A Survey of Pursuit-Evasion Games, Distributed Control, Differential Games, Multi-Agent Systems, Cooperative Control, and Game Theory

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Abstract

This survey paper provides a comprehensive examination of interconnected fields, including pursuit-evasion games, distributed control, differential games, multi-agent systems, cooperative control, and game theory. These areas collectively explore strategic interactions among agents with competing objectives, employing mathematical models to optimize actions over time. The paper highlights the significance of pursuit-evasion games in modeling adversarial interactions across various domains, from military operations to autonomous vehicle control, and their application in real-world scenarios, such as network security and robotics. The interconnectedness of these fields is underscored by the integration of game-theoretic principles into distributed control frameworks, enabling effective coordination among agents. The survey systematically explores the theoretical foundations, strategies, and recent advancements in algorithms and methods, emphasizing their practical implications in robotics, aerospace, energy management, and public policy. Key challenges, such as computational complexity and communication constraints, are addressed through innovative solutions, enhancing the robustness and efficiency of multi-agent systems. The paper concludes with a discussion on future directions and emerging trends, highlighting potential advancements in strategic decision-making and resource optimization in complex environments.

1 Introduction

1.1 Significance of Pursuit-Evasion Games

Pursuit-evasion games are vital across diverse fields, particularly in mathematics and engineering, due to their strategic complexity and wide-ranging applicability. They effectively model adversarial interactions, such as military operations, where pursuers and evaders engage in strategic decision-making to optimize outcomes under competitive conditions [1]. The stochastic nature of these interactions requires robust strategies, especially in scenarios characterized by incomplete information, commonly found in military contexts [1].

In autonomous vehicles, pursuit-evasion games serve as a framework for addressing challenges such as longitudinal velocity control, emphasizing the behavioral differences between autonomous and human-driven vehicles [2]. This distinction is crucial for developing strategies that ensure safety and efficiency in mixed traffic environments.

The significance of pursuit-evasion games also extends to social dynamics, where they model complex interactions within evolving systems. Understanding the evolutionary nature of these games is essential for predicting behaviors in social contexts, necessitating dynamic models that adapt to changing environments [3].

In artificial intelligence and graph theory, pursuit-evasion games, exemplified by the Cops and Robber game, illustrate their applicability in network security and algorithmic problem-solving [4]. The

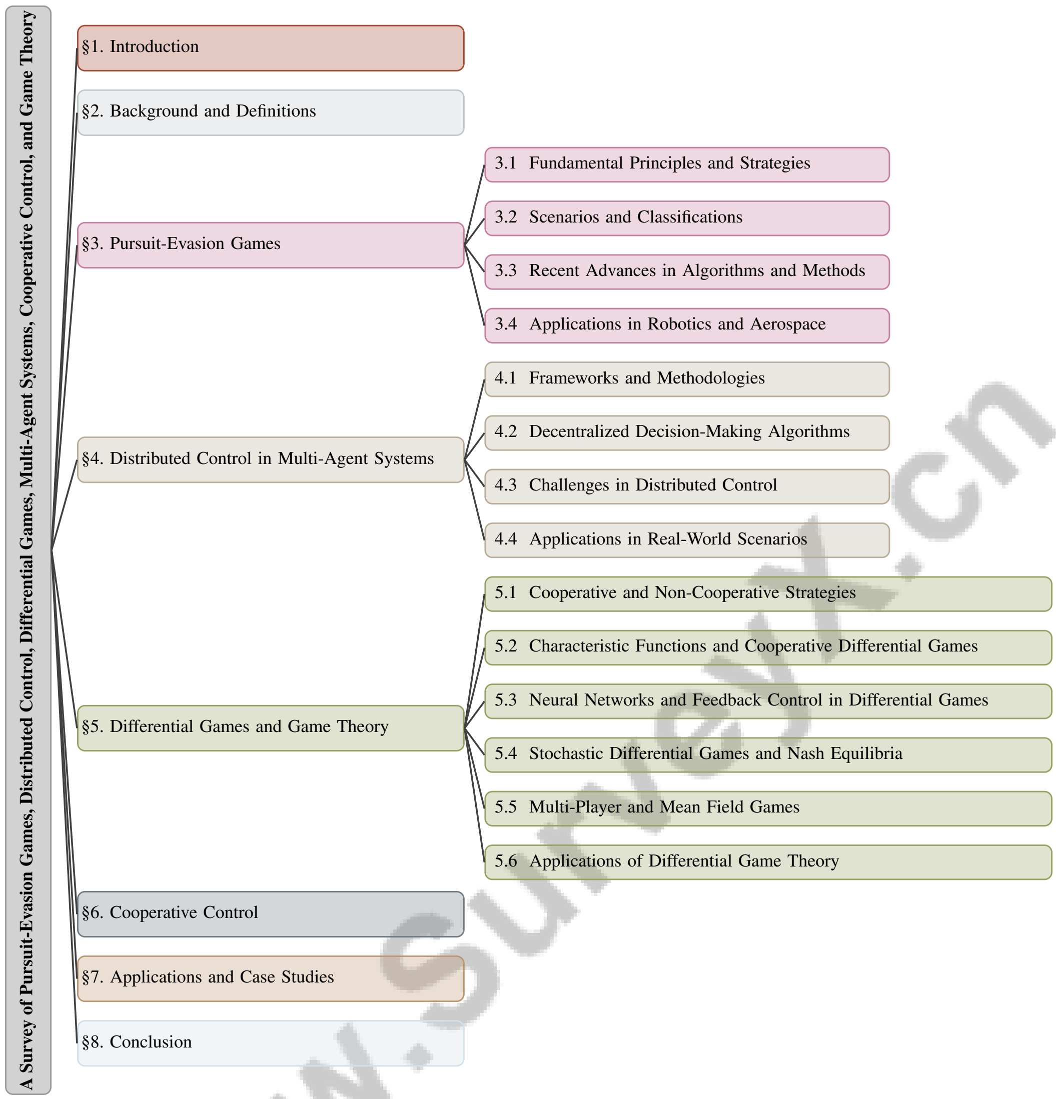


Figure 1: chapter structure

strategic depth is further highlighted in scenarios requiring bounded rationality, where traditional assumptions of perfect rationality are often computationally prohibitive [5].

Moreover, pursuit-evasion games are crucial for addressing dynamic environments and periodic constraints prevalent in many real-world applications [6]. They provide a foundational framework for complex strategic interactions, offering insights applicable to various challenges, from robotics to network theory, thus underscoring their importance in advancing both theoretical and practical aspects of strategic decision-making [7].

1.2 Interconnectedness of Fields

The interconnectedness of pursuit-evasion games, distributed control, differential games, multi-agent systems, cooperative control, and game theory forms a cohesive framework for optimizing strategic interactions across various domains. Pursuit-evasion games are intrinsically linked to differential games, especially when players operate under incomplete information, necessitating advanced strategies to manage uncertainties [1]. This connection is exemplified by mean field game frameworks, which bridge microscopic differential games with macroscopic models, such as those used in autonomous vehicle traffic flow [2].

