1

Introduction

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1.1 Introduction

Many military and civilian applications require a team of agents to coordinate with each other to perform specific tasks without human intervention. In those systems, individual agents (e.g., unmanned underwater/ground/aerial vehicles) have limited capabilities due to short sensing and communication ranges, and small computational power. However, their collective behavior exhibits significant advantages compared to a single sophisticated agent, including large-scale spatial distribution, robustness, high scalability, and low cost [1]. The deployment of large-scale multi-agent systems with constrained costs and smaller sizes can thus achieve tasks that are otherwise unable to be finished by a single agent. Teams of engineered multi-agent systems can collect and process data and perform tasks cooperatively [2–8]. Multi-agent systems play an important role in a wide range of applications such as search and rescue [9], tracking/classification [10–14], surveillance [15, 16], space exploration [17], and radiation shielding and site clearing [18]. Multi-agent systems have also been considered and utilized in fields such as cooperative mobile robotics [19], distributed artificial intelligence and computing [20–22], wireless sensor

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networks [23], biology [24], social study [25], smart grids [26], traffic management [27, 28], and supply-chain management [29]. Therefore, the use of multi-agent system technologies in both everyday modern society and national defense and homeland security is bound to tremendously increase. In this book, we aim to provide an overview of recent progresses made in the cooperative control of multi-agent systems on both fundamental theory development as well as applications.

In the control community, multi-agent system theory has focused on developing vehicle motion control laws for various tasks including consensus and formation control [2, 30–43], coverage control [44–48], target search and tracking [3–5, 49, 50], task allocation problems [25, 51–53], sensor management problems [14], output regulation [54, 55], optimization [56], and estimation. Three types of control schemes for multi-agent systems have been proposed in the open literature, that is, centralized [57], decentralized [58], and distributed multi-agent control [1]. The centralized control scheme assumes global knowledge of the multi-agent system and seeks to achieve some control objective considering all agents' states, which inevitably suffers from the scalability issue. The decentralized control scheme computes control actions based only on an agent's local information while the more popular distributed control scheme takes both the agent's own information and neighboring agents' information into account to calculate the control action. Both the decentralized and distributed control algorithms provide scalable solutions and can be implemented under minimal connectivity properties. On the other hand, connectivity preserving protocols are developed for multi-agent systems to keep connected and hence guarantee motion stability [59, 60]. The problem has been considered in scenarios such as flocking [61, 62], rendezvous [59, 63], and formation control [64, 65]. The control hierarchy for multi-agent systems can be categorized into two classes, that is, top-down and bottom-up methodologies [66]. The top-down scheme assigns an overarching objective for the multi-agent system and designs control action for each individual agent to achieve this objective. The top-down multi-agent task decomposition is often difficult. While the bottom-up scheme directly defines each individual agent's local control action and their cooperation protocol, which however cannot guarantee any global objective. The paper [67] provides an overview of progresses made in the distributed multi-agent coordination. The books [64, 68] provide an introduction to the distributed control of multi-agent systems. The book [1] discusses the distributed control of multi-agent systems from four main themes, or dimensions: distributed control and computation, adversarial interactions, uncertain evolution, and complexity management. A special category of multi-agent systems, multi-robot systems, has become one of the most important areas of research in robotics [19]. Significant advance has been made in distributed control and collaboration of multi-robot systems in control theory and artificial intelligence [68–70]. There are a considerable amount of works on multi-agent consensus and formation control, and synchronization. We briefly summarize the main results as follows.

