Coordination Between Unmanned Aerial and Ground Vehicles: A Taxonomy and Optimization Perspective

Jie Chen, *Senior Member, IEEE*, Xing Zhang, Bin Xin, *Member, IEEE*, and Hao Fang, *Member, IEEE*

***Abstract*—The coordination between unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) is a proactive research topic whose great value of application has attracted vast attention. This paper outlines the motivations for studying the cooperative control of UAVs and UGVs, and attempts to make a comprehensive investigation and analysis on recent research in this field. First, a taxonomy for classification of existing unmanned aerial and ground vehicles systems (UAGVSs) is proposed, and a generalized optimization framework is developed to allow the decision-making problems for different types of UAGVSs to be described in a unified way. By following the proposed taxonomy, we show how different types of UAGVSs can be built to realize the goal of a common task, that is target tracking, and how optimization problems can be formulated for a UAGVS to perform specific tasks. This paper presents an optimization perspective to model and analyze different types of UAGVSs, and serves as a guidance and reference for developing UAGVSs.**

***Index Terms*—Cooperative control, heterogeneous multivehicle, multivehicle system, optimization, unmanned aerial vehicle (UAV), unmanned ground vehicle (UGV).**

I. Introduction

The ADVENT of the single-wing unmanned aerial vehicle (UAV) in 1927 caused a great sensation in the world, which marks another milestone of aviation technology development since human beings flew into the sky. In the ensuing decades, aided by the rapid development of automation and artificial intelligence technologies, research on UAVs has blossomed and made substantial progress. In terms of their different structures, UAVs can be further categorized into fixed- and rotary-wing ones which are similar but still very different. Fixed-wing UAVs generally have quicker speed and heavier payload capacity than rotary-wing ones while the rotary-wing UAVs can hover and vertically take off and land. Since tasks faced by UAVs are of increasing complexity, a single UAV is usually not competent for given tasks. Recently, a significant shift of focus occurred as researchers began to investigate problems involving multiple UAVs, rather than single. Coordinating multiple UAVs and even multiple UAV groups to perform tasks can dramatically improve the effectiveness of the whole systems from the viewpoint of performance in accomplishing tasks and robustness, and reliability. Nowadays, cooperative control of multiple UAVs has become a highly active research area, and has been extensively employed in various applications, such as border patrol [1], fire detection [2], [3], cooperative target tracking [4], [5], mobile sensor network [6], and so on.

Likewise, interest in unmanned ground vehicles (UGVs) has grown significantly over the past decades. Recently, some UGVs with high intelligence appear constantly. A bionic robot called “Robo Lobster (BUR-001)” invented by the Northeastern University can perceive environments like a real animal. The BigDog developed for the U.S. troop by the Boston Dynamics engineering company can balance itself relying on active sense to environments and traverse through complex terrains. These kinds of robots, as the extension of soldiers’ hands, eyes and ears, can assist them to accomplish tasks more efficiently especially for hazardous tasks like bomb disposal. Recently, research on cooperative control of multiple UGVs such as formation control [7], [8], area search [9], and consensus control [10] has been widely conducted. Additionally, a variety of robotics competitions such as RoboCup and the robotic contest organized by the American Institute of Aeronautics and Astronautics have greatly propelled the research on multiple UGVs systems.

In practice, small UAVs and UGVs are well suited to be widely deployed and employed due to their low cost. Table I lists the characteristics of interest with respect to UAVs and UGVs. It can be observed from the table that, on one hand, both UAVs and UGVs have their own limitations, which notably reduce their efficiency in performing tasks to some extent. On the other hand, it is also obvious that UAVs and UGVs share strong complementarities in the characteristics that we are concerned with. The complementarities of UAVs and UGVs are primarily embodied in the following aspects. First, when capturing ground features, sensors

Manuscript received June 7, 2014; revised January 13, 2015; accepted March 23, 2015. Date of publication April 17, 2015; date of current version March 15, 2016. This work was supported in part by the National Science Fund for Distinguished Young Scholars under Grant 60925011, in part by the Projects of Major International (Regional) Joint Research Program NSFC under Grant 61120106010, in part by the National Natural Science Foundation of China under Grant 61304215, in part by the Foundation for Innovative Research Groups of the National Natural Science Foundation of China under Grant 61321002, in part by the Beijing Outstanding Ph.D. Program Mentor under Grant 20131000704, and in part by the Research Fund for the Doctoral Program of Higher Education of China under Grant 20131101120033. This paper was recommended by Associate Editor T. H. Lee. *(Corresponding author: Bin Xin.)*

The authors are with the School of Automation, Beijing Institute of Technology, Beijing 100081, China, and also with the Key Laboratory of Intelligent Control and Decision of Complex Systems, Beijing Institute of Technology, Beijing 100081, China (e-mail: brucebin@bit.edu.cn).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TCYB.2015.2418337

TABLE I
ADVANTAGES AND DISADVANTAGES OF DIFFERENT KINDS OF SMALL UNMANNED VEHICLES

Unmanned vehicle types		Advantages	Disadvantages
UAV	Fixed-wing UAV	Quick speed, large scope of observation, strong communication ability	Low payload capability, Low observation accuracy
	Rotary-wing UAV	Vertical taking off and landing, hovering ability, precise inspection capability	Low payload capability
UGV		Large payload capability, precise observation of the targets on the ground	Small field of view, slow motion speed, weak communication ability

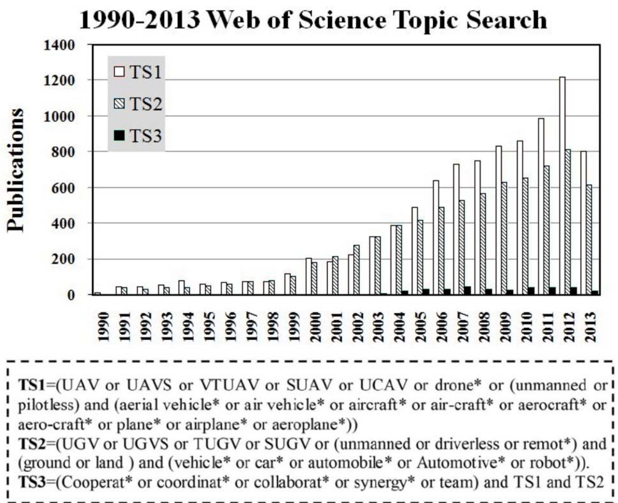


Fig. 1. Web of Science data showing the number of publications per year on the three topics.

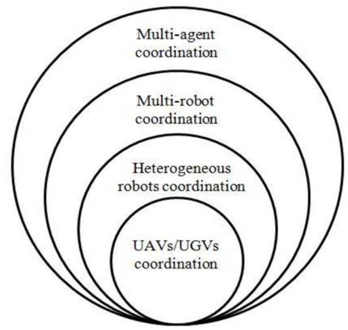


Fig. 2. Four typical research topics related to coordination of autonomous agents.

located on UAVs (especially fixed-wing ones) are usually limited by operating airspeed and altitude while UGVs can be deployed to accurately locate ground targets [11]. Second, due to advantages in altitude, communication links among UAVs can be less blocked by obstacles than that among UGVs. Hence, disconnected UGVs located at different positions can be connected indirectly with the support of UAVs serving as communication relays. Finally, UAVs (especially small ones) are usually restricted by their short voyage due to the limitation of carried energies, while UGVs have larger payload capability. To sum up, coordination between UAVs and UGVs has promised a bright prospect due to strong complementarities between them in sensing, communication, payload abilities, and so on.

Nguyen *et al.* [12] from Space and Naval Warfare Systems Center Pacific, provided a review of recent accomplishments and current status of a number of projects in land, sea and air unmanned system research. It can be seen that the research on cooperative control of aerial platforms and ground (or sea) ones has been rarely seen. As a research topic, the study of UAVs, UGVs and the cooperative control of UAVs and UGVs has gained increasing attention. Fig. 1 shows the data from the Web of Science resulting from a topic search on three terms marked by TS1, TS2, and TS3, respectively. Each year's results indicate the number of publications appearing in that year. It is quite clear that there is a significantly increasing interest in research on both UAVs and UGVs. However, the research on cooperative control of UAVs and UGVs, as opposed to that of UAVs or UGVs, is still fairly limited. Existing studies are still placed at theoretical research stage, and there are numerous technical bottlenecks that need to be broken through urgently to speed up the related research from theory to practice.

Generally speaking, an unmanned aerial and ground vehicles system (UAGVS) can be characterized as a set of UAVs and a set of UGVs operating in the same field to work together to achieve a common goal. In a broad sense, as shown in Fig. 2, the topic of coordination between UAVs and UGVs falls under the field of heterogeneous robots coordination, multirobot coordination, and multiagent coordination. Multirobot systems (MRSs) are typical examples of multi-agent systems (MASs) in physical world, and much attention has been given to MRS. In [13], the authors surveyed the current applications of cooperative control of multivehicle systems and summarized some of the key technical approaches that had been explored. To clearly classify the large variety of MRS, scholars have proposed many different methods. In [14], three criteria for characterizing MRS are proposed in light of the types of interactions from the perspective of distributed intelligence, while in [15], another taxonomy which is focused on the coordination aspect is developed. Heterogeneous robots coordination which is one of the branches of MRS research is, nowadays, an important research topic. UAVs/UGVs coordination, one of the most typical scenarios of heterogeneous robots coordination, has drawn special and wide attention. The great heterogeneity and complementaries between UAVs and UGVs in dynamics, speed, sensing, communication, functions, and so forth, make the UAGVSs powerful to complete a variety of complicated task. In contrast to existing works on MRS which are mainly focused on either UAVs or UGVs, the need to deal with the information from two totally different platforms and the need to effectively coordinate the behaviors of UAVs and UGVs, make the research on UAGVSs more challenging.