The role of cooperative differential game theory in enhancing physical human-robot interaction (pHRI) applications underscores the synergy between cooperative control and pursuit-evasion games, highlighting their shared principles and methodologies [8]. This synergy extends to multi-agent systems, where collaborative coalitions are essential for controlling large-scale systems, emphasizing the importance of inter-agent collaboration to improve overall system performance [9].

Integrating game-theoretic principles into distributed control frameworks is critical for coordinating multi-agent systems, enabling agents to achieve common objectives through cooperative and competitive interactions [3]. This integration is also evident in applying pursuit-evasion strategies to complex network security problems, modeled by the Cops and Robber game, which leverages graph theory to analyze strategic interactions [4].

Furthermore, the application of pursuit-evasion games in three-dimensional environments highlights the limitations of traditional two-dimensional methods, necessitating innovative approaches incorporating differential game theory [7]. These interconnected fields advance theoretical understanding and enhance practical applications, demonstrating their profound relevance in addressing complex challenges across various sectors.

1.3 Structure of the Survey

This survey is systematically organized to comprehensively explore pursuit-evasion games and their interconnected fields, including distributed control, differential games, multi-agent systems, cooperative control, and game theory. The paper begins with an **Introduction** section, emphasizing the significance and interrelatedness of these fields, setting the stage for a detailed examination of their theoretical and practical implications.

In **Section 2**, titled **Background and Definitions**, we delve into foundational concepts and terminologies, providing a clear understanding of the mathematical models and frameworks that underpin these areas, establishing a common ground for subsequent discussions.

Section 3 focuses on **Pursuit-Evasion Games**, exploring fundamental principles, strategies, scenarios, and recent advancements in algorithms and methods. This section also highlights practical applications in fields such as robotics and aerospace, demonstrating the real-world relevance of these games.

The role of **Distributed Control in Multi-Agent Systems** is examined in **Section 4**, discussing frameworks, methodologies, decentralized decision-making algorithms, and challenges in implementing distributed control. This section provides real-world examples, illustrating the practical impact of distributed control strategies.

In **Section 5**, we turn to **Differential Games and Game Theory**, discussing both cooperative and non-cooperative strategies, characteristic functions, neural networks, feedback control, stochastic differential games, and Nash equilibria. This section also covers multi-player and mean field games, concluding with applications of differential game theory across various domains.

Section 6 analyzes **Cooperative Control**, focusing on strategies for enabling cooperation among agents and identifying challenges and solutions in this area. This section emphasizes the importance of cooperation in achieving common goals within multi-agent systems.

The survey culminates in **Section 7**, which presents **Applications and Case Studies** that illustrate successful implementations of game-theoretic models across diverse sectors. These examples encompass security and defense applications, such as police pursuit coordination and cybersecurity strategies; energy and environmental management initiatives; economic and financial systems analysis; and healthcare decision-making frameworks utilizing epidemic models. By showcasing these applications, the section highlights the practical significance and versatility of game theory in addressing complex real-world challenges [10, 11, 12, 13, 14].

In **Section 8**, the **Conclusion** synthesizes the principal findings presented throughout the paper, offering insights into the current landscape of research in pursuit-evasion games and their applications. This section highlights significant advancements in understanding multi-agent interactions across various environments and discusses potential future research avenues that could further illuminate the complexities of these games, delivering a thorough overview of the field's evolution and emerging trends that may shape its trajectory [15, 16, 17].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Conceptual Framework and Definitions

Pursuit-evasion games, a dynamic games subset, explore strategic interactions where pursuers aim for capture and evaders seek evasion, often modeled with differential equations to depict agents' dynamics, especially in urban graph-based environments [13]. Decomposition techniques address computational challenges in high-dimensional spaces [18], while strategies for incomplete information are essential for effective outcomes [19].

In multi-agent systems, distributed control involves decentralized coordination, allowing agents to function on local data, thus reducing centralized control's computational load [20]. An example is the connected quadrangle virtual tube passing problem, where agents navigate constrained spaces without collisions [20].

Differential games extend these principles to continuous-time systems, often in zero-sum contexts, such as in Wasserstein spaces, where random initial conditions influence the state process [21]. This framework facilitates analyzing adversarial interactions in abstract spaces [11].

Multi-agent systems, composed of interacting agents, require coordination and cooperation to achieve collective objectives in complex settings [22]. Cooperative control aligns individual and collective goals through local decision rules [23]. The containment control problem for second-order multi-agent systems guides follower agents to the convex hull formed by dynamic leaders under directed graphs [24].

Game theory provides a mathematical basis for analyzing strategic interactions among rational decision-makers, covering models like zero-sum and non-zero-sum games, where payoffs depend on all players' strategies. In pursuit-evasion and differential games, these principles are crucial for understanding complex strategic behaviors [25]. Integrating game theory with reinforcement learning enables advanced methodologies for decentralized optimal strategies, addressing challenges like the curse of dimensionality [26].

Mean field games approximate collective agent behavior in complex multi-agent systems, aiding the analysis of large-scale interactions [2]. Cooperative differential game theory exemplifies applications in physical Human-Robot Interaction (pHRI) [8]. Differential and stochastic games are pivotal in modeling epidemic spread and control within human-in-the-loop systems [10].

Aggregative games, where each agent's payoff is influenced by its strategy and the overall population behavior, illustrate these concepts' complexity and applicability in dynamic environments [6]. The Cops and Robber game's parameterized analysis, which involves computing a graph's cop number to ensure a robber's capture, highlights pursuit-evasion strategies' strategic depth in network security [4].

2.2 Mathematical Models and Frameworks

Mathematical models and frameworks underpinning pursuit-evasion games, distributed control, differential games, multi-agent systems, cooperative control, and game theory are crucial for understanding strategic interactions. Zero-sum differential games (ZSDGs) provide a robust foundation for modeling adversarial decision-making, employing differential equations to encapsulate strategic interactions in dynamic environments. The objective functional incorporates the state process distribution and a stochastic target variable, reflecting decision-making complexities in scenarios like epidemic control, financial trading, or network security [27, 28, 17, 12, 29].

In distributed control, the coordination of dynamical multi-agent systems is vital, particularly in multi-vehicle systems [24]. This decentralized approach allows agents to optimize performance based on local information and interactions. The containment control problem, for example, focuses on guiding follower agents to a region defined by leaders, crucial for coordinated movement in multi-agent systems [24].

The mean field games framework simplifies large-scale agent interactions, beneficial for modeling scenarios like autonomous vehicle traffic flow, enabling optimal strategy derivation in complex interactions [2]. Cooperative differential game theory extends this framework, facilitating shared reference tracking and cooperation among agents through mathematical models that align individual actions with collective goals [8].