The multi-agent consensus control problem ensures that a group of mobile agents stays connected and reaches agreement while achieving some performance objective [64]. The papers [71, 72] provide a good survey of consensus problems in multi-agent cooperative control. In [64], the consensus problem is considered over dynamic interaction graphs by adding appropriate weights to the edges in the graphs. Theoretical results regarding consensus seeking under both time-invariant and dynamically changing information exchange topologies are summarized. Applications of consensus protocols to multi-agent coordination are investigated. In [73, 74], consensus algorithms are extended for second-order nonlinear dynamics in a dynamic proximity network. Necessary and sufficient conditions are given to ensure second-order consensus. In [75], leader-following consensus algorithms are developed for a linear multi-agent system on a switching network, where the input of each agent is subject to saturation. In [76], multi-agent consensus based on the opinion dynamics introduced by Krause is studied. A new proof of convergence is given with all agents in the same cluster holding the same opinion (represented by a real number). Lower bounds on the inter-cluster distances at a stable equilibrium are derived. In [33], multi-agent consensus is considered for an active leader-tracking problem under variable interconnection topology. The effects of delays on multi-agent consensus have been considered in [77].

The paper [78] provides a survey of formation control of multi-agent systems. The existing results are categorized into position-, displacement-, and distance-based control. The finite-time formation control for nonlinear multi-agent systems is investigated in [43]. A small number of agents navigate the whole team based on the global information of the desired formation while the other agents regulate their positions by the local information in a distributed manner. A class of nonlinear consensus protocols is first ensured and then applied to the formation control. In [79], a model-independent coordination strategy is proposed for multi-agent formation control in combination with tracking control for a virtual leader. The authors show that the formation error can be stabilized if the agents can track their respective reference points perfectly or if the tracking errors are bounded. In [80], a decentralized cooperative controller for multi-agent formation control and collision avoidance is developed based on the navigation function formalism. The control law is designed as the gradient of a navigation function whose minimum corresponds to the desired formation. Multi-agent formation control with intermittent information exchange is considered in [81]. Energy-based analysis is utilized to derive stability conditions. The paper [82] investigates rotating consensus and formation control problems of second-order multi-agent systems based on Lyapunov theory. Both theoretical and experimental results are presented in [42] on multi-agent decentralized control that achieves leader–follower formation control and collision avoidance for multiple nonholonomic robots.

In [83], synchronization approach is developed for trajectory tracking of multiple mobile robots while maintaining time-varying formations. In [84], synchronization algorithms are designed in a leader–follower cooperative tracking control problem where the agents are modeled as identical general linear systems on a digraph containing a spanning tree. The control framework includes full-state feedback control, observer design, and dynamic output feedback control. In [54], a distributed control scheme is adopted for robust output regulation in a multi-agent system where both the reference inputs and disturbances are generated by an exosystem. In [55], the output regulation problem is extended to multi-agent systems where a group of subsystems cannot access the exogenous signal. In [85], output consensus algorithms are developed for heterogeneous agents with parametric uncertainties. The multi-agent output synchronization problem is also studied in [86] where the coupling among the agents is nonlinear and there are communication delays. In [87], a general result for the robust output regulation problem has been studied for linear uncertain multi-agent systems. In [88], finite-time synchronization is proposed for a class of second-order nonlinear homogenous multi-agent systems with a leader–follower architecture. A finite-time convergent observer and an observer-based finite-time output feedback controller are developed to achieve the goal.

In [89], distributed tracking control is developed for linear multi-agent systems and a leader whose control input is nonzero, bounded, and not available to any follower. The paper [90] considers multi-agent tracking of a high-dimensional active leader, whose state not only keeps changing but also may not be measured. A neighbor-based local state-estimator and controller is developed for each autonomous following agent. A collision-free target-tracking problem of multi-agent robot system is considered in [91], where a cost function using a semi-cooperative Stackelberg equilibrium point component with weights tuned by a proportional-derivative (PD)-like fuzzy controller is formulated. The distributed finite-time tracking control of second-order multi-agent systems is considered in [92]. Observer-based state feedback control algorithms are designed to achieve finite-time tracking in a multi-agent leader-follower system and extended to multiple active leaders. There are also a lot of works focusing on multi-agent target tracking. In [93], the optimal sensor placement and motion coordination strategies for mobile sensor networks are developed in a target-tracking application. Gradient-descent decentralized motion planning algorithms are developed in [94] for multiple cooperating mobile sensor agents for the tracking of dynamic targets. The problem of target tracking and obstacle avoidance for multi-agent systems is considered in [95]. A potential function-based motion control algorithm is proposed to solve the problem where multiple agents cannot effectively track the target while avoiding obstacles at the same time.