A. Motivations of This Paper

According to the literature survey, a variety of specific applications of UAGVSs have been proposed and validated, but infrequently analyzed. In addition, current research results on MRS cannot be directly applied to UAGVSs due to the great difference between UAVs and UGVs, and a mass of new characteristics exhibited in UAGVSs should be payed special attention and be researched further. Duan and Liu [11] presented a preliminary survey of recent research on this topic, in which some key issues involved in the topic were discussed and some future directions were also analyzed. Here, we extend current surveys on UAGVSs, propose a taxonomy for classification of existing UAGVSs, and develop an optimization framework to allow different types of UAGVSs to be described in a unified way.

B. Contributions

The main contribution of this paper is the proposal of the taxonomy for unfolding different coordination patterns/mechanisms in UAGVS as well as an optimization-based decision-making framework for UAGVS. The taxonomy provides a tool and guidance for analyzing various UAV–UGV coordination patterns, and the framework allows the decision-making problems for different types of UAGVSs to be described in a unified way. Besides, as a secondary contribution, this paper also makes a comprehensive investigation and analysis on recent research regarding UAGVS.

The remainder of this paper is organized as follows. In Section II, some basic symbolic notations and definitions are introduced. In Section III, we propose a taxonomy for classification of UAGVSs, followed by an analysis of some reprensentative types of UAGVSs in Section IV. In Section V, we use a typical example, cooperative target tracking, to show how different types of UAGVSs can be built to achieve the same goal and highlight their differences from an optimization perspective. In Section VI, the conclusion is given.

II. Preliminaries

A key challenge in UAGVS research is determining the control inputs of UAVs and UGVs they should take to contribute to the overall system objective, which can be viewed as an optimization problem. It will be helpful to have a clear notion of terms which are used to formulate the problems in the sequel.

It is assumed that N_A UAVs and N_G UGVs are involved in the system. We assume that the dynamics of the ith UAV can be written as

$$\begin{cases} \dot{x}_i^A = f_i^A\left(x_i^A, u_i^A\right), x_i^A \in R^{n_A}, u_i^A \in R^{m_A} \\ y_i^A = h_i^A\left(x_i^A\right) \end{cases} \quad i = 1, 2, \ldots, N_A$$

where x_i^A is the state of the ith UAV, u_i^A is the input that controls the state of the UAV, f_i^A represents its dynamics, and y_i^A is the output which mainly includes the position and posture of the UAV in 3-D space. n_A and m_A are dimensions of the state and inputs of UAVs, respectively. Similarly, the dynamics of the jth UGV can be written as

$$\begin{cases} \dot{x}_j^G = f_j^G\left(x_j^G, u_j^G\right), x_j^G \in R^{n_G}, u_j^G \in R^{m_G} \\ y_j^G = h_j^G\left(x_j^G\right) \end{cases} \quad j = 1, 2, \ldots, N_G$$

where the symbols are akin to that of UAVs. For ease of presentation, let $X_A = (x_1^A, x_2^A, \ldots, x_{N_A}^A)$ and $U_A = (u_1^A, u_2^A, \ldots, u_{N_A}^A)$ represent the complete state and inputs for a collection of N_A UAVs, and $X_G = (x_1^G, x_2^G, \ldots, x_{N_G}^G)$ and $U_G = (u_1^G, u_2^G, \ldots, u_{N_G}^G)$ for UGVs.

Different types of UAVs (fixed- versus rotary-wing UAVs) and UGVs (wheeled versus tracked UGVs) characterize different dynamics, and are suited to different application domains. Real dynamics models of vehicles are usually very complex since sophisticated constraints on state and control varialbes, which makes the real-time computation for practical applications infeasible. Therefore, simplified models such as Dubins vehicle [16] for fixed-wing UAVs, Reeds and Sheep vehicle [17], car-like model [18] for UGVs, are frequently applied in practice.

Additionally, it is assumed that the vehicles are able to communicate with each other only if they enter into their effective communication range in carrying out the task. We define an interaction graph $\mathcal{G}$ to describe possible communication channels among vehicles

$$\mathcal{G} = \left\{\mathcal{V}, \mathcal{E}(t)\right\}$$

where $\mathcal{V}$ is the set of nodes representing individual vehicles, and $\mathcal{E}(t) \subset \mathcal{V} \times \mathcal{V}$ is the set of time-varying edges indicating the communication channels between vehicles. Denote by N^i the neighbors of vehicle i, that is the set of vehicles which can communicate with it, and denote by $|N^i|$ the number of the elements of N^i.

Given these definitions, we can define a task in terms of the performance function

$$J = \int_0^T L(X_A, U_A, X_G, U_G|E)dt + V(X_A(T), X_G(T)|E)$$

where T is the horizon time over which the task should be accomplished, L represents the cost of the task (e.g., energy cost), V represents the terminal cost of the task (e.g., task completion time), and E indicates environmental factors including terrains, obstacles, wind fields, and so on, which may be either static or dynamic.

Given the optimization objective for a task, the control inputs of UAVs and UGVs in theory can be derived by solving the following optimization problem:

$$\begin{aligned} \arg\min \quad & J = \int_0^T L(X_A, U_A, X_G, U_G|E)dt + V(X_A(T), X_G(T)|E) \\ \text{s.t.} \quad & f(X_A, U_A, X_G, U_G|E) = 0 \\ & g(X_A, U_A, X_G, U_G|E) \geq 0 \end{aligned}$$

where f and g are relevant equality and inequality constraint functions, respectively.

In practice, finding the optimal solution to the optimization problem is intractable due to the great complexity of objectives and constraints. Most often, the optimization objective

TABLE II
SOME TYPICAL INSTANCES OF OBJECTIVES AND CONSTRAINTS FOR THE OPTIMIZATION FORMULATION OF UAGVSS

Optimization objectives	Formation control		$J=\sum_{i=1}^{N_A+N_G}(\int_0^T L_i^V(x_i^V(t),N^i(t))dt+w_i\cdot\int_0^T\|u_i^V(t)\|_R^2)dt)$, V represents A or G, where L_i^V represents the formation error between the ith vehicle and its neighbors (see Ref.[13] for details of the error function), and w_i is a weight to impose penalty on the control cost of the ith vehicle.
	Target tracking		$J=\int_0^T P(D/X_A(t),X_G(t))dt+w_A\cdot\sum_{i=1}^{N_A}\int_0^T\|u_i^A(t)\|_R^2dt+w_G\cdot\sum_{j=1}^{N_G}\int_0^T\|u_j^G(t)\|_R^2dt$,where $P(D/X_A(t),X_G(t))$ represents the marginal detection probability(see Ref. [20] for its computation method), w_A and w_G are the weighting coefficients for the control cost of UAVs and UGVs, respectively.
Constraints	Obstacle avoidance		$P_i^A(t)\notin Z,\ P_j^G(t)\notin O,\forall i=1,2,...,N_A, j=1,2,...,N_G, t\in(0,T]$,where Z and O denote the set of no-fly zones for UAVs, and the set of ground obstacles for UGVs, respectively, $P_i^A(t)$ and $P_j^G(t)$ denote the position of the ith UAV and the jth UGV, respectively.
	Collision avoidance		$d(x_i^A(t),x_j^A(t))>R_{safe}^A,\ d(x_m^G(t),x_n^G(t))>R_{safe}^G$ $\forall i,j=1,2,...,N_A, i\neq j;\forall m,n=1,2,...,N_G, m\neq n;\forall t\in(0,T]$ where R_{safe}^A and R_{safe}^G denote the safety distance between UAVs and that between UGVs, respectively.
	Connectivity	Planar network	$\lambda_2(\mathcal{G})\neq 0$,where $\lambda_2(\mathcal{G})$ denotes the second-smallest eigenvalue of the Laplacian Matrix of the interaction graph[21].
		Hierarchical network	$\lambda_2(\mathcal{G}^A)\neq 0,\forall j=1,2,...,N_G, d(x_j^G(t),x_{K_j}^A(t))\leq\min(r_j^G,r_{K_j}^A)$, where $\mathcal{G}^A$ denotes the interaction graph constructed by UAVs, K_j denotes the index of UAV which is nearest to the jth UGV, and r_j^G and $r_{K_j}^A$ are the effective comunication ranges of the jth UGV and the K_jth UGV[22].
	Task requirement	Time constraint	$p(T_i)<p(T_j)$,where $p(T_i)$ denotes the precedence order of the completion time of the ith task[23].

includes contradictory sub-objectives such as using minimal resource expenditure to achieve maximal benefit, which makes the optimization problem very challenging. Moreover, complex and diversified constraints also contribute to the problem difficulties. Commonly, both UAVs and UGVs are constrained by their dynamics, collision avoidance, limited energy, task-related constraints, and so on. In particular, UAVs, especially smaller ones, are sensitive to environmental factors (e.g., wind fields), which should be taken into account in the planning [19]. In some special applications like target surveillance, occlusion of the line of sight of UAVs by ground buildings reduces the feasible observation space of UAVs. Meanwhile, connectivity maintenance which is a significant precondition to coordinate the behaviors of vehicles is another vital constraint we should consider. Besides the above mentioned factors, the uncertainty of environments, real-time requirement, and so on, should also be taken into account in the resolution of the optimization problem. Table II presents some typical objectives and constraints which were frequently considered in literatures.

III. TAXONOMY OF UAGVSS

In view of the great heterogeneity and strong complementarities between UAVs and UGVs, the way of interaction between them may be fairly complex. To date, a variety of UAGVSs have been developed for specific applications. To clearly understand the types of UAGVSs, we propose a taxonomy of UAGVSs along three different axes as shown in Fig. 3.