Stochastic control approaches are pivotal in addressing uncertainties in these systems. Constrained stochastic differential games, modeled by Markov regime-switching jump-diffusion processes, emphasize innovative methods to enhance existing solutions, particularly in environments with regime changes and stochastic perturbations [30]. Integrating stochastic game frameworks with differential games models pursuit-evasion scenarios under incomplete information, necessitating robust strategies [1].

In pursuit-evasion contexts, differential game frameworks model agent interactions in varying dimensions, such as a faster pursuer in three-dimensional space and a slower evader in two-dimensional space, underscoring dimensional considerations' importance in developing effective pursuit strategies [7].

The Cops and Robber game's parameterized analysis highlights strategic interaction challenges, particularly due to the W[2]-hardness of the problem when parameterized by the cop number, limiting existing methods' effectiveness [4]. This underscores the necessity for innovative mathematical tools and frameworks to tackle complex strategic challenges across various domains.

3 Pursuit-Evasion Games

The strategic interactions in pursuit-evasion games are shaped by principles and methodologies that dictate the behaviors of pursuers and evaders. Understanding these elements is crucial for analyzing game dynamics and crafting effective strategies. Table 1 offers a comprehensive comparison of different methods employed in pursuit-evasion games, emphasizing strategic focus, algorithm types, and application areas. Figure 2 illustrates the hierarchical structure of pursuit-evasion games, detailing fundamental principles and strategies, diverse scenarios and classifications, recent algorithmic advances, and applications in robotics and aerospace. Each category is broken down into specific subcategories, highlighting the complexity and strategic depth of pursuit-evasion interactions. The following subsection explores these fundamental principles and strategies defining pursuit-evasion games, offering further insights into the interactions between competing agents.

3.1 Fundamental Principles and Strategies

Pursuit-evasion games involve complex interactions where pursuers aim to capture targets, and evaders seek to avoid capture. These games find applications in missile guidance, UAVs, and robotics, where cooperative control is vital. Advanced strategies, such as formation tactics for pursuers and escape maneuvers for evaders, are informed by mathematical frameworks and simulations [25, 31]. The challenge of partial monitoring, where pursuers rely on intermittent sensor communication while evaders continuously sense pursuers, adds complexity to strategic formulation.

In multi-agent settings, complexity increases with multiple pursuers and evaders, necessitating both continuous control strategies and discrete assignment decisions to ensure capture before evaders reach boundaries [32]. This complexity is magnified in three-dimensional spaces, requiring matching-based strategies to optimize capture [33]. Isochrones facilitate real-time strategy adjustments in high-dimensional state spaces [7].

Adaptive strategies are key in uncertain environments, underscoring the importance of adaptive game theory in pursuit-evasion scenarios [34]. Bounded rationality simplifies decision-making, allowing agents to make effective decisions without the computational burden of perfect rationality [5].

Fictitious play convergence in finite-agent stochastic differential games provides a framework for achieving Nash equilibrium, enhancing strategic depth and adaptability [35]. Deep fictitious play expands this by iteratively adjusting strategies based on observations [36].

Environmental factors like winds or sea currents pose additional challenges, requiring optimal strategies that consider these dynamics. Collaborative adaptation of pursuers is crucial for successful

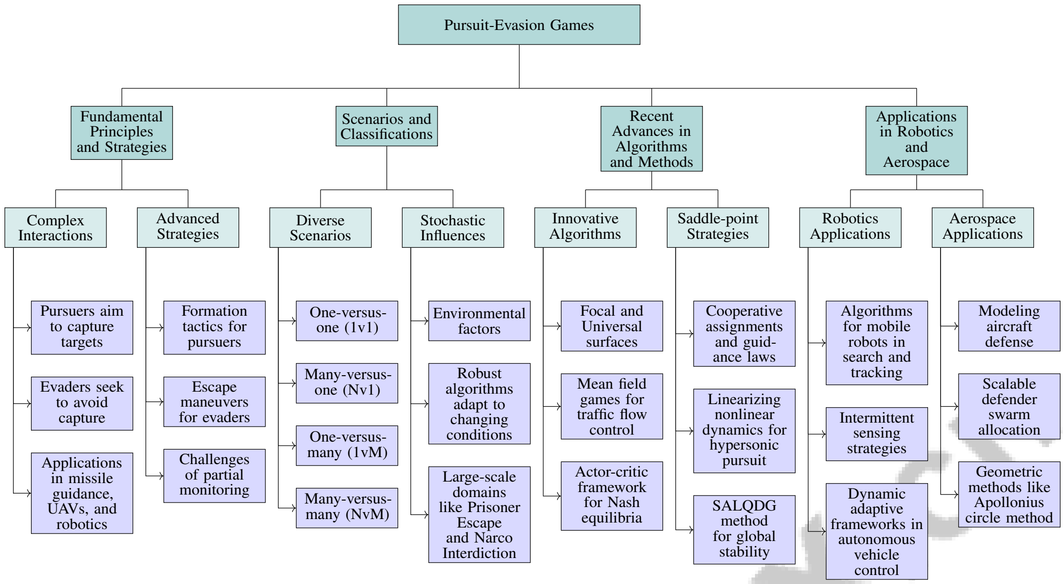


Figure 2: This figure illustrates the hierarchical structure of pursuit-evasion games, detailing fundamental principles and strategies, diverse scenarios and classifications, recent algorithmic advances, and applications in robotics and aerospace. Each category is broken down into specific subcategories, highlighting the complexity and strategic depth of pursuit-evasion interactions.

capture [15]. The vertex cover number in the Cops and Robber game illustrates strategic depth in network security contexts [4].

As illustrated in Figure 3, pursuit-evasion games are dynamic interactions characterized by strategic principles such as bounded rationality, adaptive strategies, stochastic modeling, and advanced differential game techniques. This figure highlights advanced strategies, challenges and solutions, and theoretical frameworks that underpin the strategic depth and adaptability in these dynamic interactions. Such games, involving agents with varying rationality, require sophisticated algorithms like Markov Decision Processes and cognitive hierarchy theory for optimal strategies. Advances in differential game theory have enabled multi-agent conflict analysis, fostering cooperative strategies and optimal guidance laws in high-dimensional scenarios [5, 37].