The book [96] gives an overview of optimal and adaptive control methods for multi-agent systems. In [56], a distributed subgradient method is developed to solve a multi-agent convex optimization problem where every agent minimizes its own objective function while exchanging information locally with other agents in the network over a time-varying topology. An inverse optimality-based distributed cooperative control law is designed in [97] to guarantee consensus and global optimality of multi-agent systems, where the communication graph topology interplays with the agent dynamics. The work [98] applies stochastic optimal control theory to multi-agent systems, where the agent dynamics evolve with Wiener noise. The goal is to minimize some cost function of different agent–target combinations so that decentralized agents are distributed optimally over a number of targets. An optimal control framework for persistent monitoring using multi-agent systems is developed in [99] to design cooperative motion control laws to minimize an uncertainty metric in a given mission space. The problem leads to hybrid systems analysis, and an infinitesimal perturbation analysis (IPA) is used to obtain an online solution.

Coverage control considers the problem of fully covering a task domain using multi-agent systems. The problem can be solved by either deploying multiple agents to optimal locations in the domain or designing dynamic motion control laws for the agents so as to gradually cover the entire domain. The former solutions entail locational optimization for networked multi-agent systems. Voronoi diagram–based approaches are introduced in [100] to develop decentralized control laws for multiple vehicles for optimal coverage and sensing policies. Gradient descent–based schemes are utilized to drive a vehicle toward the Voronoi centeriod for optimal localization. In [101], the discrete coverage control law is developed and unified with averaging control laws over acyclic digraphs with fixed and controlled-switching topology. In [102], unicycle dynamics are considered and the coverage control algorithms are analyzed with an invariance principle for hybrid systems. The latter solutions focus on the case when the union of the agents' sensor cannot cover the task domain and hence dynamic motion control needs to be designed so that the agents can travel and collaboratively cover the entire domain [103]. A distributed coverage control scheme is developed in [104, 105] for mobile sensor networks, where the sensor has a limited range and is defined by a probabilistic model. A gradient-based control algorithm is developed to maximize the joint detection probabilities of random events taking place. Effective coverage control is developed to dynamically cover a given 2D region using a set of mobile sensor agents [46, 106]. Awareness-based coverage control has been proposed to dynamically cover a task domain based on the level of awareness an agent has with respect to the domain [48]. The paper [107] extends the awareness coverage control by defining a density function that characterizes the importance of each point in the domain and the desired awareness coverage level as a nondecreasing differentiable function of the density distribution. In [108], awareness and persistence coverage control are addressed simultaneously so that the mission domain can be covered periodically while the desired awareness is satisfied.

Passivity-based control approaches have also been developed to guarantee the stability of multi-agent systems [109]. Passivity is an energy-based method and a stronger system property that implies stability [110, 111]. A system is passive if it does not create energy, that is, the stored energy is less than the supplied energy. The negative feedback interconnection and parallel interconnection of passive systems are still passive. The paper [112] discusses the stabilization and output synchronization for a network of interconnected nonlinear passive agents by characterizing the information exchange structure. In [113], a passivity-based cooperative control is developed for multi-agent systems and the group synchronization is proved with the proposed backstepping controller using the Krasovskii–LaSalle invariance principle. The paper [114] introduces a discrete-time asymptotic multi-unmanned aerial vehicle (UAV) formation control that uses a passivity-based method to ensure l_2^m stability in the presence of overlay network topology with delays and data loss. Passivity-based motion coordination has also been used in [115] for the attitude synchronization of rigid bodies in the leader–follower case with communication delay and temporary communication failures. The work [116] uses the multiple Lyapunov function method for the output synchronization of a class of networked passive agents with switching topology. The concept of stochastic passivity is studied for a team of agents modeled as discrete-time Markovian jump nonlinear systems [117]. Passivity-based approaches have also been widely used in the bilateral teleoperation of robots and multi-agent systems. A good amount of work has utilized the scattering wave transformation and two-port network theory to provide stability of the teleoperation under constant communication delays for velocity tracking. A passifying PD controller is developed in [118] for the bilateral teleoperation of multiple mobile slave agents coupled to a single master robot under constant, bounded communication delays. The paper [119] extends the passivity-based architecture to guarantee state (velocity as well as position) synchronization of master/slave robots without using the wave scattering transformation. Passivity-based control strategies are also utilized for the bilateral teleoperation of multiple UAVs [120].