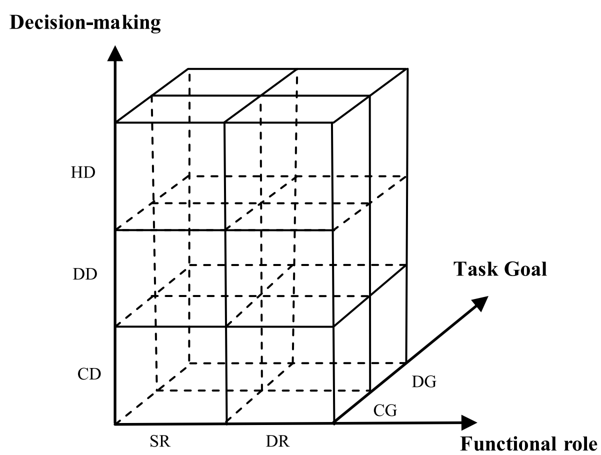


Fig. 3. Visual representation of the three axes used in the taxonomy. Same role (SR), different roles (DRs), coupled goal (CG), decoupled goal (DG), centralized decision-making (CD), decentralized decision-making (DD), and hybrid decision-making (HD).

Different from the work of [14] and [15] which are mainly focused on the coordination mechanism within UAVs or

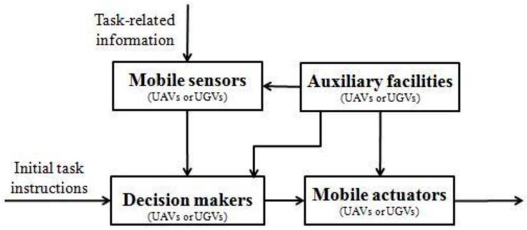


Fig. 4. Simplified block diagram of a UAGVS.

UGVs, the emphasis of the proposed taxonomy is laid on the coordination patterns between UAVs and UGVs. For a suitable classification of the works, it is important to clearly define the axes that are used. In the following, we define the classification axes and discuss the different cases that may appear along each axis.

A. Functional Role: Same Role Versus Different Roles

The axes defined here mainly describe the functional roles played by UAVs and UGVs in a task. An easy division of tasks is achieved by assigning roles according to the skills and capabilities of individual vehicles. Fig. 4 depicts the main functional modules of a UAGVS where we define four functional roles: mobile sensor, mobile actuator, decision maker, and auxiliary facility. Theses roles are primarily identified from a control system viewpoint.

In many situations, UAVs and UGVs play the same functional roles in tasks. For example, both UAVs and UGVs act as mobile sensors when they are used for situational awareness in a given region or used to track an evader.

There are indeed several cooperation schemes in which the complementarities of such heterogeneous robots can be exploited to enhance the efficiency of autonomous robotic operations. A variety of systems with UAVs (UGVs) serving as an auxiliary facility to assist UGVs (UAVs) have been developed to improve the efficiency of the whole system. An auxiliary facility can provide chief agents with energy, communication, computation, and other services other than the function of sensors, actuators and decision makers. The scenarios in which UAVs and UGVs play different functional roles in existing literatures mainly include the following two cases [24].

1) UGVs Act as Mobile Actuators, UAVs Act as Decision Makers, Mobile Sensors, or Auxiliary Facilities: In these systems, UGVs act as mobile actuators, and UAVs make decisions for UGVs [25]–[29], provide UGVs with environment and task information [30]–[32], or act as communication relays to provide communication links with the remote operator station and between UGVs [22], [33], [34].

2) UAVs Act as Mobile Sensors or Actuators and UGVs Act as Auxiliary Facilities: In these systems, UAVs act as mobile sensors or actuators. However, in some cases, the low payload capacity and short flight endurance of UAVs (especially smaller ones) greatly restrict their efficiency in accomplishing tasks. As an alternative, UGVs can assist UAVs (especially small rotary-wing ones) to complete tasks more efficiently by providing them with energy or transporting them in large fields [35]–[38].

B. Task Goal: Coupled Goal Versus Decoupled Goal

It is concerned with the task goals that the two kinds of vehicles are aimed. For coupled task goals, the actions of both kinds of vehicles should be tightly coordinated so that the task objective is optimized [39]. In some special cases, tasks can be broken up or decomposed into multiple steps or subtasks, where different parts of the task can be accomplished by different kinds of vehicles. In this case, the shared task goal can be decoupled into different sub-goals so that each sub-goal can be achieved by only UAVs or UGVs.

For ease of presentation, it is generally considered that the equality and inequality constraints are included in the objective function of the task (e.g., via Lagrange multipliers). In the following, a strict definition of decoupled task goal with respect to UAVs and UGVs is given from a view of optimization.

Definition 1: For a minimization (or maximization) task goal function $J = \int_0^T L(X_A, U_A, X_G, U_G|E)dt + V(X_A(T), X_G(T)|E)$, it can be said that the task goal is decoupled with respect to UAVs and UGVs if the following two conditions are satisfied.

1) The task goal can be decomposed into two independent optimization sub-goals with respect to UAVs and UGVs as follows:

$$J_A = \int_0^T L^A(X_A, U_A|E)dt + V^A(X_A(T)|E)$$
$$J_G = \int_0^T L^G(X_G, U_G|E)dt + V^G(X_G(T)|E)$$

where J_A and J_G are sub-goal functions which are only relevant to the states and control inputs of UAVs and UGVs, respectively.

2) The goal function of the whole task J can be written as $J = F(J_A, J_G)$, and there is a positive correlation or negative correlation between J and J_A (J_G) under the assumption that $J_G(J_A)$ remains constant.

The first condition ensures that the UAVs (UGVs) can make their decisions irrespective of the control inputs and states of UGVs (UAVs), and the second condition ensures that the overall goal function of the task can be improved by independently optimizing two sub-goals. In these cases, UAVs and UGVs make their own decisions independently, and approaches developed for homogeneous vehicles can be easily applied for both of them. Obviously, the decoupling characteristic of task goals can greatly ease the difficulty of problem-solving. Unfortunately, the task goal cannot be decoupled in many cases.

C. Decision-Making: Centralized Decision-Making Versus Decentralized Decision-Making Versus Hybrid Decision-Making

It is concerned with the way of decision-making among UAVs and UGVs, which mainly includes centralized decision-making (CD), decentralized decision-making (DD), and hybrid decision-making (HD). In a centralized way, a central vehicle collects task-related information from both UAVs and UGVs and makes decisions for all members. Although higher communication and computation load on the central vehicle occurs in centralized approaches, the optimality of solution can be guaranteed in theory. In contrast, if a decentralized scheme is adopted, each vehicle has autonomy and makes its own decisions by only using information of its neighbors. Hence, decentralized approaches have better robustness and scalability than centralized ones at the loss of optimality of solution.

Both kinds of approaches (centralized and decentralized ones) have their own advantages, and are suitable for certain situations. For small-scale systems, centralized approaches are likely a better choice while decentralized approaches are fit for large-scale systems. In HD approaches, both centralized and decentralized approaches are applied. Hybrid approaches can be implemented in a variety of ways. The simplest implementation can be that both UAVs and UGVs make their own decisions in a centralized way, and then the leader of UAVs and the leader of the UGVs negotiate to achieve a consensus decision. HD approaches combine the advantages of both centralized ones and decentralized ones, which can achieve a better tradeoff between solution quality and time cost for decision-making.

Remark 1: The first two axes "functional role" and "task goal" are concerned with the interrelationship between UAVs and UGVs, while the third one "decision-making" is concentrated on the decision-making manner of the whole system. The main reasons why we select the three axes lie in two aspects. On one hand, the three axes mentioned here are not meant to be exhaustive, but are broad enough to characterize most of current UAGVSs. On the other hand, corresponding optimization models and solving strategies for UAVs and UGVs can be determined once the properties of a UAGVS along the three axes are identified. So, the taxonomy along with specifically designed axes provides a useful tool to describe different kinds of UAGVSs under a generalized optimization framework, which benefits a comprehensive understanding and general analysis of UAGVSs.

IV. Analysis on Representative Types of UAGVSs

In this section, some representative types of UAGVSs from the taxonomy proposed in Section III are discussed. We denote a particular type of UAGVSs by a triple of two-letter abbreviations drawn from Section III (sometimes may only include parts of the axes for classification). For each kind of UAGVS, some existing research results are also presented and analyzed. Finally, some common issues involved in various UAGVSs are discussed.

A. Representative Types of UAGVSs

1) Same Functional Role and Decoupled Goal: In this type of UAVGS, UAVs, and UGVs play the same functional role, and they act as mobile sensors or mobile actuators. In this case, UAVs and UGVs can be viewed as two independent sub-systems and independently make their own decisions to achieve decoupled sub-goals.

For example, consider the problem of monitoring a given area including both land and sea where both UAVs and UGVs act as mobile sensors. The UGVs are appointed to monitor the part of the land while UAVs are for the part of the sea. Control inputs of UAVs and UGVs can be derived through solving two independent optimization problems. In this scenario, the optimization function can be simply defined as (other forms could be used)

$$\begin{cases} U_A = \arg\min J_A = w_1 \cdot \int_0^T E_A(t)dt + w_2 \cdot t_f^A \\ U_G = \arg\min J_G = w_1 \cdot \int_0^T E_G(t)dt + w_2 \cdot t_f^G \end{cases}$$

where $E_A(t)$ and $E_G(t)$ denote the energy consumed by UAVs and UGVs during the task, t_f^A and t_f^G are the task completion time for UAVs and UGVs, respectively, and w_1 and w_2 are weighting coefficients. In this case, algorithms developed for homogeneous robot can be directly applied to solve the corresponding optimization problem with respect to UAVs and UGVs.

A typical application of this kind of UAGVS is shown in the work of Tanner [40] who developed a switched cooperative control scheme to coordinate groups of ground and aerial vehicles for the purpose of locating a moving target in a given area. In this paper, the task goals of UAVs and UGVs are decoupled, with UGVs building a guarding formation and UAVs uniformly scanning the enclosed region.

