Journal of Zhejiang University-SCIENCE A 2026 27(5):549-554
www.jzus.zju.edu.cn; www.springer.com/journal/11582
E-mail: jzus_a@zju.edu.cn

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https://doi.org/10.1631/jzus.A2500295

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Can chess-style strategic planning revolutionize high-speed engagement?

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1 Introduction

Drawing inspiration from the triumph of artificial intelligence in complex board games, we propose a novel game-theoretic framework for optimizing decision-making in high-speed vehicle (HSV) pursuit–evasion game scenarios. The interaction between HSVs and defensive systems is reframed as a high-stakes game characterized by extreme dynamics, compressed decision windows, and partial observability; this presents computational challenges that mirror the strategic depth of board games like Go. To overcome the limitations of existing methods, we adapt the Monte Carlo tree search (MCTS) algorithm to a continuous domain. The adapted MCTS method can be applied to handle HSV-specific kinematics and interceptor constraints, resulting in a framework that implements a cycle of autonomous detection, online MCTS search, and optimal execution. Furthermore, we posit that MCTS offers distinct advantages over alternative algorithms, particularly in terms of adaptability to dynamic scenarios, real-time performance, and interpretability. Overall, this study establishes MCTS as a rational and promising methodology for advancing autonomous decision-making in high-speed adversarial engagements.

HSVs exhibit capabilities such as impressive flight speeds, wide maneuverability envelopes, and strong engagement potential. These capabilities enable unique mission profiles with valuable strategic implications, and thus HSVs have attracted substantial research attention and represented a paradigm shift in the aerospace field (Chen et al., 2024). However, evolving defensive systems are progressively challenging the advantages of HSVs. Key vulnerabilities now include detectability and trackability, systemic support constraints, and limitations on sustained maneuverability under interception threats (Ding et al., 2022). Indeed, the interactions between HSVs and defensive systems constitute a pursuit–evasion game, where the HSV strives to evade detection, interception, and destruction, while the defense system tries to detect, track, and capture the vehicle, as shown in Fig. 1. Enhancing the survivability of HSVs in such an adversarial environment has become a key research focus, as this is crucial for maintaining operational effectiveness and ensuring resilience in increasingly contested domains.

In this study, we analyze the current state of pursuit–evasion game strategies for HSVs, assessing the capabilities and constraints of existing methodologies. Building upon advancements in artificial intelligence—particularly those that have proven effective in complex board games like Go—we propose a novel decision-making framework for HSV pursuit–evasion dynamics

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Received July 6, 2025; Revision accepted Jan. 4, 2026; Crosschecked Mar. 25, 2026; Online first Apr. 16, 2026

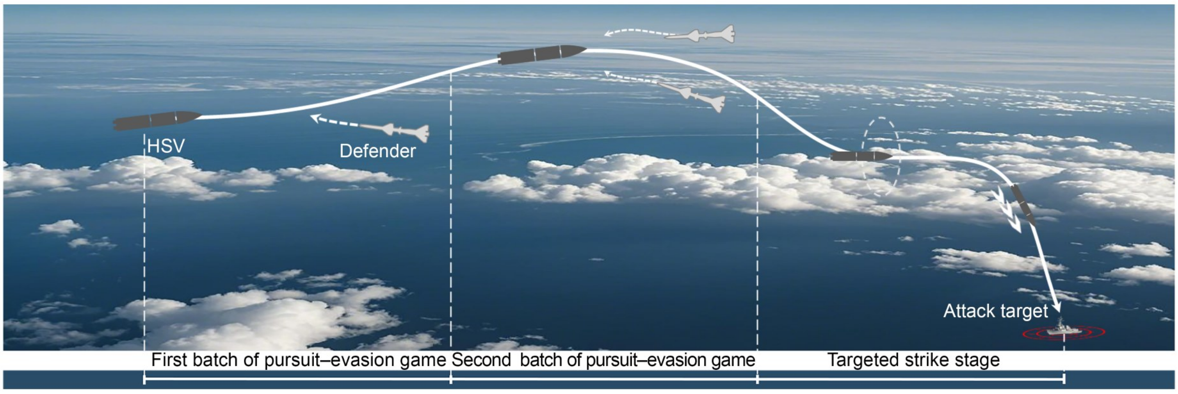

Fig. 1 Pursuit–evasion game scenario

based on MCTS. This approach represents a leap forward in addressing the core computational challenges of HSV pursuit–evasion scenarios and establishes a foundation for enhancing HSV survivability.