Extensive results presenting algorithms and control methodologies for multi-agent systems cooperation rely on continuous communication between agents. Continuous actuation and continuous measurement of local states may be restricted by particular hardware limitations. A problem in many scenarios is given by the limited communication bandwidth where neighboring agents are not capable of communicating continuously but only at discrete time instants. Limitations and constraints on inter-agent communication may affect any multi-agent network. Consensus problems, in particular, have been analyzed in the context of noncontinuous actuation and noncontinuous inter-agent communication. Several techniques are devised in order to schedule sensor and actuation updates. The sampled-data (periodic) approach [121–123], and [124] represents a first attempt to address these issues. The implementation of periodic communication represents a simple and practical tool that addresses the continuous communication constraint. However, an important drawback of periodic transmission is that it requires synchronization between the agents in two similar aspects: sampling period and sampling time instants, both of which are difficult to meet in practice. First, most results available require every agent to implement the same sampling period. This may not be achievable in many networks of decentralized agents and it is also difficult to globally redefine new sampling periods. Second, not only the agents need to implement the same sampling periods, but also they need to transmit information all at the same time instants. Under this situation each agent is also required to determine the time instants at which it needs to transmit relevant information to its neighbors. Even when agents can adjust and implement the same sampling periods, they also need to synchronize and transmit information at the same time instants for the corresponding algorithms to guarantee the desired convergence properties. Besides being a difficult task to achieve in a decentralized way, the synchronization of time instants is undesirable because all agents are occupying network resources at the same time instants. In wireless networks, the simultaneous transmission of information by each agent may increase the likelihood of packet dropouts since agents that are supposed to receive information from different sources may not be able to successfully receive and process all information at the same time.

Therefore, event-triggered and self-triggered controls for multi-agent systems have been considered for agents with limited resources to gather information and actuate. The event-triggered schemes allow each agent to only send information across the network intermittently and independently determine the time instants when they need to communicate [57]. The use of event-triggered control techniques for decentralized control and coordination has spurred a new area of research that relaxes previous assumptions and constraints associated with the control of multiple agents. In event-triggered control [125–130], a subsystem monitors its own state and transmits a state measurement to the non-collocated controller only when it is necessary, that is, only when a measure of the local subsystem state error is above a specified threshold. In general, the state error measures the difference between the current state and the last transmitted state value. The controller transmits an update by examining the measurement errors with respect to some state-dependent threshold and hence requires continuous monitoring of state error. In many instances, it is possible to reduce communication instances using event-triggered communication with respect to periodic implementations. This is of great importance in applications where bandwidth or communication resources are scarce. Consensus problems where all agents are described by general linear models [131, 132], have been studied assuming continuous communication among agents. Event-triggered control and communication methods for agents with linear dynamics were recently studied in [133–138]. Event-triggered control methods have also been applied to analyze consensus problems with limited actuation rates. In [139], agents with single integrator dynamics are considered and an event-triggered control technique is implemented in order for each agent to determine the time instants to update their control inputs. Continuous exchange of information is assumed in [139] and the event-triggered controller is only used to avoid continuous actuation at each node. In general, the decentralized event-triggered consensus problem with limited communication is a more challenging problem than the event-triggered control for limiting actuation updates. The main reason is that agents need to take decisions (on when to transmit their state information) based on outdated neighbor state updates. In this scenario, each agent has continuous access to its own state; however, it only has access to the last update transmitted by its neighbors. Several approaches for the event-triggered consensus with limited communication are documented in [140–145]. In this sense, event-triggered control provides a more robust and efficient use of network bandwidth. Its implementation in multi-agent systems also provides a highly decentralized way to schedule transmission instants, which does not require synchronization compared to periodic sampled-data approaches. Different problems concerning the transmission of information in multi-agent networks such as communication delays and packet dropouts have been explicitly addressed using event-triggered control methods [146]. In the extended self-triggered control, each agent will compute its next update time based on the available information from the last sampled state, without the necessity to keep track of the state error in order to determine when a future sample of the state should be taken. In [140], an event-based scheduling is developed for multi-agent broadcasting and asymptotic convergence to average consensus is guaranteed. This paradigm has also been extended to distributed estimation and optimization [147].

