hat{y}_{k-1} + K_1 RES_k, \\ \hat{\dot{y}}_k = \hat{\dot{y}}_{k-1} + K_2 RES_k, \\ \hat{\ddot{y}}_{T_k} = \hat{\ddot{y}}_{T_{k-1}} + K_3 RES_k \\ \hat{\dddot{y}}_{T_k} = \hat{\dddot{y}}_{T_{k-1}} + K_4 RES_k, \\ \hat{\omega}_k = \hat{\omega}_{k-1} + K_5 RES_k. \end{cases} \quad (3)$$

In there $x = \omega \cdot T_S$, T_S is sampling time or time between measurements; ω is target's maneuver frequency, unknown. The Kalman coefficients (K_1–K_5) are obtained from solving the Ricatti equations.

The extended Kalman filter is capable of estimating parameters such as relative position, relative velocity, target acceleration, target acceleration derivative and target maneuver frequency. Therefore, the corresponding guidance laws can be used in combination with extended Kalman filter to create a missile control loop which are proportional navigation, augmented proportional navigation, optimal guidance and other modern guidance laws, but the target maneuvering frequency need not be known in advance.

The extended Kalman filter is very sensitive to the initial evaluation error. If the extended Kalman filter is not initialized with an initial estimate of the target's maneuvering frequency close to the actual target maneuver frequency, the effectiveness of the extended Kalman filter may be significantly reduced.

5. Results of development of the method of complex maneuvering target parameter determination

5. 1. A new algorithm for estimating complex maneuvering target parameters

Let's consider a filter bank with three 5-state linear Kalman filters (3). Let's suppose one of the three filters is truly accurate, i. e. accurately assumes the actual target's maneuvering frequency.

If three 5-state linear Kalman filters operate in parallel, each filter is assumed to have a different maneuvering frequency of the target. The likelihood function for each filter at time k is defined [14]:

$$f_k(1) = \frac{1}{\sqrt{2\pi C_k(1)}} e^{-0.5 RES_k^2(1)/C_k(1)}; \quad (4)$$

$$f_k(2) = \frac{1}{\sqrt{2\pi C_k(2)}} e^{-0.5 RES_k^2(2)/C_k(2)}; \quad (5)$$

$$f_k(3) = \frac{1}{\sqrt{2\pi C_k(3)}} e^{-0.5 RES_k^2(3)/C_k(3)}. \quad (6)$$

The covariance $C_k(i)$ is found from the aggregate of Ricatti equations of each filter:

$$C_k(1) = H_k M_k(1) H_k^T + R_k; \quad (7)$$

$$C_k(2) = H_k M_k(2) H_k^T + R_k; \quad (8)$$

$$C_k(3) = H_k M_k(3) H_k^T + R_k. \quad (9)$$

The balance of the filters is determined:

$$RES_k(1) = y_k^* - H_k \Phi_k(1) \hat{x}_{k-1}(1) - H_k G_k u_{k-1}; \quad (10)$$

$$RES_k(2) = y_k^* - H_k \Phi_k(2) \hat{x}_{k-1}(2) - H_k G_k u_{k-1}; \quad (11)$$

$$RES_k(3) = y_k^* - H_k \Phi_k(3) \hat{x}_{k-1}(3) - H_k G_k u_{k-1}. \quad (12)$$

The probability that each filter is correct is calculated according to Bayes' rule as follows:

$$p_k(1) = \frac{f_k(1) p_{k-1}(1)}{f_k(1) p_{k-1}(1) + f_k(2) p_{k-1}(2) + f_k(3) p_{k-1}(3)}; \quad (13)$$

$$p_k(2) = \frac{f_k(2) p_{k-1}(2)}{f_k(1) p_{k-1}(1) + f_k(2) p_{k-1}(2) + f_k(3) p_{k-1}(3)}; \quad (14)$$

$$p_k(3) = \frac{f_k(3) p_{k-1}(3)}{f_k(1) p_{k-1}(1) + f_k(2) p_{k-1}(2) + f_k(3) p_{k-1}(3)}. \quad (15)$$