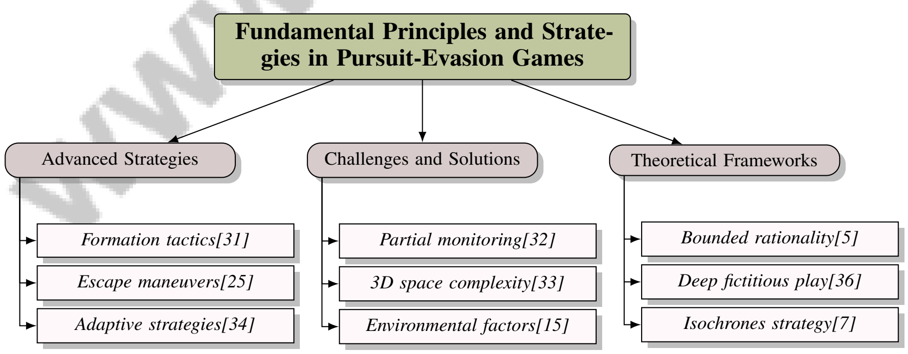


Figure 3: This figure illustrates the fundamental principles and strategies in pursuit-evasion games, highlighting advanced strategies, challenges and solutions, and theoretical frameworks that underpin the strategic depth and adaptability in these dynamic interactions.

3.2 Scenarios and Classifications

Pursuit-evasion games cover diverse scenarios, each with unique challenges requiring tailored approaches. These scenarios are classified based on the number of pursuers and evaders, such as one-versus-one (1v1), many-versus-one (Nv1), one-versus-many (1vM), and many-versus-many

(NvM) games [38]. In 1v1 scenarios, strategies focus on direct interactions, predicting and countering moves. Nv1 and 1vM settings demand coordination and role distribution among agents.

NvM scenarios, with multiple pursuers and evaders, require sophisticated algorithms for optimal outcomes. The ILQR-inspired algorithm uses successive linear-quadratic approximations to solve multi-player games, emphasizing iterative refinement [39].

Stochastic influences, like environmental factors, add complexity. The competing sailing boats problem exemplifies strategies for stochastic elements [40]. Robust algorithms adapt to changing conditions, ensuring effective strategies despite uncertainties.

Large-scale domains like Prisoner Escape and Narco Interdiction illustrate challenges in avoiding detection from heterogeneous pursuit teams [41]. Hierarchical motion planning and diffusion reinforcement learning address computational challenges in large state spaces [42]. The iGame Algorithm approximates continuous games by asynchronously updating state values [43].

Reach-avoid differential games compute initial states ensuring safety over time [44]. This is crucial for scenarios prioritizing safety and capture avoidance.

Classifying pursuit-evasion scenarios into strategic frameworks elucidates specific challenges and requirements. Advanced algorithms and stochastic considerations provide a comprehensive platform for exploring strategic depth and complexity [22].

3.3 Recent Advances in Algorithms and Methods

Recent advancements in pursuit-evasion games have introduced innovative algorithms and methodologies, enhancing strategic depth and computational efficiency. As illustrated in Figure 4, these developments can be categorized into three main areas: innovative algorithms, strategic interactions, and computational techniques. The figure highlights key advancements such as focal surfaces, mean field games, and actor-critic frameworks, which collectively enrich the understanding of game dynamics, particularly when the observing agent is faster than the differential drive robot [45].

Mean field games applied to traffic flow control model AVs' anticipatory behaviors and their impact compared to HVs [2]. This framework simulates large-scale interactions and derives optimal control strategies.

A novel actor-critic framework for Nash equilibria in multi-agent investment games under jump-diffusion models improves accuracy and efficiency [23]. This demonstrates reinforcement learning integration with game-theoretic principles for optimized decision-making.

Saddle-point strategies in multi-agent scenarios leverage cooperative assignments and guidance laws for enhanced strategic interactions [37]. This highlights collaboration's role in achieving optimal outcomes.

In hypersonic pursuit, linearizing nonlinear dynamics around a reference trajectory enables efficient auxiliary differential games formulation [46]. This facilitates robust, computationally feasible feedback strategies.

The SALQDG method introduces adaptive strategies ensuring global stability and Nash equilibrium convergence under unknown parameters [34]. This emphasizes adaptability and robustness in uncertain conditions.

Value-hardening and epigraphical techniques handle discontinuities in value functions, improving accuracy and reliability in strategic settings [47].

Lagrangian techniques integrated with stochastic differential games find optimal strategies under constraints, managing uncertainties in pursuit-evasion games [30]. This enhances deriving optimal solutions in constrained environments.

The evasion space method and maximum bipartite matching problem with conflict graph facilitate a polynomial-time approximation algorithm for three-dimensional capture strategies [33]. This innovation addresses computational challenges in high-dimensional scenarios.

Level-k thinking allows agents to respond iteratively to strategies without computing Nash equilibria, highlighting algorithmic advances [5]. Experiments using various graph structures validate these methodologies [35].

Recent advancements in pursuit-evasion games enhance algorithmic efficiency, particularly through pre-trained strategies and reinforcement learning integration. These improvements enable effective coordination of police units in urban environments and expand strategic capabilities for pursuers and evaders. This progress addresses challenges like minimizing casualties during pursuits and optimizing evasion strategies in high-dimensional settings [5, 31, 48, 13].

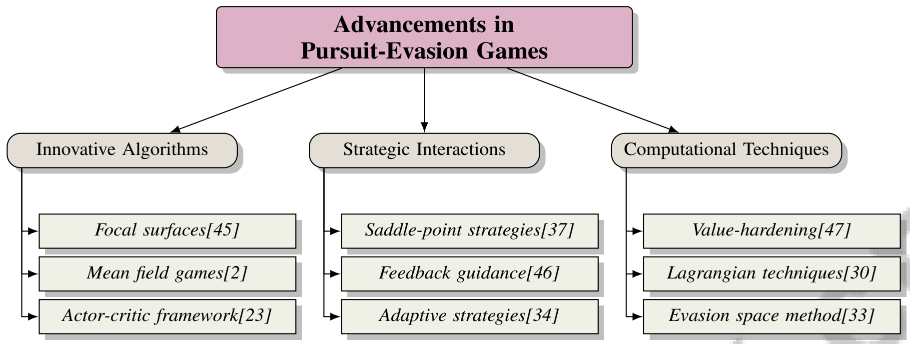


Figure 4: This figure illustrates recent advancements in pursuit-evasion games, categorizing them into innovative algorithms, strategic interactions, and computational techniques. It highlights key developments such as focal surfaces, mean field games, actor-critic frameworks, and various strategies that enhance strategic depth and computational efficiency.

3.4 Applications in Robotics and Aerospace

Pursuit-evasion games are crucial in robotics and aerospace, providing strategic frameworks for decision-making and coordination. In robotics, these games develop algorithms for mobile robots in search and tracking applications, where visibility and strategic positioning are vital [49]. Intermittent sensing strategies enhance pursuers' performance, enabling effective capture with limited sensing capabilities [50].

In aerospace, pursuit-evasion games model complex interactions like aircraft defense and secure transportation. Optimal sensing and control strategies, especially in asymmetric scenarios, improve minimizing players' performance, critical in pursuit-evasion applications [51]. Barriers in reach-avoid differential games exemplify strategic depth in aerospace applications, such as multiple pursuers versus a single evader [52].