2) Different Functional Role and Decoupled Goal: Due to the strong complementarities between UAVs and UGVs, each kind of vehicles can improve its efficiency in completing tasks with the assistance of the other in many cases. This type of UAGVS primarily consists of the following two situations.

a) UGVs act as mobile acutators, UAVs act as mobile sensors, decision makers, or auxiliary facilities: Although UGVs can perform increasingly sophisticated tasks, the restrictions of speed, view scope, communication and so on, sometimes limit their application ranges. In this case, UAVs can aid UGVs to complete tasks more efficiently. Here, we primarily focus on the following three scenarios.

i) UGVs act as mobile acutators and UAVs act as decision makers: Michael *et al.* [25] developed an abstraction method for the team of ground robots, which allows the aerial vehicle to control the team without any knowledge of the specificity of individual vehicles. An ellipsoidal approximation of the shape of the team formation is adopted, and the position and orientation of the team in the plane are also defined. The controllers are derived that allow the team of robots to move in formation while avoiding collisions and respecting the abstraction commanded by the aerial vehicle.

Chaimowicz and Kumar [26] addressed the problem of deploying groups of tens or hundreds of UGVs in urban environments. The results presented in [26] were extended to the scenario with multiple UAVs and multiple UGV groups. These UAVs are taken as "aerial shepherds," and a probabilistic approach based on expectation maximization is proposed to assign the shepherds to the UGV groups. In the process of movement, these aerial shepherds control the splitting and merging of the UGV swarm into groups according to the environment information.

Rao *et al.* [27] proposed a controller which can generate control strategies for a UGV with feedback from overhead image obtained by a UAV. Similarly, Frietsch *et al.* [28] used an unmanned micro aerial vehicle (MAV) to improve the navigation solution of a UGV. The MAV detects the UGV from the image acquired by an on-board camera and further estimates the location and yaw angle of the UGV. Then, the information is transmitted to the UGV and utilized to improve its navigation. The navigation ability provided by UAVs to UGVs can effectively expand the application ranges of UGVs in complex environments, especially in GPS-denied cases.

With the exploration and exploitation of ocean moving forward, unmanned underwater vehicles (UUVs) have been extensively adopted in ocean operations. Sujit *et al.* [29] provided a mechanism to coordinate UUVs and a UAV to perform an ocean exploration mission. The main mission for the UAV is to acquire information from UUVs and assign tasks to them. Different from UGVs, UUVs can communicate with the UAV only when they surface. Hence, the UAV needs to consider the uncertainty of the surfacing of a UUV when it generates a new mission plan for the UUV.

Using UAVs to provide effective management and control support to UGVs not only improves the capability of UGVs to perform tasks in complex environments, but also provides possibilities to deploy large-scale UAGVSs.

ii) UGVs act as mobile actuators and UAVs act as mobile sensors: UAVs can fast capture environment and task information because of their quick speed. So, using UAVs to transmit gathered environment and task information to UGVs can remarkably aeccelerate the response of UGVs.

MacArthur *et al.* [30] concentrated on the detection and disposal of mines using cooperative UAVs and UGVs. The UAV first surveys the target area and creates a map of the area. The map was transmitted to the base station and processed to extract the locations of the targets. Then, corresponding waypoints were generated for the UGV to navigate. Then, the UGV proceeded to each of the targets and disposed the ordnances. Cheung and Grocholsky [31] used a PackBot UGV and a small Raven UAV to pursuit and track a dynamic target. The UAV first surveys the area and localizes the target. Then, the Raven-PackBot team will collaboratively pursue the target to maintain track on the target.

Ramirez *et al.* [32] presented a sea rescue system based on a coordinated team of a sensing/monitoring UAV and a rescuing unmanned surface vessel (USV). First, an artificial neural network (ANN), trained before the rescue, is used to predict the castaway location using the map of the sea wind and currents. Based on the predicted location, the UAV searches for the castaways using another ANN trained with searching behaviors. Then, the USV employs particle filtering to estimate the castaway location using all the predicted and measured data.

iii) UGVs act as mobile actuators and UAVs act as auxiliary facilities: As mentioned in Section III-A, an auxiliary facility can provide energy, communication, computation, and other services to chief agents. For example, maintaining communication connection among all UGVs is one of the preconditions to efficiently accomplish specified tasks. However, short communication range of UGVs greatly limits their operations in large fields. Using UAVs as auxiliary facilities to provide communication links between UGVs is a promising approach. The key problem in this case is how to place these UAVs at proper positions so that all UAVs form a connected network and each UGV can communicate with at least one UAV. The problem can be solved by optimizing the positions of UAVs given the following optimization objective and constraints:

$$\begin{aligned} \min\ & J = H(X_A, X_G) \\ \text{s.t.}\ & r(\mathcal{G}) = 1 \\ & \forall j = 1, 2, \ldots, N_G, d\left(x_j^G, x_{K_j}^A\right) \le \min\left(r_j^G, r_{K_j}^A\right) \end{aligned}$$

where H is a measure concerning the performance of the network such as the energy cost, reliability, and so on. $r(\mathcal{G})$ is an evaluation on the connectivity of the graph constructed by UAVs whose detailed definition can be found in the literature [33]. K_j, r_j^G and $r_{K_j}^A$ are defined the same as that in Table II. The first constraint ensures that the network constructed by UAVs is connected while the second one ensures the connectivity between aerial and ground vehicles.

This problem can be solved in either a centralized manner or a distributed manner. Chandrashekar *et al.* [34] achieved full connectivity to disconnected ground nodes by dynamically placing UAVs to act as relay nodes using a heuristic algorithm. The authors considered both the minimal number of UAVs required to provide full connectivity and their corresponding locations. One distributed approach is given in the work of Gil *et al.* [22], who took the communication-link quality into account and developed a gradient-based distributed controller to position a team of aerial vehicles so as to optimize the communication-link quality. Using UAVs as relays to provide communication service to UGVs remarkably extends the operational range of UGVs.

b) UAVs act as mobile sensors and UGVs act as auxiliary facilities: Small UAVs, especially rotary-wing ones with vertical takeoff and landing abilities, are usually limited by their payload capability which limits the amount of batteries that can be carried as well as the operating range of UAVs. On the contrary, UGVs can take more payloads. Therefore, one possible solution is the application of UGVs for the purpose of recharging long-range transportation for UAVs.

Voos and Bou-Ammar [35] proposed a novel nonlinear controller for rotary-wing aerial vehicles to track and land on a moving base station. Wills *et al.* [36] described the automated UAV mission system for small vertical takeoff and landing (VTOL) UAVs, which can provide forward staging, refueling, and recovery capabilities for the VTOL UAV through a host UGV. In this case, UGVs serve as launch/recovery platforms and service stations.

Tokekar *et al.* [37] studied the problem of coordinating a symbiotic UAV and UGV system to collect data for a precision agriculture application. Measurements collected by a UAV and a UGV are used for estimating Nitrogen levels across a farm field. These estimates in turn guide fertilizer application. Taking into account the limited voyage of the UAV, the authors used a symbiotic UAV/UGV system where the UGV can mule the UAV to various locations. Simulation results demonstrated that, compared with the scenario using UAVs only, UAV/UGV coordination can greatly raise the operational efficiency.

Saska *et al.* [38] built a UAGVS for periodical surveillance in indoor environments. During the mission, a UGV follows a preplanned path and sequentially scans the places of interest by its sensors. Once a position of interest cannot be reached by the UGV due to environment constraints, a UAV is launched from the UGV to perform the inspection. After the UAV completes the inspection, it returns to the UGV helipad, and they continue toward the next place. The use of UAVGS not only overcomes the limitation of UAVs in their short voyage, but also reduces the susceptibility of UGVs sensing ability to environmental factors.

Remark 2: In SR–DG and DR–DG types of UAGVSs, UAVs and UGVs have decoupled task sub-goals, which means that they can make their own decisions independently. If UAVs and UGVs make their own best decisions, then the whole task goal can be reached optimally. In this case, simultaneous consideration of the decision-making for UAVs and UGVs is needless. Different kinds of decision-making approaches, such as centralized, decentralized, and hybrid approaches, can be adopted within UAVs and UGVs according to specific task requirements.

3) Same Functional Role, Coupled Goal, and Centralized Decision-Making: In most cases, UAVs and UGVs act as the same functional role and share a coupled task goal where tight coordination mechanism should be designed to complete the task effectively. An intuitive and simple way to address the problem is using a centralized approach, where information of both UAVs and UGVs is collected, and decisions for UAVs and UGVs are made by one vehicle or by a central controller. The control inputs of UAVs and UGVs can be derived via solving the following optimization problem:

$$[U_A, U_G] = \text{argmin } J = \int_0^T L((X_A, U_A, X_G, U_G)|E)dt + V(X_A(T), X_G(T)|E).$$

Although CD approaches can find the best solutions to corresponding optimization problems in theory, their weak robustness, poor scalability, and the extended period of time required to obtain final solutions usually limit their applications. Hence, CD approaches are prone to be used for initial planning at the start or be used for online planning for small-scale UAGVSs.

One application of this system is presented in the work of Phan and Liu [41], who conducted research on the task assignment problem in wildfire detection and fighting using cooperative UAVs/UGVs platforms. A cooperative control framework for a hierarchical UAVs/UGVs platform is presented. In the top-most level, an airship is used as a mobile mission controller to perform mission planning, assignment and system-level decision-making for both UAVs and UGVs. Then, the task assignment problem is formulated as a pure integer linear program which can be easily solved by MATLABs optimization toolkit. The algorithm proposed for task allocation is typically a centralized one whose effectiveness highly relies on the airship.