At any time k then

$$p_k(1) + p_k(2) + p_k(3) = 1. \quad (16)$$

P_k (1) represents the correct probability of the first filter at time k. Assuming that at the initial time, each filter has the same probability of accuracy:

$$p_0(1) = \frac{1}{3}; \quad (17)$$

$$p_0(2) = \frac{1}{3}; \quad (18)$$

$$p_0(3) = \frac{1}{3}. \quad (19)$$

At each time, it is possible to calculate the correct probability of each filter, then take the evaluation of each filter multiplied by the correct probability of that filter, and finally get the parameter evaluation result of the filter bank as follows:

$$\hat{\omega}_k = p_k(1)\omega_1 + p_k(2)\omega_2 + p_k(3)\omega_3; \quad (20)$$

$$\hat{x}_k = p_k(1)\hat{x}_k(1) + p_k(2)\hat{x}_k(2) + p_k(3)\hat{x}_k(3). \quad (21)$$

Thus, expressions (20), (21) are algorithms for determining complex maneuvering parameters without knowing the maneuvering frequency of the target in advance.

5. 2. System model

The proposed model is shown in Fig. 1.

Guidance law [2, 3]

$$n_L = \frac{N}{t_{go}^2} \left[\begin{array}{l} y + \dot{y} t_{go} + \dfrac{1 - \cos\omega t_{go}}{\omega^2} \ddot{y}_T + \\ + \dfrac{\omega t_{go} - \sin\omega t_{go}}{\omega^3} \dddot{y}_T - n_c T^2 \left(e^{-x} + x - 1 \right) \end{array} \right], \quad (22)$$

where $x = t_{go}/T$; t_{go} – time to go; T – autopilot time constant.

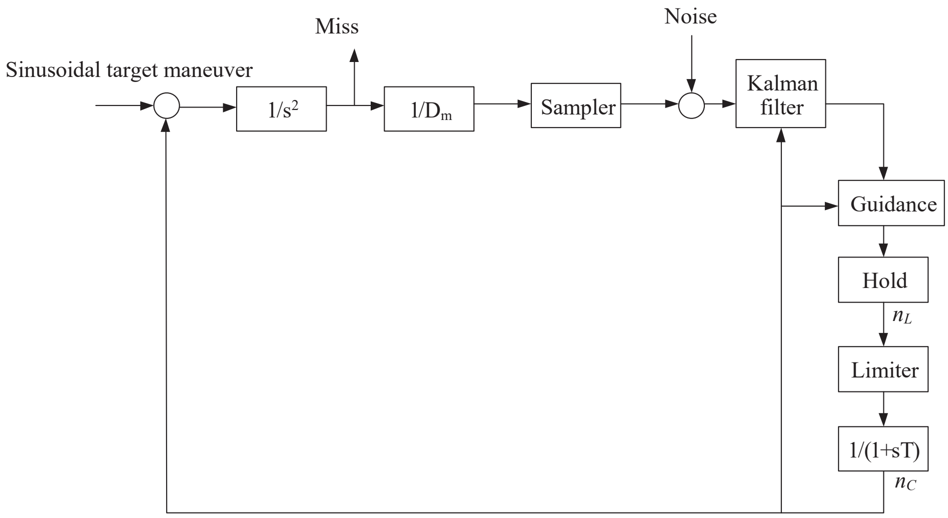

Fig. 1. Guidance system model for miss distance analysis

The scaling coefficient of the guidance law [2, 13]

$$N = \frac{6x^2\left(e^{-x} - 1 + x\right)}{2x^3 + 3 + 6x - 6x^2 - 12xe^{-x} - 3e^{-2x}}. \quad (23)$$

The algorithm for determining complex maneuvering target parameters is verified with the guidance law (23) in homing loop.

5. 3. Simulation results

Input data for modeling – system input parameter (Fig. 1) [3–5]:

– sinusoidal maneuvering amplitude of target: $n_T = 50$ (m/s^2);
– missile velocity: $V_M = 1100$ (m/s);
– measurement noise (seeker): 0.15 (mr);
– closing velocity: $V_C = 3000$ (m/s);
– autopilot time constant: $T = 0.55$ (s);
– target maneuver frequency: $\omega = 1 \div 8$ (rad/s);
– flight time: $t_F = 15$ (s);
– sampling time: $T_s = 0.001$ (s).