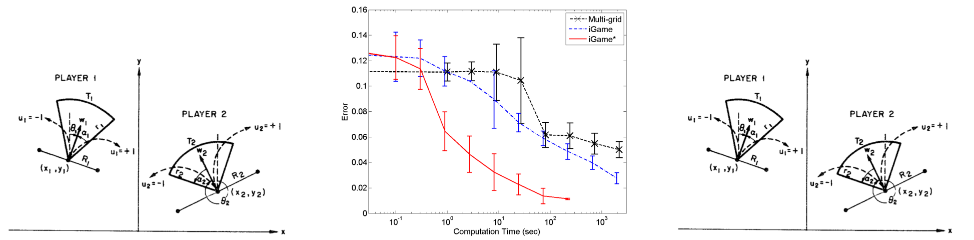
Dynamic adaptive frameworks in autonomous vehicle control improve accuracy and efficiency, highlighting pursuit-evasion strategies' potential in aerospace systems [53]. Feedback strategies in hypersonic pursuit allow offline optimal trajectory computation, adaptable online to evasive actions, underscoring adaptability's importance in hypersonic guidance [46].

Scalable defender swarm allocation against intruder swarms in simulations showcases pursuit-evasion strategies' effectiveness in managing complex multi-agent interactions [14]. The Apollonius circle method ensures capture within a defined region, demonstrating geometric methods' applicability in aerospace [54].

Matching-based capture strategies have potential applications in robotic competitions and dynamic collision avoidance, emphasizing pursuit-evasion strategies' versatility [33]. The reachability-based method computes reachable sets for multiple agents, allowing efficient scenario analysis in decentralized settings [15]. Experiments using various graph classes validate methods' applicability in network security contexts [4].

Pursuit-evasion games offer a comprehensive framework for analyzing and optimizing strategic interactions in robotics and aerospace. By employing differential game theory, these games synthesize intelligent strategies considering adversaries' potential actions, enhancing autonomous systems' effectiveness and precision. Recent advancements have classified scenarios into categories, providing unique methodologies and insights. This framework aids in innovative solutions for surveillance and navigation, promoting cooperation among agents to counter adversarial threats [55, 37, 31, 38].

As shown in Figure 5, pursuit-evasion games, a fascinating area of study in game theory, have significant applications in robotics and aerospace, as illustrated by the examples provided. These



(a) Two-dimensional game of chance[38]

(b) The image shows a graph comparing the error of three different methods over a range of computation times.[43]

(c) Two Players in a Two-Dimensional Space[55]

Figure 5: Examples of Applications in Robotics and Aerospace

games typically involve two players, a pursuer and an evader, each with specific strategies to either catch or escape the other. The first example, "Two-dimensional game of chance," showcases a scenario where two players are strategically positioned in a two-dimensional space, highlighting the spatial dynamics and decision-making involved in pursuit-evasion interactions. The second example presents a graph that compares the error rates of three computational methods—Multi-grid, iGame, and iGame*—over various computation times, emphasizing the importance of efficient algorithmic approaches in real-time applications. Lastly, the "Two Players in a Two-Dimensional Space" example further explores the geometric aspects of pursuit-evasion games, with players represented as triangular regions, illustrating the complexity of movement and strategy in a confined space. Together, these examples underscore the critical role of pursuit-evasion games in advancing technologies in robotics and aerospace, where autonomous systems must navigate complex environments and make split-second decisions [38, 43, 55].

Feature	Fundamental Principles and Strategies	Scenarios and Classifications	Recent Advances in Algorithms and Methods
Strategic Focus	Adaptive Strategies	Coordination	Computational Efficiency
Algorithm Type	Game Theory	Ilqr-inspired	Actor-critic
Application Area	Robotics	Large-scale Domains	Traffic Flow

Table 1: This table provides a comparative analysis of various methods used in pursuit-evasion games, focusing on strategic focus, algorithm types, and application areas. It highlights the fundamental principles and strategies, scenarios and classifications, and recent advances in algorithms and methods, illustrating the diversity and complexity inherent in these games.

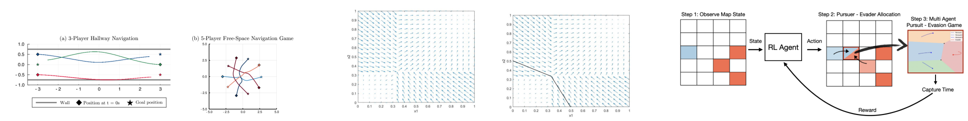
4 Distributed Control in Multi-Agent Systems

4.1 Frameworks and Methodologies

Distributed control in multi-agent systems optimizes large-scale management by coordinating agents through decentralized protocols, especially when centralized control is infeasible due to computational and communication limitations. Bounded rationality frameworks utilize finite-state Markov Decision Processes (MDPs) to facilitate efficient decision-making in complex pursuit-evasion scenarios [5]. Differential game theory enhances system performance by modeling dynamic interactions in real-time, identifying singular surfaces, and optimal control regions [25]. Approximating stochastic differential game value functions with convex positive-homogeneous functions further strengthens these models [56].

Inverse linear-quadratic non-zero-sum differential games demonstrate the flexibility of distributed control methodologies, adapting strategies based on environmental variations to improve resilience [57]. Addressing the containment control problem in second-order multi-agent systems, which accounts for irregular communication delays and intermittent information exchange, extends algorithm applicability [24]. Distributed algorithms using subgradient and projection techniques effectively solve convex feasibility problems, underscoring mathematical optimization's role in distributed settings [58].

Sophisticated modeling techniques for three-dimensional pursuit-evasion scenarios yield applicable strategies for real-world problems [7]. These methodologies emphasize adaptability and precision in managing dynamic, uncertain environments. The integration of theoretical insights, computational techniques, and adaptive strategies enhances multi-agent systems' efficiency and adaptability, crucial for improving predictive accuracy in scenarios demanding precise coordination and decision-making [53].



(a) 3-Player Hallway Navigation and 5-Player Free-Space Navigation Game[59]

(b) Phase portrait of a system with two variables[60]

(c) Multi-Agent Pursuit-Evasion Game with RL Agent[14]

Figure 6: Examples of Frameworks and Methodologies

As illustrated in Figure 6, distributed control frameworks and methodologies are depicted through scenarios showcasing multi-agent interactions and control frameworks. These examples highlight spatial coordination, system behavior, and reinforcement learning applications, emphasizing strategic deployment and decision-making capabilities in controlled environments [59, 60, 14].

4.2 Decentralized Decision-Making Algorithms

Decentralized decision-making algorithms optimize multi-agent system interactions, allowing agents to make autonomous decisions based on local information, crucial in environments where centralized control is impractical. Characterizing equilibria in collaborative decision-making is challenging, as actions are no longer unilateral [9]. Fixed-point policy-iteration-type algorithms refine payoff estimates and strategies by leveraging game symmetry to enhance convergence [61].