4) Same Functional Role, Coupled Goal, and Decentralized Decision-Making: For coupled task goals, CD approaches are capable of obtaining high-quality solutions. However, they are sometimes computationally unfeasible and unreliable especially for large-scale systems. Meanwhile, in view of the constraints on physical systems such as limited computational resources and energy, limited wireless communication ranges and bandwidths, the decentralized approaches have been payed more attention and widely appreciated. In SR–CG–DD systems, the decision-making for UAVs and UGVs can be given as follows:

$$U_A = \text{argmin } J = J\big(X_A, U_A, \tilde{X}_G, \tilde{U}_G\big)$$
$$U_G = \text{argmin } J = J\big(X_G, U_G, \tilde{X}_A, \tilde{U}_A\big)$$

where $\tilde{X}_G$ and $\tilde{U}_G$ ($\tilde{X}_A$ and $\tilde{U}_A$) are the states and control inputs of UGVs (UAVs) received by UAVs (UGVs) throughout the communication network between UAVs and UGVs.

Roughly speaking, DD manners can be mainly splitted into two categories: emergent and intentional coordination.

a) Emergent coordination: It is rooted in the observation of large-scale animal behavior such as flocks of birds and schools of fishes which can travel information to defend themselves against predators. Applying the idea of animal coordination to multivehicle coordination, intelligent activities can be achieved through simple and distributed agent-to-agent interactions where each vehicle makes its own decision only based on the information of its neighbors [42]–[48].

In emergent coordination manners, relatively simple control laws executed by vehicles result in emergent group behavior without the need for a complex coordination architecture. These kind of systems are well suited for large-scale development, but they are usually applied to very simple tasks such as flocking [42]–[44], formations [45], coverage [46], search [47], rendezvous [48], and so on.

b) Intentional coordination: In intentional coordination approaches, robots cooperate with purpose, and the common objective is optimally achieved often through task-related communication and negotiation between vehicles. It can be asserted that, as compared with emergent coordination manners, intentional coordination manners are better suited to perform complicated tasks, and have higher requirements of vehicles' performance such as computational and communication ability. Here, we examine the intentional coordination approaches for a typical problem in MRS: motion coordination.

An important problem in MRS is the motion coordination for multiple vehicles through a shared workspace, which requires vehicles to move through the workspace in a coordinative way so that fleet-level task objectives are optimized while avoiding collisions between vehicles. The most used optimization criteria include the minimization of total vehicle path lengths, the minimization of consumed time and energy, and so forth. Substantial literatures for motion coordination are based on intentional coordination, such as the idea of cooperative variables and cooperative function [49], game theory-based approach [50], sequential decision approach [51], and so on.

5) Same Functional Role, Coupled Goal, Hybird Decision-Making: For a large-scale UAGVS, CD approaches are usually computationaly infeasible while DD approaches consume more time and the optimality of solutions cannot be guaranteed. To achieve a better tradeoff between optimality and efficiency, a promising way is using HD approaches, which incorporates the advantages of both centralized and decentralized ones.

HD can be achieved in a variety of ways according to different types of system organizations. A typical way is that, all vehicles are divided into some small-scale sub-teams, and each sub-team selects one vehicle as its leader. Each leader makes decisions for all members in this sub-team and coordinates the behaviors of different sub-teams using a decentralized approach.

One conceivable application scenario of this type of system is wildfire fighting with multiple fire-points in a large field. In such a dynamic, uncertain, and real-time environment, how to realize the real-time planning and control is a very challenging problem. Managing the whole system on a team level can promote the efficiency of making decisions and achieve a better tradeoff between solution quality and solution time. It is assumed that both UAVs and UGVs act as mobile actuators, and all vehicles are divided into several sub-teams. Each sub-team consists of a certain number of UAVs and UGVs, and one vehicle (e.g., a UAV) is selected as the leader of this sub-team. Each sub-team, represented by the leader, participates in the decision-making as a whole. During the mission, all the leaders constitute a connected network. Each leader makes decisions for all members in the sub-team, and coordinates its behaviors through negotiation with other leaders in a decentralized way. Within each team, a centralized approach is adopted to solve a small-scale optimization problem, which guarantees the quality of solutions to some extent. Among all sub-teams, decentralized coordination approaches improve the robustness and scalabality of the whole system.

B. *Common Issues Involved in Various UAGVSs*

In the above, some representative types of UAGVSs are presented, and their corresponding optimization models are also established. In this section, two common issues, computational complexity and real-time peroformance, involved in various UAGVSs are discussed in detail.

1) Computational Complexity: Taking the SR–CG–CD system as an example, the decision-making for the UAGVS is formulated as follows:

$$\begin{aligned}[U_A, U_G] = \operatorname{argmin} \quad & \left\{ J = \int_0^T L((X_A, U_A, X_G, U_G)|E)dt \right. \\ & \left. + V(X_A(T), X_G(T)|E) \right\} \\ \text{s.t.} \quad & f(X_A, U_A, X_G, U_G|E) = 0 \\ & g(X_A, U_A, X_G, U_G|E) \geq 0.\end{aligned}$$

The solution of the problem should be expressed as continuous control inputs of UAVs and UGVs over the whole time horizon. For ease of calculation, the whole time horizon is decomposed into a series of small time horizons, and a constant control input is generated during the period of each small time horizon. Denote the duration of each small time horizon by ΔT. So, the total number of optimization variables is $\lceil T/\Delta T \rceil \cdot (N_A m_A + N_G m_G)$. Assume that each variable is discretized into δ levels. Then, the total number of possible solutions is $(\lceil T/\Delta T \rceil \cdot (N_A m_A + N_G m_G))^\delta$. Obviously, the time for evaluating a solution is approximate to $t' = t_{\text{objective}}(N_A, N_G) + t_{\text{constraint}}(N_A, N_G)$, where $t_{\text{objective}}(N_A, N_G)$ and $t_{\text{constraint}}(N_A, N_G)$ denote the time for calculating the objective and constraints, respectively, and both of them are functions with respect to the number of UAVs and that of UGVs. So, the total time for evaluating all solutions is $(\lceil T/\Delta T \rceil \cdot (N_A m_A + N_G m_G))^\delta \cdot t'$. In other words, the worst-case computational complexity of the optimization problem using enumeration methods is $O((\lceil T/\Delta T \rceil \cdot (N_A m_A + N_G m_G))^\delta \cdot t')$.

TABLE III
COMPUTATIONAL COMPLEXITY OF REPRESENTATIVE UAGVSS

System type	Computational complexity
SR-CG-CD	$O((\lceil T/\Delta T \rceil \cdot (N_A m_A + N_G m_G))^\delta \cdot t')$
SR-CG-DD	$O(N_A \cdot (\lceil T/\Delta T \rceil \cdot m_A)^\delta \cdot t' + N_G \cdot (\lceil T/\Delta T \rceil \cdot m_G)^\delta \cdot t')$
SR-CG-HD	$O((\lceil T/\Delta T \rceil \cdot (N_A m_A))^\delta \cdot t' + (\lceil T/\Delta T \rceil \cdot (N_G m_G))^\delta \cdot t')$
SR-DG-DD DR-DG-DD	$O(N_A \cdot (\lceil T/\Delta T \rceil \cdot m_A)^\delta \cdot t'_A + N_G \cdot (\lceil T/\Delta T \rceil \cdot m_G)^\delta \cdot t'_G)$
SR-DG-HD DR-DG-HD	$O((\lceil T/\Delta T \rceil \cdot (N_A m_A))^\delta \cdot t'_A + (\lceil T/\Delta T \rceil \cdot (N_G m_G))^\delta \cdot t'_G)$

The analysis on the computational complexity of SR–CG–CD system can be extended to other types of systems in a similar way. It is noteworthy that different schemes for implementing DD or HD may result in different computational complexity. For example, as a possible way of the DD, the sequential decision-making by which agents make decisions one by one according to certain priorities gives rise to computational complexity of

$$O\big(N_A \cdot (\lceil T/\Delta T \rceil \cdot m_A)^\delta \cdot t' + N_G \cdot (\lceil T/\Delta T \rceil \cdot m_G)^\delta \cdot t'\big).$$

As illustrated in Definition 1, for a decoupled task goal, UAVs and UGVs have independent individual sub-goals. Denote by t'_A and t'_G the time of calculating their individual sub-goals, respectively. The result of complexity analysis on typical UAGVSs is presented in Table III where DD is achieved by sequential decision-making. For HD, it is assumed that the centralized manner is used for interUAVs (interUGVs), and the decentralized manner is adopted between UAVs and UGVs.

2) Real-Time Performance: In practical applications, real-time performance is an important index reflecting the system performance especially for online decision-making. The real-time performance of doing mathematical optimization has changed very much thanks to the developing of computers and computing algorithms.

It is assumed that, at each decision time, the maximum allowed time for producing the final solution is $T_{\max}$. To satisfy the real-time requirement, the maximum number of solution evaluations in the optimization algorithm must satisfy the following constraint:

$$N_{\max} \cdot (t + t'') \leq T_{\max}$$

where t can be t', t'_A, or t'_G, and t'' denotes the time consumed by the operations of the optimization algorithm itself, such as the generation of a solution, comparison between two solutions, and so on.