1.2 Chapter Summary and Contributions

Chapter 2 develops sensor deployment algorithms for a team of autonomous unmanned vehicles (AUVs) for path coverage problem with monitoring applications in GPS-denied environments. The approach used in this chapter tracks the AUV position in GPS-denied environments by analyzing the radio signals received from a suitably positioned network of proxy landmarks. This problem is referred to as the landmark placement problem (LPP) and it is required to use minimum number of landmarks to cover the entire path of the AUV. Two α-approximate ($\alpha = 13$ and 5, respectively) algorithms are proposed to solve the LPP in polynomial time and provide solutions whose cost is at most α times from the optimum. It is assumed that a target in a vehicle's path is defined to be covered by a landmark and the distance between a target and a landmark is at most equal to R. A greedy algorithm is first proposed for a simpler LPP where all the targets lie within a vertical strip of width equal to $\sqrt{3}R$ and the landmarks are restricted to be on a single, vertical line. The algorithm is then extended to a general LPP by partitioning the plane into vertical strips of width $\sqrt{3}R$ with approximation ratio $\alpha = 13$. The second approximate algorithm with $\alpha = 5$ is developed based on a 4-approximation algorithm for a unit disc problem. Two phases are involved in this algorithm: (i) identification of a subset of targets using a simple greedy algorithm and (ii) addition of landmarks in the vicinity of each target in the subset. Both theoretical guarantees and numerical simulations are provided to show the performance of the proposed approximation algorithms.

Chapter 3 proposes vision-based cooperative target tracking control laws for two fixed-wing UAVs in measurements gathering and real-time decision-making tasks. To mitigate a single UAV's inability to maintain close proximity to a target and hence obtain accurate measurements for tracking purpose, multiple UAVs are deployed for cooperative target tracking. In this chapter, the standoff target tracking approach is used where two UAVs orbit the target at a nominal standoff distance while maintaining orthogonal viewing angles so as to minimize the joint/fused geolocation error covariance. The work promotes a practical solution that yields robust coordination under the following realistic conditions: unknown constant wind, non-negligible roll dynamics with roll-angle setpoint limits, unpredictable and evasive target motion, and the availability of only noisy, partial information of the overall system's states. The motion of the individual vehicles is optimized and robust so as to gather the best joint measurements of a given quantity, object, or area of interest and take into account real-world conditions, such as environmental disturbances and unmodeled dynamics. An output-feedback control approach is deployed to achieve the desired robustness, and a fourth-order Dubins vehicle model with roll dynamics is considered. The tracking solution incorporates adaptive estimates of the wind into the online model predictive control (MPC) and moving horizon estimation (MHE) optimization. The MPC and MHE are combined into a single min–max optimization, that is, a desired cost function is maximized with respect to disturbance and measurement noise variables and minimized with respect to control input variables. Simulations are performed using aircraft models having six degrees of freedom and target logs taken from live tracking experiments.