2 Problem analysis

Currently, there are two main solutions to the HSV pursuit–evasion problem: traditional (Gong et al., 2020; Yan et al., 2020) and intelligent methods (Hui et al., 2025; Shi et al., 2025). However, with the continuous advancement of detection and interception systems, HSVs are facing increasingly complex pursuit–evasion scenarios, such as cooperative confrontations. These existing methods have the following limitations, which can be exploited by advanced defense systems.

2.1 Traditional methods facing analytical challenges

Traditional solutions rely on mathematical modeling of the pursuit–evasion problem and the entities involved in the game. These methods consider constraints such as performance, situational factors, and energy consumption, often using optimal control theory and game theory to determine the best strategy under specific conditions. While these solutions are grounded in solid theoretical frameworks and are highly interpretable, they face inherent challenges in complex pursuit–evasion scenarios. For one, they are limited by the high-dimensional state space, which leads to significant computational demands and difficulties in deriving solutions. Furthermore, the strategic parameters and operational capabilities of interceptors remain uncertain, game environments are difficult to model accurately, and pursuit–evasion dynamics resist precise mathematical representation. These limitations severely hinder the effectiveness of traditional approaches in dynamic, high-speed, and intricately coupled game situations.

2.2 Intelligent methods encountering difficulties in interpretability

Currently, deep reinforcement learning (DRL) strategies, such as twin delayed deep deterministic policy gradient (TD3) and soft actor–critic (SAC), are the primary forms of intelligent approaches. In these processes, HSV pursuit–evasion games are formulated as Markov decision processes (MDPs). Through iterative interactions with the environment, the agent extracts key features and refines its strategy via reward-guided optimization, with the goal of maximizing the cumulative rewards to solve the pursuit–evasion problem. However, due to the “black-box” nature of deep neural networks, the agent’s decision-making process lacks transparency, and the interpretability of the strategy is limited. As game complexity increases and the state space dimension expands, designing an effective reward function becomes more challenging, and training convergence efficiency decreases. Most critically, if there is a significant mismatch between the algorithm’s training scenario and its real-world application, and the agent’s generalizability is poor, the approach may fail to generate an effective pursuit–evasion strategy.

In summary, existing methods for HSV pursuit–evasion face challenges in analytical complexity and interpretability. To ensure effective evasion and strike capabilities in such scenarios, there is a pressing need to develop innovative pursuit–evasion strategies for HSVs.

3 Analysis of requirements

Note that the future operational modes of HSVs will inevitably involve system-level confrontations. In the complex game scenario of cooperative confrontations, the interceptors' strategies are unpredictable, making it impossible to accurately model the pursuit–evasion problem. Furthermore, ensuring consistency between the algorithm's training scenario and its real-world application scenario remains challenging, which significantly limits the applicability of existing methods. Meanwhile, as the number of interceptors increases, the dimensionality of the game state space expands, necessitating robust high-dimensional information-processing capabilities. Additionally, the rapid flight and wide-area maneuvering features of HSVs introduce short-term, highly dynamic characteristics to the game, placing stringent demands on the solution's real-time performance and generalizability. Overall, solving the problem of short-term, highly dynamic HSV pursuit–evasion games in cooperative confrontation scenarios requires fulfillment at the following three levels:

1. Model level. There must be weak dependence on precise scenario modeling and robust adaptability to different scenarios. In pursuit–evasion games involving HSVs, the unpredictability of interceptors' strategies—coupled with inconsistencies across different scenarios—renders game strategies relying on precise modeling ineffective. Only solutions that are characterized by weak dependence on detailed scenario modeling and high adaptability can consistently generate robust and effective game strategies. This is vital in complex environments where interceptors' strategies and confrontation situations change rapidly, as HSVs require an accurate means to deal with pursuit–evasion challenges.

2. Computation level. The methodology must enable high-dimensional information processing with real-time performance. With game state space dimensionalities growing rapidly and HSVs exhibiting highly dynamic characteristics, computational performance faces extremely stringent requirements. Solutions to this pursuit–evasion problem need to possess potent high-dimensional information processing capabilities while ensuring superior real-time performance. Second-level or even millisecond-level parsing of situational data and generation of game strategies must be achieved in order to accurately capture key information in complex situations; in this way, HSVs will be able to make timely and accurate countermeasures and realize dominance in dynamic scenarios.

3. Application level. The approach needs to be interpretable. In practical implementations, the interpretability of strategies is imperative for technological deployment and helps facilitate system reliability and continuous optimization. When the decision-making processes of pursuit–evasion solutions lack transparency, assessing the rationality of strategies within dynamic adversarial environments becomes arduous, and it is difficult to identify potential risks and vulnerabilities; this will also hinder the optimization of strategies. A transparent decision-making process helps identify and correct biases and errors in strategies, ensuring that the system can make effective decisions in the face of complex and variable confrontation environments.