In leader-based coordination scenarios, solving coupled Hamilton-Jacobi equations remains complex due to multi-agent system intricacies [62]. Distributed control algorithms managing follower movements toward leaders' convex hulls demonstrate effectiveness despite communication disruptions [24]. Subgradient and projection operations in distributed algorithms address nonlinearity, complicating consensus processes and solution convergence [58].

The receding horizon control framework allows agents to base decisions on local predictions while considering overall system impacts, enhancing real-time adaptability [6]. Decentralized decision-making algorithms, characterized by adaptability, robustness, and optimization capabilities, significantly improve coordination and performance in multi-agent systems through collaborative decision-making [63, 9, 13, 58].

4.3 Challenges in Distributed Control

Distributed control in multi-agent systems faces challenges due to inherent complexity and decentralization. A primary challenge is computational complexity in optimizing control strategies as agent numbers increase, hindering real-time applications [37]. Communication constraints, including delays and losses, complicate coordination, as many methods assume ideal scenarios not reflecting practical environments [24].

Cyber-physical attacks threaten system resilience, necessitating mechanisms to identify and isolate compromised agents [64]. Nonlocal controls in equilibrium strategies add complexity, as traditional algorithms often fall short in continuous action scenarios [65]. Promising solutions include visibility optimization in surveillance-evasion games, reducing computational overhead [66], and potential iLQR approaches offering scalable solutions for trajectory planning [67].

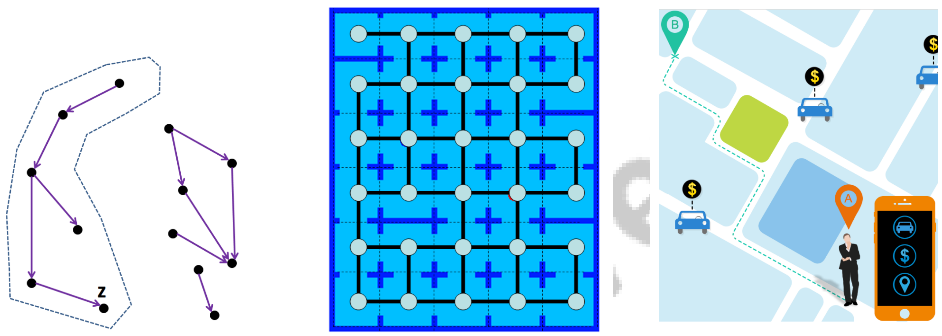
Decomposing control inputs into linear and nonlinear components proves effective, enabling robust convergence to solution sets of convex feasibility problems [58]. Despite significant challenges, recent innovations in resilient learning-based control protocols, game-theoretic approaches, and decentralized architectures offer promising foundations for overcoming obstacles, improving resilience, and operational efficiency in complex environments [68, 69, 70, 64, 71].

4.4 Applications in Real-World Scenarios

Distributed control systems are pivotal in various real-world applications due to their decentralized nature and ability to manage complex interactions efficiently. In smart grids, distributed control optimizes energy generation and distribution, enhancing efficiency and reliability [64]. In robotics, distributed control coordinates multi-agent systems, particularly in leader-follower dynamics, demonstrating resilience to communication delays [62, 24].

Beyond energy and robotics, distributed control frameworks apply to security and surveillance operations, enhancing robustness in power systems and sensor networks [72, 64]. In urban drainage systems, distributed control optimizes water flow and mitigates flooding risks, leveraging multi-agent systems and game-theoretical strategies for efficient infrastructure utilization [71, 20]. This application highlights distributed control's importance in responding to environmental challenges.

Distributed control systems enhance performance and resilience across various applications, from energy management and robotics to security and environmental control. Advances in game theory and multi-agent systems are set to enhance operational capabilities, facilitating broader adoption and greater impact in complex scenarios [73, 36, 33, 13, 14].



(a) Graphical Representation of a Network[43]

(b) Grid with Circles and Crosses[49]

(c) Navigation and Transportation: A Mobile App for Car Sharing[74]

Figure 7: Examples of Applications in Real-World Scenarios

As shown in Figure 7, real-world applications of distributed control in multi-agent systems illustrate practical implementations of theoretical concepts. The examples highlight network connectivity, spatial organization, and practical applications in daily life, showcasing distributed control's versatility and significance across various domains [43, 49, 74].

5 Differential Games and Game Theory

Strategic interactions in differential games are pivotal for understanding agent dynamics. This section delves into cooperative and non-cooperative strategies, revealing complexities in strategic decision-making within dynamic environments. By contrasting these strategies, we explore the nuances of agent collaboration and individual optimization.

5.1 Cooperative and Non-Cooperative Strategies

Cooperative strategies in differential games enhance agent collaboration, leveraging collective information to optimize performance, especially in stochastic environments [5]. In mean field games, cooperative strategies necessitate optimal control due to numerous agents with conflicting objectives [7]. Non-cooperative strategies prioritize individual payoffs, crucial in zero-sum contexts where gains and losses are directly opposed [57]. The complexity of these strategies is heightened in scenarios with incomplete information, such as limited knowledge of attackers' speeds [75]. Hybrid games integrate both strategy types, employing Isaacs' method for optimal control transitions [76]. Understanding these strategies is essential for optimizing interactions in dynamic settings, with the concept of uniform value being critical in pursuit-evasion games [5].

AI-generated, for reference only.

5.2 Characteristic Functions and Cooperative Differential Games

Characteristic functions are vital in cooperative differential games, assessing coalition benefits and equitable payoff distribution [77]. These functions facilitate reward allocation and enhance cooperative strategies, particularly in Nash equilibria contexts. The integration of deep learning with fictitious play has advanced large-scale game handling, emphasizing the role of characteristic functions in complex interactions [78]. Theoretical frameworks incorporate u-stability and v-stability concepts, extending stability notions to mean field games [79]. These stability properties are crucial for understanding dynamics in large agent populations. In large population games, the propagation of chaos aids in deriving moment and concentration bounds, supporting Nash equilibrium convergence [80]. Characteristic functions systematically assess player contributions, enhancing understanding of cooperation dynamics in applications like pollution control and multi-player pursuit-evasion scenarios [17, 29, 81, 25, 82].

5.3 Neural Networks and Feedback Control in Differential Games

Neural networks and feedback control significantly optimize strategies in differential games. Deep neural networks enhance Nash equilibrium computation, as seen in Deep Fictitious Play, which generalizes decoupling processes and converges to true Nash equilibria [36]. Feedback control allows real-time strategy adjustments, crucial in dynamic environments. Feedback-Nash equilibrium strategies ensure optimal actions amidst changing conditions [65, 83]. In scenarios with incomplete information, deceptive strategies introduce new interaction dimensions [75]. The ILQNG framework illustrates feedback control integration with neural networks, aligning observed behaviors with theoretical predictions [57]. This integration enhances convergence results for optimal control values, even with state constraints and nonlinear dynamics [84, 85].