The extended Kalman filter accurately evaluates the target's maneuvering frequency after a period of more than 3 seconds (Fig. 2). The error is very small.

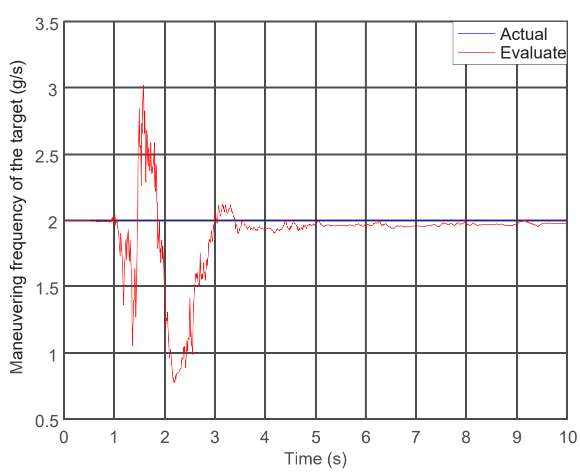

Fig. 2. Evaluation of the target's maneuvering frequency

Where the target's actual maneuvering frequency is 2 rad/s, and if the initial estimate of the target's maneuvering frequency is 1 rad/s, that is the initial estimate of the target's maneuvering frequency is equal to 1 rad/s. The extended Kalman filter can still evaluate the target's maneuvering frequency well after more than 3 seconds Fig. 3.

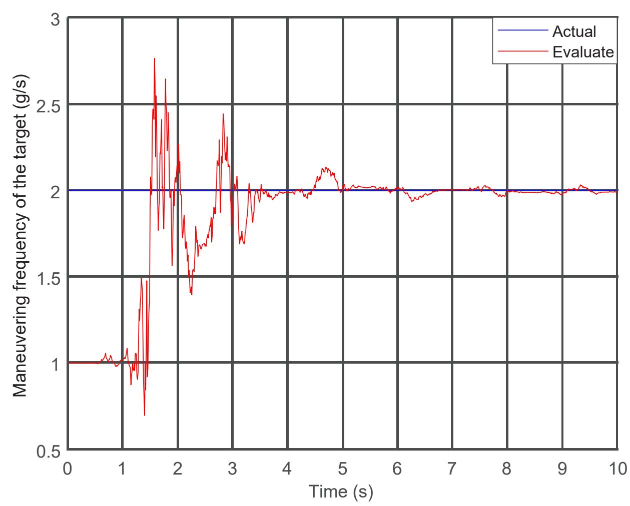

Fig. 3. Evaluation of the target's maneuvering frequency when the initial evaluation error is 1 rad/s

When the target maneuver is complex with different frequencies Fig. 4, the extended Kalman filter can still evaluate the target's maneuvering frequency well after more than 3 seconds. A filter with an initial evaluation error close to the target's maneuvering frequency has a probability of 1. When the filter has an initial evaluation error that is far different from the target's maneuvering frequency, the probability is toward zero.

When using a combination of three 5-state Kalman filters, the error in the target acceleration evaluation is very small (Fig. 5, 6) almost zero after more than 5 seconds, and the error at the initial time is negligible. This shows the high accuracy of the algorithm.

Fig. 7, 8 show respectively the target acceleration derivative and target acceleration derivative evaluation error.

Fig. 9, 10 show respectively the target maneuvering frequency when using a 5-state Kalman filter where the initial evaluated frequencies are close together and Target maneuvering frequency when using a 5-state Kalman filter where the initial evaluated frequency is far apart (6 rad/s).