4 Proposed strategy

The recent success of artificial intelligence (AI) in mastering games like Go—which is renowned for its profound strategic depth and long-term decision-making requirements (Silver et al., 2016, 2018)—provides a compelling paradigm for complex adversarial interactions. This success stems from AI's ability to efficiently navigate vast state spaces, evaluate long-term consequences of actions, and dynamically adapt strategies in uncertain conditions. Algorithms like MCTS often underpin these capabilities, offering a structured framework for decision-making in intractably large search spaces.

MCTS is an intelligent algorithm that combines Monte Carlo random sampling with tree-search-based structured decision-making. It involves four main steps: selection, expansion, simulation, and backpropagation (Cao et al., 2025), as illustrated in Fig. 2. This process incrementally builds and refines a probabilistic understanding of optimal actions, making it well suited for games like Go where the number of combinations precludes exhaustive search. The core relevance of MCTS to HSV pursuit–evasion lies in its ability to handle high-dimensional, partially observable, and dynamic adversarial scenarios through guided simulation and learning.

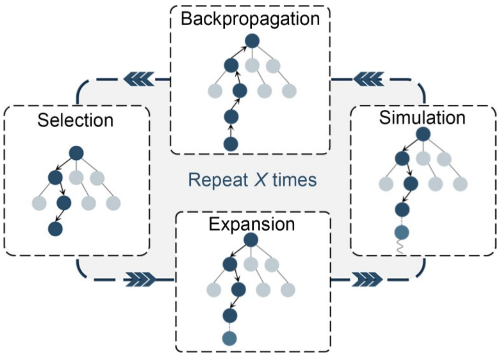

Fig. 2 Process of the MCTS algorithm

Beyond board games, MCTS has demonstrated significant potential in various other domains, often sharing key characteristics of sequential decision-making, adversarial dynamics, and complex environments. Example applications include dynamic path planning for unmanned aerial vehicles (UAVs) (Rivière et al., 2024; Yu et al., 2025) and unmanned ground vehicles (Świechowski et al., 2023), as well as air combat decision-making. Notably, recent studies have further expanded MCTS to multi-UAV cooperative task assignment (Xu et al., 2023; Song et al., 2024) and three-dimensional (3D) collision avoidance (Jiang et al., 2022). However, its application to HSV pursuit–evasion games remains unexplored. While exhibiting similar adversarial dynamics to piloted air combat, the HSV domain presents distinct characteristics: the interceptor (pursuer) typically operates under known guidance laws, resulting in a more constrained and predictable action space compared to a manned fighter jet. This predictability reduces the inherent stochasticity required for simulations, potentially lowering computational demands and enhancing the suitability of MCTS for this task.

Nevertheless, the environment of HSV pursuit–evasion games is unique, with its own specific and stringent requirements. To effectively apply the MCTS algorithm in this domain, the algorithm needs to be adapted to enhance its environmental perception and decision-making capabilities. Technically, such adaptation could be realized through approaches like progressive action space expansion or kernel regression-based approximation, thereby circumventing the combinatorial explosion caused by static discretization and efficiently handling continuous action spaces. Furthermore, physics-informed heuristics, exemplified by metrics like the zero effort miss (ZEM), can potentially serve as heuristics for optimizing search convergence. Crucially, making the algorithm more lightweight and leveraging hardware-level parallel acceleration are indispensable for adapting to limited on-board computing resources, thus ensuring it can meet the demands of the second-level game window. Looking forward, integrating deep neural networks into the MCTS framework (similar to AlphaGo Zero) could further enhance decision efficiency by replacing the computationally expensive simulation phase with learned value approximations.

The execution process and anticipated effects of an MCTS-based evasion strategy are depicted in Fig. 3. Upon detection of an incoming interceptor by detection equipment, the first step is to determine the engagement starting point. Using this point as a reference, an online search for the optimal evasion trajectory is initiated using the MCTS algorithm. When the HSV reaches the engagement starting point, it executes evasive maneuvers according to the trajectory retrieved from the online search, thereby establishing an evasion strategy framework defined by a cycle of