The above analysis shows that problem formulations, algorithms, and computer performance all have important impacts on the real-time performance of the system. Next, we will talk about some commonly used measures to improve the real-time performance.

a) Choose appropriate computation platforms with desirable performance: Given a specific optimization formulation and optimization algorithm, the computation platform should be selected to satisfy

$$t + t'' \leq \frac{T_{\max}}{N_{\max}}.$$

In other words, a platform with better computation ability allows more time to be used to find a better or even the best solution.

b) Simplify the problem formulation: Besides the optimization scale of the problem, the actual problem formulation itself also has a significant impact on the real-time performance of the system. Taking the optimization objective for target tracking problem shown in Table II as an example, the objective function is the sum of integral terms, and the detection probability $p(D|x^A(t), x^G(t), E)$ is determined by a variety of factors such as the models of onboard sensors, the relative position and heading between the UAV (UGV) and the target, the occlusion of light of the sight by obstacles like buildings, and so on. In addition, the real kinematic models of UAVs and UGVs are usually very complex. It will consume large amount of time by the computer to calculate their accurate values. To reduce calculation burden, some equivalent presentation can be adopted. For example, the relative position between the UAV (UGV) and the target is the most important factor in the detection probability intuitively, so the accurate calculation of detection probability can be replaced by a function of the relative position between the vehicle and the target. In addition, the integral term can be calculated approximately by the sum of some critical sampling points. For the kinematic models of UAVs and UGVs, some simplified models such as Dubins car model for fixed-wing UAVs and mass point model for UGVs can be used.

c) Given the specific platform and the optimization formulation, corresponding optimization algorithm should be selected and designed: To solve the optimization problems, a large number of algorithms including constructive methods and search methods can be used as candidates. Constructive methods, often referred to as constructive heuristics, generate feasible solutions by some heuristic rules which may be extracted from the problem structure or domain knowledge [52]. Search methods rely on samplings in solution space to find a better or even the best solution. Enumeration, random sampling, traditional gradient-based search, improvement heuristics (e.g., local search methods), various meta-heuristics including trajectory search (e.g., tabu search), and population-based search (e.g., genetic algorithm and differential evolution) all can be classified as search methods [53]. Constructive methods usually feature simple operations but cannot guarantee optimality. In contrast, search methods, especially meta-heuristics, are effective for problems with complex landscapes. However, they usually consume much more time than constructive methods.

According to the real-time constraint, the maximum number of solution evaluations for the optimization algorithm must be less than $T_{\max}/(t' + t'')$, which provides us a principle to select a suitable algorithm. For example, if $T_{\max}/(t' + t'')$ is pretty small, it is impossible to rely on population-based search to find the best or even a satisfactory solution within very limited time. In this case, constructive methods (e.g., some greedy heuristics) can be specially chosen or designed.

V. Different Types of UAGVSs For Typical Application: Target Tracking

In the above, different types of UAGVSs have been explored, and a general optimization framework has been developed. In this section, we make a detailed discussion on the diverse possibilities of achieving target tracking by using UAGVSs according to the proposed taxonomy.

The reasons why UAVs and UGVs are coordinated to track the evaders lie in two aspects. First, from illustration above, UGVs are suitable for accurately locating ground targets but they do not have the ability to move rapidly and see through obstacles such as buildings and fences while UAVs can make up these deficiencies. Second, fusing data from different vehicles which are described by distinct types can effectively remedy the drawback of low accuracy and reliability caused by using only one kind of vehicles. For ease of analysis, it is assumed that one UAV and one UGV are involved to track one evader. A variety of models can be built to formulate this problem. Here, we cast the problem in a probabilistic framework whose objective is to detect the evader with the biggest probability. In the following, we first give some basic definitions.

Given the evader location $x^T(t)$, the UAV location $x^A(t)$, and the UGV location $x^G(t)$ at time t, we let $p(D/x^A(t), x^G(t), x^T(t), E)$ represent the joint detection probability of the target by the UAV and the UGV, where D is an event that the evader is detected correctly, and E indicates environmental factors including obstacles, buildings, and so on. These environmental factors make great effect on the feasible motion space of vehicles, and occlusion of the line of sight between vehicles and targets should be taken into account in the planning. Then, the marginal detection probability given the UAV location and the UGV location at time t can be given by

$$p\Big(D/x^A(t), x^G(t), E\Big) = \sum_{x^T(t)} p\Big(D/x^A(t), x^G(t), x^T(t), E\Big) \cdot p\Big(x^T(t)\Big)$$

where $p(x^T(t))$ means the probability that the evader occupies $x^T(t)$ which can be estimated by a presupposed motion model. Here, the motion state of the evader is described by using dynamic occupancy grids, which separate the environment into a grid of equally spaced cells representing varying beliefs about the evader state. The motion of the evader can be estimated by a predefined model such as second-order Markov chain model [20], random walk model [54], and so on.

A. Different Coordination Patterns for Target Tracking by UAGVS

1) DR–DG–DD System for Target Tracking: In some special cases, the final objective is to capture the evader or the target. In these systems, the main mission of the UAV is tracking the evader and transmitting obtained information to the UGV while the UGV moves toward the target and captures it. In this kind of UAGVS, the UAV acts as mobile sensor and the UGV acts as mobile actuator.

2) SR–DG–DD System for Target Tracking: The coordinative target tracking by UAVs and UGVs is essentially a problem with a coupled goal. However, some researchers solve it with decoupling methods like the work of Owen *et al.* [20], in which the UAV and UGV track the target independently and there is no information exchange between them. In this case, the control inputs of the UAV and UGV can be derived by solving two separate optimization problems as follows:

$$u^A = \arg\max J_A = \int_0^T P\Big(D\Big|x^A(t), E\Big)dt + w_A \cdot \int_0^T C^A(t)dt$$
$$u^G = \arg\max J_G = \int_0^T P\Big(D\Big|x^G(t), E\Big)dt + w_G \cdot \int_0^T C^G(t)dt$$

where u^A and u^G denote the control input sequence of the UAV and UGV over the whole horizon, respectively. $P(D|x^A(t), E)$ and $P(D|x^G(t), E)$ are the marginal detection probability by the UAV and the UGV, respectively. $C^A(t)$ and $C^G(t)$ are the energy cost of the UAV and UGV, respectively. The drawback of the approach is that both UAV and UGV plan their own paths using only the information gathered by itself.

3) SR–CG–CD System for Target Tracking: Tight coordination between the UAV and UGV can significantly improve the efficiency of the whole system. A simple and direct way to achieve a coupled task goal is using a centralized approach where the control inputs of the UAV and UGV are optimized by one vehicle (the UAV or UGV) or by a central station

$$\begin{aligned}\Big[u^A, u^G\Big] = \arg\max J = &\int_0^T p\Big(D\Big|x^A(t), x^G(t), E\Big)dt \\ &+ w_A \cdot \int_0^T C^A(t)dt + w_G \cdot \int_0^T C^G(t)dt.\end{aligned}$$

4) SR–CG–DD System for Target Tracking: In light of the larger computation burden in centralized approaches, a feasible method is to break the original problem into smaller sub-problems which can be solved by individual vehicles. A variety of decentralization mechanisms such as the game-based approaches [50], sequential decision-making [51], and so on, can be applied.

B. Simulation

Here, a simple simulation is provided to intuitively demonstrate the differences of diverse UAGVSs. Two representative types of UAGVSs, SR–DG–DD and SR–CG–CD, are built to track the target by a UAV and a UGV. Due to uncertain movement of the target, decision-making over the whole time horizon is needless. Receding horizon optimization is adopted to generate h steps look-ahead control inputs for the UAV and UGV. According to the discussion on real-time performance in Section IV, simplified problem formulations based on receding horizon optimization strategy for the UAV and UGV are presented as follows.

For SR–DG–DD system, the UAV and UGV have respective optimization sub-goals and make their own decisions independently. Intuitively, maximum detection probability can be achieved by the UAV (UGV) through keeping a certain distance to the target. So, the accurate calculation of detection probability can be replaced by an equivalent function with respect to the relative distance between the UAV (UGV) and the target. At the meantime, the Dubins car model is adopted to approximate the kinematic of the UAV. The optimization formulation for the UAV at time t_k is given as follows:

$$u^A(k) = \arg\max \left\{ J_A = \sum_{j=0}^{h} e^{-\left|d\left(P^A(t_k+j\cdot\Delta t), P^T(t_k+j\cdot\Delta t)\right)-d_e\right|} \right\}$$
$$\text{s.t.} \quad \begin{cases} \dot{x}^A = v^A\cos\big(\theta^A\big) \\ \dot{y}^A = v^A\sin\big(\theta^A\big) \\ \dot{v}^A = 0, \dot{\theta}^A = \frac{v^A}{r^A}u^A, u^A \in [-1, 1] \end{cases}$$

where $P^A(t_k + j \cdot \Delta t)$ and $P^T(t_k + j \cdot \Delta t)$ denote the positions of the UAV and the target at time $t_k + j \cdot \Delta t$, respectively, and $d(P^A(t_k + j \cdot \Delta t), P^T(t_k + j \cdot \Delta t))$ denotes the Euclidean distance between the two positions. (x^A, y^A), v^A, θ^A, and r^A denote the position, velocity, heading, and turning radius of the UAV, respectively. Δt denotes the duration of each time horizon, and d_e denotes the expected distance between the UAV and the target.

Similarly, the optimization model for the UGV is formulated as follows:

$$u^G(k) = \arg\max \left\{ J_G = \sum_{j=0}^{h} e^{-\left|d\left(P^G(t_k+j\cdot\Delta t), P^T(t_k+j\cdot\Delta t)\right)-d_e\right|} \right\}$$
$$\text{s.t.} \quad \begin{cases} \dot{x}^G = v^G\cos\big(\theta^G\big) \\ \dot{y}^G = v^G\sin\big(\theta^G\big) \\ v^G \in \big[v^G_{\min}, v^G_{\max}\big] \end{cases}$$

where $v^G_{\min}$ and $v^G_{\max}$ denote the minimal and maximal velocities of the UGV, respectively.