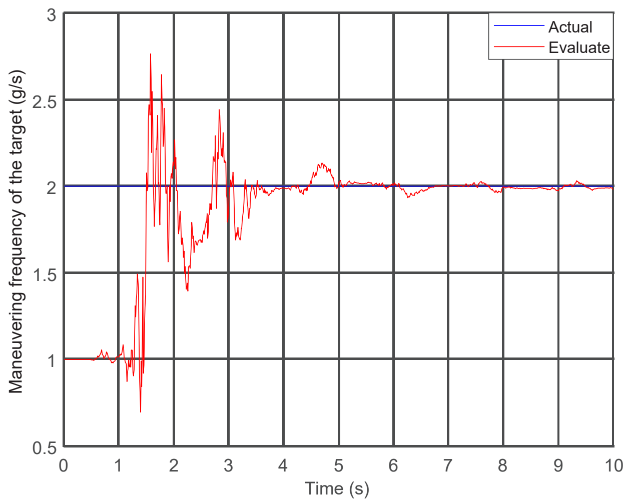

Fig. 4. Probability to evaluate the target's maneuvering frequency

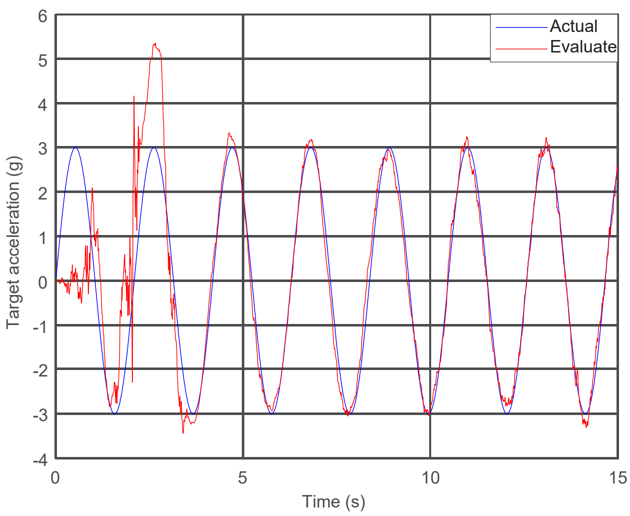

Fig. 5. Target acceleration

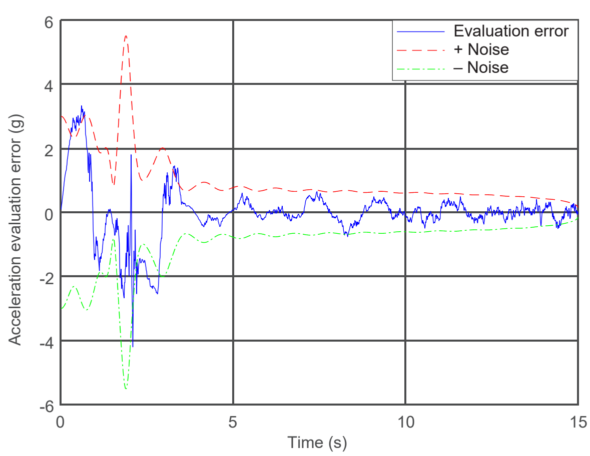

Fig. 6. Target acceleration evaluation error

The case, when using a 5-state Kalman filter, in which the target's actual maneuvering frequency and the filter's initial evaluated frequency are not close or are far apart. In Fig. 11, it is shown that if the actual maneuver frequency is 3 rad/s and the initial evaluation of the target's maneuver frequency is 8 rad/s. That is, the initial evaluation error of the target's maneuver frequency is 5 rad/s. Then the 5-state extended Kalman filter cannot evaluate the target's maneuver frequency well. The evaluation error of the maneuver frequency increases significantly, or even cannot be evaluated, and the evaluation signal divergence may appear.