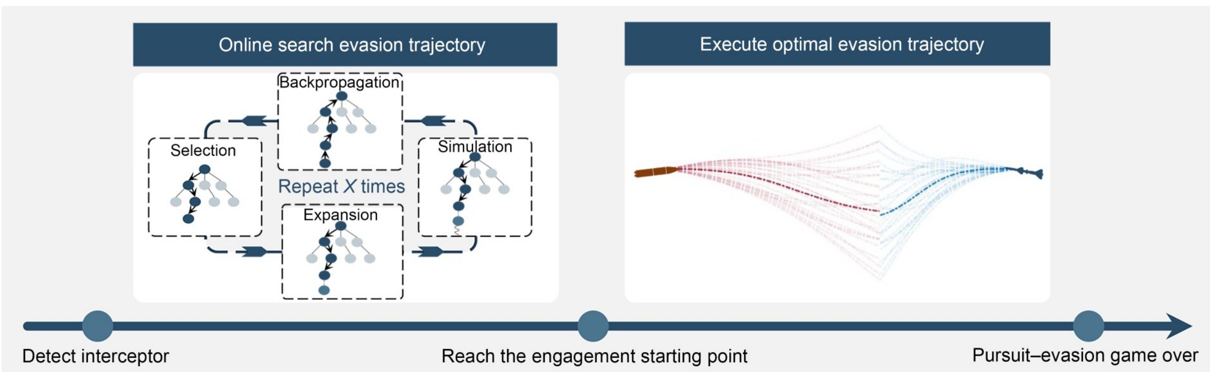

Fig. 3 MCTS-based HSV evasion strategy process

autonomous detection, online search, and optimal execution.

Fundamentally, the MCTS algorithm, with its strong adaptability, interpretability, and real-time performance, offers substantial application value for an evasion strategy framework. Its ability to efficiently optimize decision-making in dynamic environments makes it a promising solution to the challenges of complex high-speed pursuit–evasion games. This is primarily reflected in the following two aspects:

1. Adaptability to dynamic scenarios. MCTS excels in scenarios where precise, real-time modeling of an adversary or environment is infeasible. Instead of requiring an exact model, it approximates optimal actions through stochastic simulations of possible future states. This is directly analogous to its success in Go, where perfect foresight is impossible. In the context of HSVs, even with predictable interceptor guidance, inevitable uncertainties in sensor data, positioning, and potential counter-countermeasures necessitate a probabilistic approach. The MCTS algorithm can rapidly explore vast trajectory spaces through simulations, dynamically updating its strategy based on reward feedback (e.g., survivability probability, weighted threat levels, and miss distance), thus providing robust decision support in the face of uncertainties.

2. Real-time decision-making and interpretability. Unlike opaque “black-box” methods like DRL, MCTS is inherently interpretable. Its tree structure and explicit cycle of selection, expansion, simulation, and backpropagation provide a transparent decision trail. Metrics like node visit counts and accumulated rewards offer quantifiable justifications for the chosen actions. This transparency is crucial for validation, trust, and debugging in safety-critical HSV applications. Moreover, the algorithm’s structure is inherently suited for parallelization. By leveraging parallel computing, the computational throughput necessary to meet the stringent real-time demands (sub-second decision cycles) of HSV evasion becomes achievable; thus, MCTS offers an ideal balance between solution quality and calculation speed.

5 Conclusions

As the complexity of high-speed pursuit–evasion game scenarios increases, current solution methods are becoming less effective. Based on an analysis of the characteristics of short-term, highly dynamic game processes, an ideal solution method should possess capabilities such as minimal dependence on the game situation, efficient processing of high-dimensional information, online real-time decision-making, and the generation of interpretable and generalizable strategies. The MCTS game framework proposed in this study effectively addresses these technical requirements. It provides a novel pathway for improving the engagement effectiveness and strategic deterrence capabilities of HSVs, establishing an intelligent, interpretable, and generalizable decision-making paradigm for dynamic pursuit–evasion game scenarios. This approach is expected to offer both theoretical and practical support in the field of HSV adversarial engagement.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (No. 62303380), the Hunan Provincial Natural Science Foundation of China (No. 2025JJ60072), the Open Research Subject of State Key Laboratory of Intelligent Game (No. ZBKF-24-01), the Postdoctoral Fellowship Program of CPSF (No. GZB20240989), and the China Postdoctoral Science Foundation (No. 2024M754304).

Author contributions

Can LIU and Shuangxi LIU wrote the first draft of the manuscript. Wei ZHAO and Tao YANG helped organize the manuscript. Tian YAN and Wei HUANG revised and edited the final version.

Conflict of interest

Can LIU, Wei ZHAO, Tao YANG, Tian YAN, Wei HUANG, and Shuangxi LIU declare that they have no conflict of interest.

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