Chapter 4 discusses how to find the convergence rate of continuous-time consensus algorithms for multi-UAV simultaneous arrival problem. The requirement is that the UAVs must achieve consensus on the expected time-to-arrival (ETA) before any actual arrivals. Assume that a team of agents are required to simultaneously visit some prespecified targets and the path for each individual agent to follow has been precomputed. To arrive at their targets at the same time, agents have to adjust their velocities during the motion, based on the information communicated with their neighbors. Real-time planning schemes need to be developed to overcome the uncertainties due to UAVs flying in dynamical environments. This chapter considers the consensus-based simultaneous arrival problem with fixed velocity constraints under a connected and undirected communication graph. It is challenging to analyze the stability and the convergence rate of the consensus algorithms. Each UAV estimates its own ETA and communicates it with its neighbors in real-time so that they can reach consensus on the ETA. A continuous-time projection operator is introduced to ensure smoothness of the state and input trajectories, when saturation happens due to the velocity constraints. The projection-based operator is used to enforce the constraints on the velocity. The convergence of the resulting closed-loop system is proved. The aforementioned consensus algorithm shows asymptotic property, and hence simultaneous arrival will be reached in an infinite amount of time. In practice, the length of the paths is always finite, and the agents are required to achieve consensus in finite amount of time. Hence, the ϵ-consensus approach is further investigated for practical consideration. An upper bound on the convergence rate is derived when ϵ-consensus can be achieved. A sufficient condition in terms of the path length and UAVs' minimal and maximal velocity is presented to guarantee feasibility of the simultaneous arrival problem.

Chapter 5 addresses the weapon–target assignment (WTA) problem, that is, how to assign defensive weapons to intersect the aimed targets to minimize the damage of assets or maximize the probability of destroying the target and hence the damage of targets. This work particularly focuses on time-dependent WTA (TSWTA) problems that seek to find the optimal launching time of a weapon to maximize the sum of asset values after defensive weapons are assigned to corresponding targets. The TSWTA problem is formulated as a mixed-integer nonlinear program (MINLP), under the assumption that target–assets engagements are independent of weapon–target engagement. It is shown that the TSWTA exhibits the monotonically non-decreasing property similar to other WTA problems. Based on this property, the TSWTA can be formulated as the problem that maximizes the nondecreasing objective function under a partition matroid constraint. A provable suboptimality lower bound of the value achieved by a greedy heuristic maximization algorithm is obtained. Computational experiments are also conducted to demonstrate good performance achieved by the proposed heuristic algorithms for this combinatorial optimization problem.

Chapter 6 presents a cooperative decision problem in which a group of UAVs is tasked to eliminate a set of targets while minimizing different cost terms during the duration of the mission. The environment where the mission is performed contains a set of threats representing radar sites that are able to identify and potentially harm the UAVs. The radar sites are more effective in identifying a given UAV if the UAV travels near the threat position. In a first instance of the problem, each UAV needs to independently compute its own optimal path in order to reach the destination point where a main target is located. The optimal path is the one that minimizes a combined cost that captures path length and threat risks. In order to minimize threat risk, the approach followed in Chapter 6 is to design a Voronoi diagram using the threat positions. This means that the UAVs minimize exposure to threats when traveling along the edges of the Voronoi diagram. The optimal trajectory to reach a main target is transformed into a graph search where the weights of each edge are determined by two factors: the length of the edge and the threat risk that the UAV is exposed to by traveling along that edge. The problem is further extended by endowing the UAVs with extra munitions that can be used to eliminate a subset of threats. A problem of distributed assignment of threats is then formulated and solved by identifying individual optimal decisions and by implementing a distributed consensus-based auction algorithm. The assignment of threats to eliminate is performed sequentially in order for UAVs to take advantage of other UAVs decisions and assignments. In this way, cooperation among UAVs is induced since the cost of the new optimal path of each UAV can be significantly improved not only by its own decisions but also by traveling along paths where previous threats have already been eliminated by other UAVs. The timing constraints associated with the distributed decisions and assignments of threats is explicitly considered in Chapter 6. In addition, the existence of multiple main targets is considered and different approaches to assign UAVs to main targets are proposed.