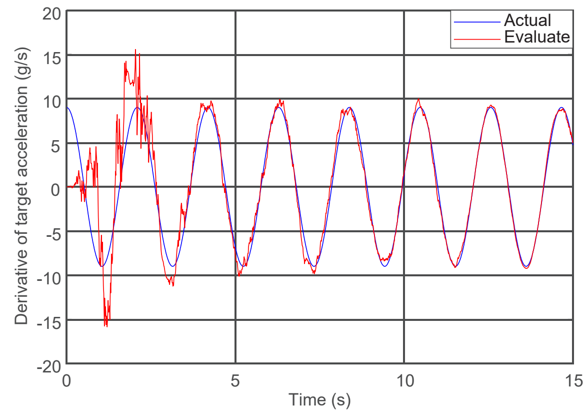

Fig. 7. Target acceleration derivative

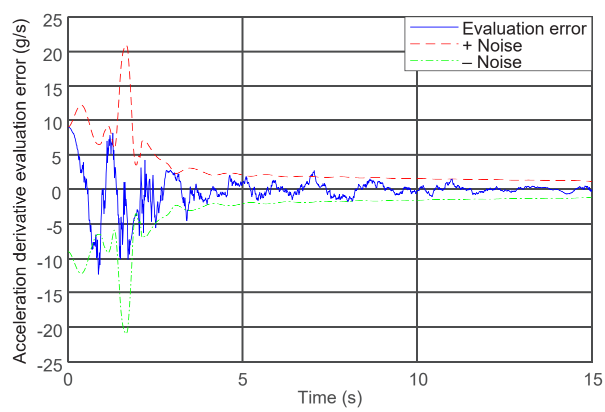

Fig. 8. Target acceleration derivative evaluation error

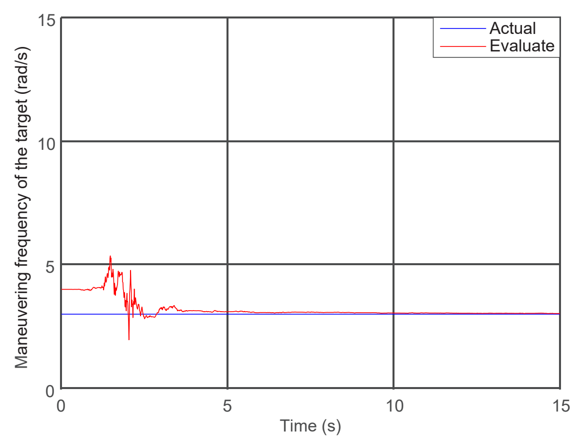

Fig. 9. Target maneuvering frequency when using a 5-state Kalman filter where the initial evaluated frequencies are close together

In the case of using three 5-state Kalman filters. Even if the initial maneuver evaluation frequency is far from the target's actual maneuver frequency, the filter still evaluates it accurately. In Fig. 10, 12, it is shown that if the actual maneuver frequency is 3 rad/s and the initial evaluate of the target's maneuver frequency is 8 rad/s, meaning here the initial evaluate error of the target's maneuver frequency is 5 rad/s. Then it takes more than 5 seconds for the multi-model adaptive filtering algorithm to completely determine with certainty which of the three filters is correct. It demonstrates an algorithm combining three 5-state Kalman filters with high convergence and sustainability when evaluating maneuvering frequencies.

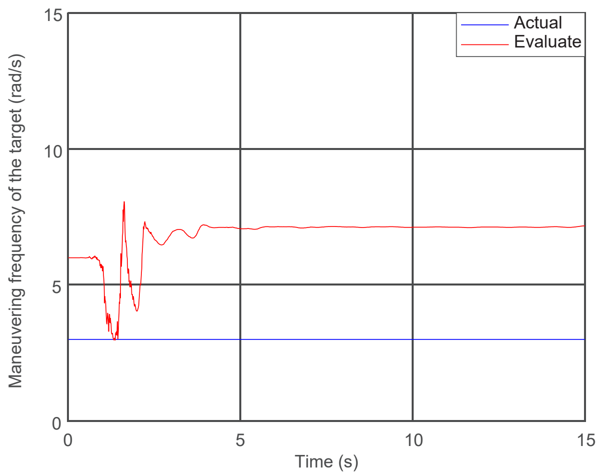

Fig. 10. Target maneuvering frequency when using a 5-state Kalman filter where the initial evaluated frequency is far apart (6 rad/s)