For the SR–CG–CD system, the UAV and UGV share a common objective of maximizing the marginal detection probability. From the perspective of data fusion, the UAV and UGV are expected to keep themselves on different sides of the target with a certain distance to enhance the complementarity of detecting the target. Analogously, a heuristic optimization

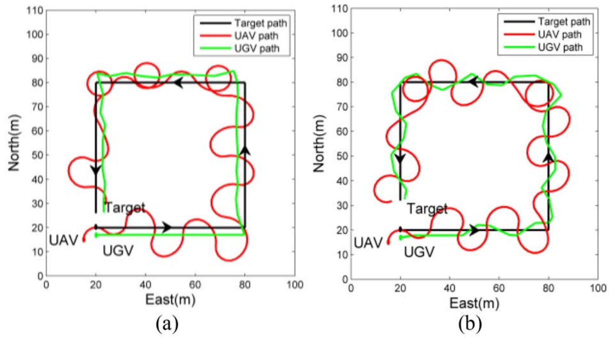


Fig. 5. Results of target tracking for the UAGVS with different system types. The result for the UAGVS with system types (a) SR–DG–DD and (b) SR–CG–CD.

objective is adopted. The optimization model for the UAGVS is formulated as follows:

$$\left[u^A(k), u^G(k)\right] = \arg\max \left\{ J = \sum_{j=0}^{h} e^{-\min(d_1, d_2)} \right\}$$

$$\begin{aligned} d_1 &= d\Big(P^A(t_k + j \cdot \Delta t), P_R(t_k + j \cdot \Delta t)\Big) \\ &\quad + d\Big(P^G(t_k + j \cdot \Delta t), P_L(t_k + j \cdot \Delta t)\Big) \\ d_2 &= d\Big(P^G(t_k + j \cdot \Delta t), P_R(t_k + j \cdot \Delta t)\Big) \\ &\quad + d\Big(P^A(t_k + j \cdot \Delta t), P_L(t_k + j \cdot \Delta t)\Big) \end{aligned}$$

$$\text{s.t.} \begin{cases} \dot{x}^A = v^A \cos\big(\theta^A\big) \\ \dot{y}^A = v^A \sin\big(\theta^A\big) \\ \dot{\theta}^A = \frac{v^A}{r^A} u^A, u^A \in [-1, 1] \\ \dot{v}^A = 0 \end{cases}$$

$$\begin{cases} \dot{x}^G = v^G \cos\big(\theta^G\big) \\ \dot{y}^G = v^G \sin\big(\theta^G\big) \\ v^G \in \left[v^G_{\min}, v^G_{\max}\right] \end{cases}$$

where $P_R(t_k + j \cdot \Delta t)$ and $P_L(t_k + j \cdot \Delta t)$ are expected positions of the UAV and UGV at time $t_k + j \cdot \Delta t$, which are located at the right and left sides of the target with an expected distance d_e.

The algorithm described above is simulated in MATLAB and implemented on a PC with 2 GB RAM and 2.1 GHz Pentium dual-core CPU under Windows XP operating system. In the simulation, the model parameters of the UAV and the UGV are set to: $v^A = 5$ m/s, $r^A = 4$ m, $v^G_{\min} = 0$, and $v^G_{\max} = 3$ m/s. It is assumed that the target is located at the position (20, 20) initially, and then it moves along the black lines shown in Fig. 5 with a constant velocity 2 m/s. In the algorithm, the target position in the future is estimated according to current position with unchanged velocity and heading. In addition, differential evolution algorithm is adopted as the optimization tool, and the relevant parameters are set to: $NP = 5N_D$, $F = 0.5$, and $C_r = 0.2$ [19], where N_D is the number of the decision variables. The maximal number of evolution generations is set to 50 for the UAV and the UGV of SR–DG–DD system, and 100 for the UAGVS of SR–CG–CD system. The length of prediction horizon and the duration of each time domain are set as $h = 4$ and $\Delta t = 3$ s.

Fig. 5 presents the results of cooperative target tracking by UAGVS with two different types of systems. The initial positions of the target, UAV, and UGV are indicated in the figure. As shown in Fig. 5(b), there exists obvious coordination between the UAV and UGV, and they keep themselves on the different sides of the target for most of the time for the SR–CG–CD system. On the contrary, there is no obvious synergy behaviors exhibited by the UAV and UGV for SR–DG–DD system. Additionally, for the SR–DG–DD system, the mean optimization time for the UAV and UGV at each decision point is 0.21 s and 0.20 s, respectively. In contrast, the mean optimization time is 0.85 s for the SR–CG–CD system.

Although the example illustrated here only involves one UAV and one UGV, it sufficiently demonstrates how different coordination mechanisms can be adopted to solve a specific problem, and different types of systems may exhibit different performane. The coordination pattern can be selected according to specific task demand. For example, as to meet the demand of capturing the target, DR–DG–DD system should be selected. But for detection purpose, SR–DG–DD, SR–CG–CD, and SR–CG–DD can be selected as candidates. In practice, the coordination behavior between UAV and UGV is expected, however, obatining a satisfactory solution to the optimization problem in this case usually consumes more time especially for large-scale problems. So, besides the task demand, real-time performance is another important factor when selecting a coordination pattern.

VI. Conclusion

UAV/UGV coordination has attracted worldwide attention because of its great application value. To date, the majority of research on UAGVSs has been concentrated on specific applications and has been validated by proof-of-concept methods or by simulations. These research efforts are undeniably valuable, since they demonstrate that successful coordination between UAVs and UGVs provides a promising approach for accomplishing complex tasks. However, to date there is no systematic analysis on general coordination between UAVs and UGVs. The goal of this paper is to identify the kernel elements for the coordination of UAVs and UGVs and their possible realizations by building a taxonomy for differentiating diverse configurations of UAGVS.

In spite of diverse realization schemes for coordinating UAVs and UGVs, the decision-making for vehicles in each case can be viewed as optimization problems with the aim of determining the control inputs for UAVs and UGVs to achieve their goals in an optimal way. Here, to simplify the representation, the control inputs of vehicles are optimized directly according to the task goal. In practice, due to the complexity of the dynamics of vehicles, optimizing the control inputs of vehicles directly induces large computation burden. Therefore, the optimization problem is usually decomposed into planning and control levels. For example, in the target tracking problem, the path planning for vehicles can be done first, and then each vehicle determines its control scheme for path tracking. Although the decomposition-based approaches can reduce computational complexity, the feasibility of paths for vehicles should be considered in the planning stage.

Once the optimization model for a UAVGS is established, corresponding algorithms including intelligent optimization algorithms, others from operations research, economics, and so on, can be applied to find a solution to the problem. A remarkable feature of the decision-making for UAGVSs is the rigorous requirement on real-time performance. Therefore, a desirable tradeoff between computation cost and solution quality is a requisite in practical use of UAGVSs. Hence, designing efficient algorithms to generate approximate solutions or anytime solution which can achieve a better tradeoff between solution quality and decision-making time is also an important topic for the development of UAVGSs.

REFERENCES

[1] A. R. Girard, A. S. Howell, and J. K. Hedrick, "Border patrol and surveillance missions using multiple unmanned air vehicles," in *Proc. 43rd IEEE Conf. Decis. Control*, vol. 1. Nassau, Bahamas, 2004, pp. 620–625.

[2] D. W. Casbeer, D. B. Kingston, and R. W. Beard, "Cooperative forest fire surveillance using a team of small unmanned air vehicles," *Int. J. Syst. Sci.*, vol. 37, no. 6, pp. 351–360, 2006.

[3] L. Merino, F. Caballero, J. R. M. Dios, and A. Allero, "Cooperative fire detection using unmanned aerial vehicles," in *Proc. IEEE Int. Conf. Robot. Autom.*, Barcelona, Spain, 2005, pp. 1884–1889.

[4] U. Zengin and A. Dogan, "Real-time target tracking for autonomous UAVs in adversarial environments: A gradient search algorithm," *IEEE Trans. Robot.*, vol. 23, no. 2, pp. 294–307, Apr. 2007.

[5] S. Zhu and D. Wang, "Adversarial ground target tracking using UAVs with input constraints," *J. Intell. Robot. Syst.*, vol. 65, nos. 1–4, pp. 521–532, 2012.

[6] X. Li *et al.*, "Multi-decision making based PSO optimization in airborne mobile sensor network deployment," in *Proc. 6th Int. Symp. Embedded Multicore SoCs (MCSoC)*, Aizuwakamatsu, Japan, 2012, pp. 128–134.

[7] T. P. Nascimento, A. P. Moreira, and A. G. S. Conceição, "Multi-robot nonlinear model predictive formation control: Moving target and target absence," *Robot. Auton. Syst.*, vol. 61, no. 12, pp. 1502–1515, 2013.

[8] L. E. Barnes, M. A. Fields, and K. P. Valavanis, "Swarm formation control utilizing elliptical surfaces and limiting functions," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 39, no. 6, pp. 1434–1445, Dec. 2009.

[9] T. P. Breckon, A. Gaszczak, J. Han, M. L. Eichner, and S. E. Barnes, "Multi-modal target detection for autonomous wide area search and surveillance," *Proc. SPIE Emerg. Technol. Secur. Defence Quantum Secur. II Unmanned Sensor Syst. X*, vol. 8899, Oct. 2013, Art. ID 889913.

[10] L. Sheng, Y. L. Pan, and X. Gong, "Consensus formation control for a class of networked multiple mobile robot systems," *J. Control Sci. Eng.*, vol. 2012, Mar. 2012, Art. ID 150250.

[11] H. B. Duan and S. Q. Liu, "Unmanned air/ground vehicles heterogeneous cooperative techniques: Current status and prospects," *Sci. China Technol. Sci.*, vol. 53, no. 5, pp. 1349–1355, 2010.

[12] H. G. Nguyen *et al.*, "Land, sea, and air unmanned systems research and development at SPAWAR systems center pacific," *Proc. SPIE Defen. Secur. Sens.*, vol. 7332, May 2009, Art. ID 73321I.

[13] R. M. Murray, "Recent research in cooperative control of multivehicle systems," *J. Dyn. Syst. Meas. Control*, vol. 129, no. 5, pp. 571–583, 2007.