5.4 Stochastic Differential Games and Nash Equilibria

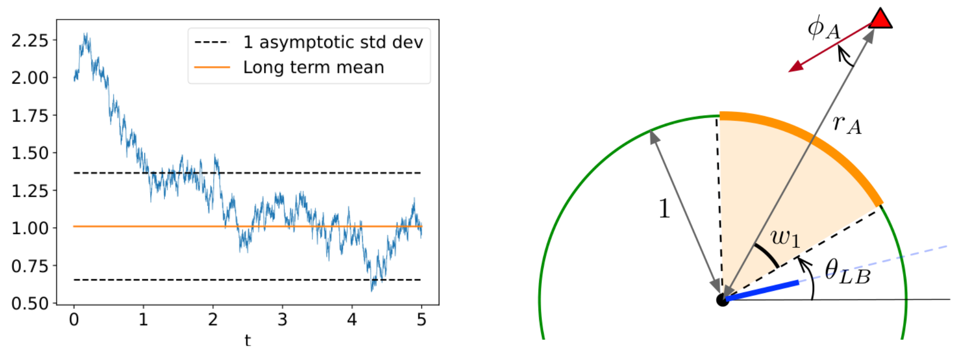
Stochastic differential games incorporate uncertainty in strategic interactions, crucial for analyzing Nash equilibria in dynamic environments. The HJBI equations underpin optimal strategy derivation, addressing stochastic games' complexities [36]. Deep learning, particularly Deep Fictitious Play, enhances Nash equilibrium approximation in large N-player asymmetric stochastic games, leveraging neural networks for high-dimensional data management [36]. Non-zero-sum stochastic games reveal complexities in player interactions with risk-sensitive criteria, linking Nash equilibria to BSDEs. Mean field theory approximates collective behaviors, achieving convergence through the propagation of chaos, supported by numerical simulations [86, 87]. Deceptive strategies and feedback control synthesis optimize strategic interactions in stochastic games [75, 76]. This framework models strategic interactions in uncertain environments, with applications in various scenarios, including cybersecurity and epidemic responses [5, 12].

5.5 Multi-Player and Mean Field Games

Multi-player and mean field games extend differential game principles to scenarios with numerous agents, necessitating advanced mathematical frameworks [12]. Mean field games analyze large agent populations' collective behavior, simplifying complex system analysis and enabling Nash equilibrium derivation [88]. Bounded domains introduce complexity, requiring boundary condition considerations [89]. The martingale approach facilitates optimal strategy derivation, leveraging stochastic game nature [90]. Neural network advancements have enhanced multi-player and mean field games analysis, showcasing deep learning's potential to revolutionize strategic interaction optimization [91]. Ongoing investigations into large-scale games are expected to yield insights for optimizing multi-agent systems [14, 15, 60, 13].

5.6 Applications of Differential Game Theory

Differential game theory models and optimizes strategic interactions across domains, offering robust solutions to complex problems. In finance, it addresses risk management and decision-making under uncertainty, with decomposition techniques simplifying value computation [57]. Zero-sum stochastic games manage risk-sensitive criteria, ensuring continuity and uniqueness of value functions [11]. Defense applications integrate differential games into adversarial strategies, enhancing tactics development in partial information scenarios [25, 72]. Robotics benefits from differential game theory in multi-agent coordination, with pursuit-evasion models facilitating real-time strategy adaptation [49, 45]. Mean field games optimize resource distribution in energy management, with applications in pedestrian flow and macroeconomic scenarios [6]. Public health utilizes game-theoretic models for epidemic dynamics, capturing decision-making processes and enhancing intervention strategies [10]. Differential game theory's adaptability addresses complex scenarios in social networks, cooperative defense, and multi-agent systems, enhancing strategic decision-making across applications [92, 25, 17, 84]. Ongoing computational advancements promise to expand differential game theory's applicability and impact.



(a) The image shows a graph with two lines representing different data sets over time.[93]

(b) Angular momentum and angular velocity[75]

Figure 8: Examples of Applications of Differential Game Theory

As shown in Figure 8, the applications of differential game theory are illustrated through two examples. The first graph depicts two lines representing different data sets over time, showcasing dynamic fluctuations captured by game-theoretic models. The second example explores the relationship between angular momentum and angular velocity, highlighting differential game theory's application in analyzing rotational dynamics. Collectively, these examples underscore the versatility of differential game theory in modeling and analyzing complex systems across various domains [93, 75].

6 Cooperative Control

6.1 Strategies for Enabling Cooperation

Cooperative strategies in multi-agent systems are essential for optimizing interactions and achieving shared objectives, particularly in complex environments like pursuit-evasion games. Integrating deep learning with traditional game theory enhances computational efficiency and enables the derivation of semi-explicit Nash equilibria through parallel processing [23]. This advancement facilitates rapid decision-making and information processing among agents.

Modeling shared reference tracking between humans and robots exemplifies effective cooperation, where a controller aligns actions to enhance synergy in scenarios requiring precise coordination, such as physical human-robot interaction (pHRI) [8]. In autonomous vehicles (AVs), game-theoretic frameworks enable cooperation in traffic flow, adapting to dynamic conditions and extending to higher-order models [2].

Robust communication strategies are crucial for effective cooperation under incomplete information, as demonstrated by the use of infinite signal sets approximated by finite sets in pursuit-evasion games [1]. This ensures agents maintain coordination despite uncertainties. In hypersonic pursuit scenarios, real-time adaptive reshaping of pursuit trajectories addresses challenges posed by evasive maneuvers, facilitating cooperation among pursuing agents [46].

Analyzing multi-objective interval differential games provides insights into cooperation among agents, offering a framework for understanding trade-offs and synergies in multi-objective scenarios [94]. This supports strategies aligning individual and collective goals, optimizing system performance.

Additionally, modeling heterogeneous interactions in stochastic differential games enhances the realism of cooperative strategies, allowing nuanced understanding of player dynamics [35].

6.2 Challenges and Solutions

Cooperative control in multi-agent systems faces challenges due to their dynamic and decentralized nature. Variability in agents' constraints and preferences complicates the development of adaptable strategies, necessitating robust methods to ensure effective cooperation as conditions evolve [6].

Ideal communication conditions assumed in theoretical models often do not reflect reality. Disruptions in sensor or vehicle-to-vehicle (V2V) communication can hinder cooperative control, particularly in connected and automated vehicle platoons [95]. Solutions must incorporate mechanisms to mitigate disruptions, such as redundant pathways or adaptive algorithms functioning with incomplete information.

The computational complexity of training deep learning models poses another challenge, especially in larger games where resource demands are substantial [96]. Efficient algorithms and computational techniques are needed to reduce resource requirements without sacrificing performance. Current studies also face difficulties due to the lack of explicit solutions and intensive computational demands of numerical simulations, which can limit scalability and practical application [86]. Research should focus on deriving approximate solutions that balance accuracy with computational feasibility.