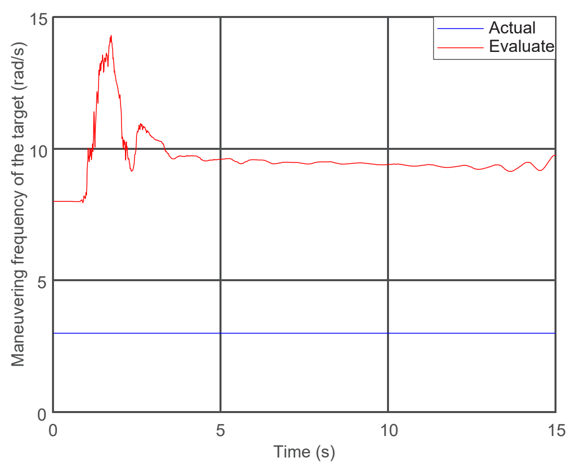

Fig. 11. Target maneuvering frequency when using a 5-state Kalman filter where the initial evaluated frequency is far apart (8 rad/s)

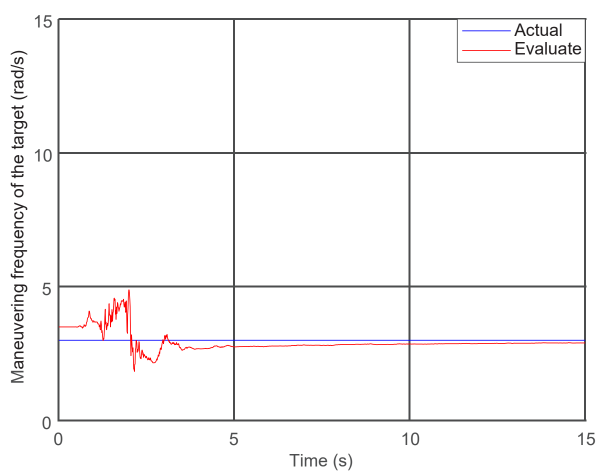

Fig. 12. Target maneuvering frequency when using three 5-state Kalman filters (3.5 rad/s)

Fig. 13, 14 show respectively the target maneuvering frequency when using three 5-state Kalman filters (4 rad/s) and probability of accurately evaluating the target maneuver frequency.

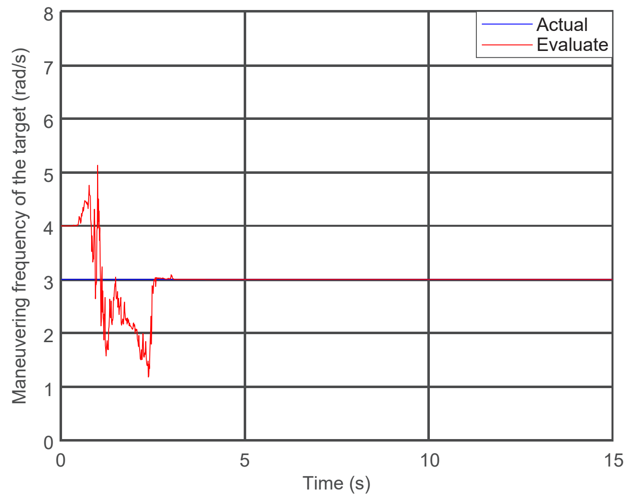

Fig. 13. Target maneuvering frequency when using three 5-state Kalman filters (4 rad/s)

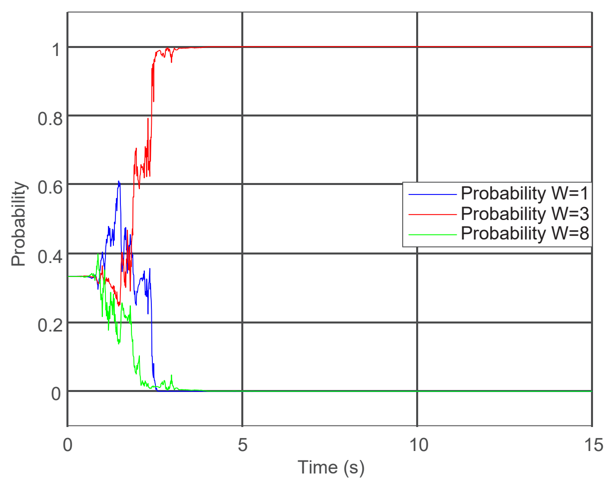

Fig. 14. Probability of accurately evaluating the target maneuver frequency

Thus, the simulation results show that the algorithm has high convergence, stability, and small errors. It can evaluate all target parameters under complex maneuvering conditions.