Chapter 7 studies event-triggered control and communication techniques for multi-agent systems coordination. This work provides an overview of several event-triggered control techniques to achieve multi-agent coordination. The focus of the chapter is on the problem of average consensus, where a group of agents seek to agree on the average of their initial states. An introduction is provided for event-triggered control strategies applied to consensus problems. Centralized event-triggered control, decentralized event-triggered communication and control, periodic event-triggered coordination are introduced in detail. A detailed comparison among different techniques is presented. Several aspects associated with the use of these techniques such as decentralization, type of event threshold employed, and continuous sensing of local states are analyzed. The chapter provides formal analysis of several controllers and event–threshold implementations. The conditions necessary to achieve average consensus are also studied. Finally, open problems within this important area of research are addressed.

Chapter 8 solves network topology design (NTD) and identification problems. For the NTD problem, a limited number of edges are considered, and these edges and the associated edge weights are optimally allocated among multiple agents to improve certain network performance. While the network topology identification (NTI) problem is to satisfy the response between specified input and observed output. Solving both problems involves determining binary variables and the combination of them is exponentially increasing. The cardinality constraint on the edge set for the NTD problem is handled as a rank constraint on the to-be-determined matrix, and the NTD problem is formulated as a rank-constrained optimization problem. The approach for solving NTI problem handles unknown binary variables as continuous variables by adding a quadratic constraint on each binary variable and then reformulates the problem as a quadratically constrained quadratic programming (QCQP) problem, which can be equivalently transformed into a rank-one constrained optimization problem. Then for both NTD and NTI problems, an iterative rank minimization algorithm is proposed to solve the uniformly formulated rank-constrained optimization problems, where each iteration is formulated as a convex optimization problem.

Chapter 9 considers stochastic interaction among groups of agents and presents relevant results about the probabilities to achieve coordination on variables of interest. The results presented in the chapter are roughly divided into two parts. The first part is concerned with fixed interaction communication graphs. In this case, the agents select the static undirected communication links and, therefore, the fixed communication graph, from a set of available candidates. In terms of communication graphs, the set of candidate graphs considered is the set of all possible undirected graphs. For each interaction graph, only one adjacency (or Laplacian) matrix is associated with it in order to uniquely define the interaction among agents. A lower bound on the probability of coordination is determined under this scenario. In addition, it is shown that the probability of coordination is strictly increasing as the number of agents increase. In the second part of Chapter 9, the probability of coordination is analyzed for the case where the directed interaction graph is switching. In this case, the communication links are not static. Instead, directed links between any two agents appear and disappear as time evolves. Under this scenario, it is demonstrated that coordination with probability 1, coordination in probability, and coordination in the *r*th mean are equivalent.

Chapter 10 develops distributed motion control algorithms of heterogeneous multi-agent systems for the coverage control of unknown and large-scale (i.e., the union of sensor regions cannot cover the entire domain) environments. To achieve full coverage of an unknown domain, the coverage task is decomposed into two distinct, however closely related, subtasks, that is, domain boundary tracking and coverage control. This work considers UAVs with down-facing board view cameras for the boundary tracking task and wheeled mobile robots (WMRs) for the coverage control task. The UAVs can move quickly and maintain a minimum altitude; however, it cannot lift a heavy payload and has to delegate the analysis of its sensor data to an off-board computer. Meanwhile, the WMRs move relatively slow but can carry more sensors and perform onboard computation. Nonholonomic constraints of the robots and nonisotropic sensor models are considered in the control law development for practical applications. A complete communication strategy between the UAVs and WMRs is discussed for information exchange. The inner (autopilot) and outer (wall follower motion control) loop feedback control strategy is adopted for the UAVs. Awareness-based coverage control law is developed for the WMRs based on dynamic awareness dynamics, 2D Leibniz rule, and practical consideration of actuation saturation. The state of awareness represents how aware each coverage robot is of the event occurring at the domain. Intermittent state updates between neighboring robots are considered for distributed multi-agent systems for the mapped part of the task domain. The awareness coverage error metrics are defined and proved to converge to zero under the proposed motion control strategies using Lyapunov-like analysis. A perturbation control law is deployed if the robot is trapped in a local minimum.

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