Despite these challenges, existing approaches offer advantages, such as decoupling observation strategies from control strategies, enabling flexible decision-making [72]. Closed-form solutions for Nash equilibria enhance the robustness of cooperative strategies, facilitating practical implementation. Identifying cost function parameters that accurately reflect player behavior is crucial for developing strategies aligned with agents' goals and preferences [57], ultimately improving system performance.

7 Applications and Case Studies

Game-theoretic principles are instrumental in enhancing strategic interactions across various sectors, particularly in security, defense, energy, environmental management, economics, finance, healthcare, and public policy. This section explores case studies demonstrating the practical applications of these theories, focusing on optimizing responses to complex adversarial scenarios and resource management.

7.1 Security and Defense Applications

In security and defense, integrating cooperative and non-cooperative strategies is crucial for optimizing responses to threats. Multi-player pursuit-evasion games illustrate how coordinated efforts between defenders and targets enhance system resilience. Techniques like role balancing and barrier construction provide optimal defense mechanisms against breaches [97, 25, 11, 98]. The Layered Graph Security Games (LGSGs) framework applies pursuit-evasion concepts to anti-terrorism and logistical interdiction, emphasizing strategic resource allocation [97]. In vehicle-manipulator systems, Limited Information Shared Control (LISC) and Adaptive Cooperation Model-Based Shared Control improve defense mechanism coordination [99, 100].

The All-Against-One (AAO) framework in linear-quadratic differential games demonstrates that Nash strategies can be effective in military applications involving multiple agents [101]. Slightly Altruistic Nash Equilibrium approaches highlight the role of altruistic behavior in enhancing security outcomes in resource-constrained scenarios [102]. Non-cooperative multi-agent algorithms show potential in managing large-scale interactions in traffic and crowd dynamics, with applications extending to defense operations [22, 103]. Quadcopter experiments in ROS environments demonstrate essential collision avoidance capabilities [67]. Stochastic evolving differential games extend these applications to urban planning and socio-economic systems [3].

The integration of game-theoretic concepts and cooperative strategies in security and defense enhances strategic interactions among adversaries, improving the effectiveness and resilience of defensive measures in adversarial environments [97, 11, 104, 25].

7.2 Energy and Environmental Management

Game-theoretic principles and distributed control strategies are pivotal in optimizing resource allocation in energy and environmental management. Distributed control frameworks are essential in smart grid operations, facilitating renewable energy integration and improving resilience through decentralized decision-making [64]. Cooperative game theory aligns incentives across stakeholders, enhancing resource efficiency and reducing emissions, particularly in microgrid management [58].

In environmental management, game-theoretic models address pollution control and resource conservation, balancing economic and environmental objectives for sustainability [2]. Mean field games model large-scale interactions, such as ecological systems and climate change mitigation, optimizing resource use and collective behaviors [6]. These approaches develop sustainable strategies for energy distribution and environmental conservation [105, 71, 106, 74].

7.3 Economic and Financial Applications

Differential game theory and cooperative control frameworks optimize strategic interactions in economics and finance. In finance, differential games model competitive interactions among firms, optimizing investment strategies and managing risk under uncertainty. Inverse linear-quadratic nonzero-sum differential games enhance financial system resilience by adapting strategies to market conditions [57].

Game-theoretic models elucidate competition and cooperation dynamics in economic systems, facilitating market behavior analysis and policy formulation for stability and growth. Mean field games optimize resource allocation and market efficiency by modeling large-scale economic interactions [2]. Cooperative game theory aligns stakeholders' incentives in financial markets, enhancing resource allocation and reducing systemic risk. Cooperative control strategies enable optimal portfolio management and risk-sharing, bolstering market stability and investor confidence [58].

Advanced techniques like stochastic differential games address the inherent uncertainty and volatility of financial markets, facilitating robust risk management strategies and improving system resilience [96]. Game-theoretic methodologies offer a comprehensive framework for optimizing strategic interactions and decision-making in economics and finance, addressing market dynamics and stability challenges [11, 96].

7.4 Healthcare and Public Policy

In healthcare and public policy, differential game theory and cooperative control advance strategic decision-making and resource allocation. In healthcare, differential games model interactions among providers, patients, and policymakers, enhancing patient outcomes and system efficiency. Adaptive differential game theory controllers are crucial for rehabilitation and assistive technologies [107].

Game-theoretic models in public policy analyze stakeholder interactions, evaluating policy interventions and social welfare impacts. Mixed strategies in zero-sum games optimize resource allocation in competitive environments, despite high computational costs [108]. Pursuit-evasion game findings have applications in robotics and autonomous systems for public health surveillance and disaster response, optimizing resource allocation and risk mitigation [109].

Integrating differential game theory and cooperative control in healthcare and public policy enhances strategic interactions and decision-making, especially in epidemic management. This framework addresses intervention timing, decision-maker roles, and cooperative strategy dynamics among stakeholders, optimizing health crisis responses and identifying research gaps [25, 10, 110]. These approaches pave the way for sustainable strategies in healthcare delivery and public policy implementation.

8 Conclusion

8.1 Future Directions and Emerging Trends

The evolution of pursuit-evasion games, distributed control, differential games, and multi-agent systems is poised for significant theoretical and practical developments. In the realm of pursuit-evasion games, examining bounded rationality within team scenarios could provide insights into how varying rationality levels influence team dynamics, thereby enhancing the understanding of strategic interactions in cooperative settings. Future research should also focus on relaxing convergence conditions in finite-agent stochastic differential games and exploring the impact of diverse graph structures on player dynamics.

In distributed control, increasing robustness against persistent disturbances remains a priority. Investigating alternative distributed control schemes could expand their applicability in environments with constant external influences. Additionally, the development of online role arbitration mechanisms and predictive models for human target behavior may enhance cooperative control strategies, thereby improving the adaptability and efficiency of multi-agent systems.

Differential games present opportunities to explore complex scenarios involving multiple players and varying maneuverability constraints. Future studies should address the implications of different risk-sensitive parameters and consider extending models to zero-sum scenarios. Refining models to incorporate network dynamics and the influence of external actions on social behaviors could offer valuable insights, particularly in evolving social systems.

In mean field games, extending models to include boundary conditions and state constraints, alongside developing numerical methods for solution approximation, are crucial areas for future research. Enhancing approximation rates and examining diverse agent interactions are also vital. Furthermore, exploring multi-class traffic models that account for heterogeneous autonomous vehicles while integrating complex behavioral factors into the mean field game framework is of great interest.

Lastly, the parameterized analysis of the Cops and Robber game suggests that future research should investigate additional structural parameters and their relationship with the cop number, as well as the applicability of these methods to more complex graph classes. Continued exploration in these areas is expected to foster innovative solutions and methodologies that address intricate strategic interactions across various disciplines.

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