6. Discussion of study results of complex maneuvering target parameter determination

The simulation results confirm the high performance and reliability of the proposed algorithm, which is based on the combination of a five-state extended Kalman filter (EKF) with a multi-model adaptive filtering technique. As outlined in the algorithm from equations (4) to (21), this synergistic approach allows the filter to overcome key limitations of prior methods and accurately estimate crucial target parameters.

A major advantage of this algorithm is its ability to precisely estimate the target's maneuvering frequency without prior knowledge. As shown in Fig. 2, EKF accurately evaluates the target's maneuvering frequency within approximately 3 seconds, with the estimation error approaching zero. This performance is maintained even when the initial frequency estimate is far from the true value. For instance, Fig. 3 illustrates a scenario where the initial estimate is 1 rad/s while the actual frequency is 2 rad/s; the filter still converges and provides a correct estimate after 3 seconds. The algorithm's robustness is further demonstrated in complex maneuvering scenarios with varying frequencies (1 to 8 rad/s), as evidenced in Fig. 4.

Furthermore, the multi-model adaptive filtering technique significantly enhances the system's stability and convergence. When a single five-state EKF is used, it fails to evaluate the target's maneuver frequency if the initial estimate is significantly different from the true value (Fig. 11). This limitation is a common issue in similar studies and highlights the dependency on accurate initial conditions. Our proposed solution effectively mitigates this problem. By combining three five-state EKF models, the algorithm accurately evaluates the target's maneuvering frequency even with a large initial estimation error of 5 rad/s (Fig. 10, 12). The system identifies the most probable filter model (probability approaches 1) within 5 seconds, demonstrating high convergence and reliability.

The accuracy of the algorithm is also evident in its estimation of target acceleration and its derivative. As shown in Fig. 5, 6, the error for both parameters becomes negligible, approaching zero after just 5 seconds. This precision is a critical benefit, as the evaluation of acceleration and its derivative is essential for implementing advanced guidance laws. In contrast to previous works that often stopped short of this capability, our algorithm provides a comprehensive solution for estimating all key dynamic parameters required for modern missile control loops. Thus, the simulation re sults collectively demonstrate the algorithm's superior convergence, stability, and small errors, making it a robust and reliable tool for practical applications.

Limitation of the algorithm follows: if the initial frequency of the filter is far from the maneuvering frequency of the target, convergence will take longer and the error may be larger (Fig.12). The extended Kalman filter is very sensitive to the initial evaluation error. If the extended Kalman filter is not initialized with an initial estimate of the target's maneuvering frequency close to the actual target maneuver frequency, the effectiveness of the extended Kalman filter may be significantly reduced.

Disadvantages of this study are follows. Currently it can be applied to the law of conduction as proportional navigation, augmented proportional navigation, optimal guidance.

This study has only been verified by simulation, not by real equipment. Therefore, a crucial next step may be to validate the algorithm experimentally, which would likely present significant experimental difficulties. This would involve integrating the algorithm into actual hardware and conducting live tests, a process that requires substantial resources and careful system engineering.

7. Conclusions

1. This study successfully developed a novel filtering algorithm by combining the extended Kalman filter and an interactive multi-model (IMM) filter. This algorithm directly addresses a significant gap in existing research by accurately estimating all parameters of a complex maneuvering target without requiring prior knowledge of its maneuver frequency.

2. The proposed model allowed to implement the algorithm for determining complex maneuvering target parameters is verified with the obtained guidance law in homing loop.

3. A key achievement is the algorithm's ability to estimate the target's position, velocity, acceleration, and jerk with near-zero error. Quantitative results show that the error becomes negligible just 5 seconds into the filtering process, which is a considerable improvement over previous methods that either cannot determine all parameters or depend on pre-existing information about the target's behavior. The algorithm's performance is attributed to its simple structure, high convergence rate, and exceptional stability. These qualities not only make it practical for real-world implementation but also allow it to meet the strict requirements of modern guidance systems.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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