[14] L. E. Parker, "Distributed intelligence: Overview of the field and its application in multi-robot systems," *J. Phys. Agents*, vol. 2, no. 1, pp. 5–14, 2008.

[15] A. Farinelli, L. Iocchi, and D. Nardi, "Multirobot systems: A classification focused on coordination," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 34, no. 5, pp. 2015–2028, Oct. 2004.

[16] L. E. Dubins, "On curves of minimal length with a constraint on average curvature and with prescribed initial and terminal positions and tangents," *Amer. J. Math.*, vol. 79, no. 3, pp. 497–516, 1957.

[17] J. A. Reeds and L. A. Shepp, "Optimal paths for a car that goes both forwards and backwards," *Pac. J. Math.*, vol. 145, no. 2, pp. 367–393, 1990.

[18] J. Peng and S. Akella, "Coordinating multiple robots with kinodynamic constraints along specified paths," *Int. J. Robot. Res.*, vol. 24, no. 4, pp. 295–310, 2005.

[19] X. Zhang, J. Chen, and B. Xin, "Path planning for unmanned aerial vehicles in surveillance tasks under wind field," *J. Cent. South Univ.*, vol. 21, no. 8, pp. 3079–3091, 2014.

[20] M. Owen, H. Yu, T. McLain, and R. Beard, "Moving ground target tracking in urban terrain using air/ground vehicles," in *Proc. IEEE GLOBECOM Workshops*, Miami, FL, USA, 2010, pp. 1816–1820.

[21] N. M. M. de Abreu, "Old and new results on algebraic connectivity of graphs," *Linear Algebra Appl.*, vol. 423, no. 1, pp. 53–73, 2007.

[22] S. Gil, M. Schwager, B. J. Julian, and D. Rus, "Optimizing communication in air-ground robot networks using decentralized control," in *Proc. IEEE Int. Conf. Robot. Autom.*, Anchorage, AK, USA, 2010, pp. 1964–1971.

[23] W. Li and C. G. Cassandras, "Centralized and distributed cooperative receding horizon control of autonomous vehicle missions," *Math. Comput. Model.*, vol. 43, nos. 9–10, pp. 1208–1228, 2006.

[24] S. Lacroix and G. Le Besnerais, "Issues in cooperative air/ground robotic systems," in *Robotics Research (the 13th International Symposium ISRR)*, K. Makoto and N. Yoshihiko, Eds. Berlin, Germany: Springer, 2011, pp. 421–432.

[25] N. Michael, J. Fink, and V. Kumar, "Controlling a team of ground robots via an aerial robot," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, San Diego, CA, USA, 2007, pp. 965–970.

[26] L. Chaimowicz and V. Kumar, "Aerial shepherds: Coordination among UAVs and swarms of robots," in *Distributed Autonomous Robotic Systems*. Tokyo, Japan: Springer, 2007, pp. 243–252.

[27] R. Rao, V. Kumar, and C. Taylor, "Visual servoing of a UGV from a UAV using differential flatness," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, vol. 1. Las Vegas, NV, USA, 2003, pp. 743–748.

[28] N. Frietsch, O. Meister, C. Schlaile, and G. F. Trommer, "Teaming of an UGV with a VTOL-UAV in urban environments," in *Proc. Pos. Locat. Navig. Symp.*, Monterey, CA, USA, 2008, pp. 1278–1285.

[29] P. B. Sujit, J. Sousa, and F. L. Pereira, "UAV and AUVs coordination for ocean exploration," in *Proc. OCEANS EUROPE 2009*, Bremen, Germany, pp. 1–7.

[30] E. Z. MacArthur, D. MacArthur, and C. Crane, "Use of cooperative unmanned air and ground vehicles for detection and disposal of mines," *Proc. SPIE Intell. Syst. Design Manuf.*, vol. 5999, Nov. 2005, Art. ID 599909.

[31] C. Cheung and B. Grocholsky, "UAV–UGV collaboration with a PackBot UGV and Raven SUAV for pursuit and tracking of a dynamic target," *Proc. SPIE Int. Soc. Opt. Eng.*, vol. 6962, Apr. 2008, Art. ID 696216.

[32] F. F. Ramirez, D. S. Benitez, E. B. Portas, and J. A. L. Orozco, "Coordinated sea rescue system based on unmanned air vehicles and surface vessels," in *Proc. OCEANS 2011*, Santander, Spain, pp. 1–10.

[33] B. You, G. Chen, and W. Guo, "A discrete PSO-based fault-tolerant topology control scheme in wireless sensor networks," in *Advances in Computation and Intelligence*. Berlin, Germany: Springer, 2010, pp. 1–12.

[34] K. Chandrashekar, M. R. Dekhordi, and J. S. Baras, "Providing full connectivity in large ad-hoc networks by dynamic placement of aerial platforms," in *Proc. Military Commun. Conf.*, vol. 3. Monterey, CA, USA, 2004, pp. 1429–1436.

[35] H. Voos and H. Bou-Ammar, "Nonlinear tracking and landing controller for quadrotor aerial robots," in *Proc. IEEE Int. Conf. Control Appl.*, Yokohama, Japan, 2010, pp. 2136–2141.

[36] M. Wills, A. Burmeister, T. Nelson, T. Denewiler, and K. Mullens, "The development of a UGV-mounted automated refueling system for VTOL UAVs," *Proc. SPIE Int. Soc. Opt. Eng.*, vol. 6230, May 2006, Art. ID. 62302G.

[37] P. Tokekar, J. V. Hook, D. Mulla, and V. Isler, "Sensor planning for a symbiotic UAV and UGV system for precision agriculture," in *Proc. IEEE Int. Conf. Intell. Robot. Syst.*, Tokyo, Japan, 2013, pp. 5321–5326.

[38] M. Saska, T. Krajnik, and L. Pfeucil, "Cooperative μUAV–UGV autonomous indoor surveillance," in *Proc. 9th Int. Multiconf. Syst. Signals Devices*, Chemnitz, Germany, 2012, pp. 1–6.

[39] R. W. Beard, T. W. Lain, D. B. Nelson, D. Kingston, and D. Johanson, "Decentralized cooperative aerial surveillance using fixed-wing miniature UAVs," *Proc. IEEE*, vol. 94, no. 7, pp. 1306–1324, Jul. 2006.

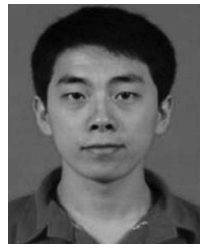
[40] H. G. Tanner, "Switched UAV–UGV cooperation scheme for target detection," in *Proc. IEEE Int. Conf. Robot. Autom.*, Rome, Italy, 2007, pp. 3457–3462.

[41] C. Phan and H. H. T. Liu, "A cooperative UAV/UGV platform for wildfire detection and fighting," in *Proc. 7th Int. Conf. Syst. Simulat. Sci. Comput.*, Beijing, China, 2008, pp. 494–498.

[42] T. Vicsek, A. Czirók, E. Ben-Jacob, I. Cohen, and O. Shochet, "Novel type of phase transition in a system of self-driven particles," *Phys. Rev. Lett.*, vol. 75, nos. 6–7, pp. 1226–1229, 1995.
[43] H. B. Duan, Y. P. Zhang, and S. Q. Liu, "Multiple UAVs/UGVs heterogeneous coordinated technique based on receding horizon control (RHC) and velocity vector control," *Sci. China Technol. Sci.*, vol. 54, no. 4, pp. 869–876, 2011.
[44] Q. N. Luo and H. B. Duan, "An improved artificial physics approach to multiple UAVs/UGVs heterogeneous coordination," *Sci. China Technol. Sci.*, vol. 56, no. 10, pp. 1–7, 2013.
[45] T. Balch and R. Arkin, "Behavior-based formation control for multi-robot teams," *IEEE Trans. Robot. Autom.*, vol. 14, no. 6, pp. 926–939, Dec. 1998.
[46] J. Cortés, S. Martínez, and F. Bullo, "Spatially-distributed coverage optimization and control with limited-range interactions," *ESAIM Control Optim. Calc. Var.*, vol. 11, no. 4, pp. 691–719, 2005.
[47] D. W. Gage, "Randomized search strategies with imperfect sensors," *Proc. SPIE Mobile Robots*, vol. 2058, pp. 270–279, Feb. 1994.
[48] J. Cortés, S. Martínez, and F. Bullo, "Robust rendezvous for mobile autonomous agents via proximity graphs in arbitrary dimensions," *IEEE Trans. Autom. Control*, vol. 51, no. 8, pp. 1289–1298, Aug. 2006.
[49] T. W. McLain and R. W. Beard, "Coordination variables, coordination functions, and cooperative timing missions," *J. Guid. Control Dyn.*, vol. 28, no. 1, pp. 150–161, 2005.
[50] S. M. Lee and H. Myung, "Cooperative particle swarm optimization-based predictive controller for multi-robot formation," in *Intelligent Autonomous Systems 12*. Berlin, Germany: Springer, 2013, pp. 533–541.
[51] Y. Kuwata and J. P. How, "Cooperative distributed robust trajectory optimization using receding horizon MILP," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 2, pp. 423–431, Mar. 2011.
[52] B. Xin, J. Chen, Z. H. Peng, L. H. Dou, and J. Zhang, "An efficient rule-based constructive heuristic to solve dynamic weapon-target assignment problem," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 41, no. 3, pp. 598–606, May 2011.
[53] B. Xin, J. Chen, J. Zhang, H. Fang, and Z. H. Peng, "Hybridizing differential evolution and particle swarm optimization to design powerful optimizers: A review and taxonomy," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 42, no. 5, pp. 744–767, Sep. 2012.
[54] A. G. Shem, T. A. Mazzuchi, and S. Sarkani, "Addressing uncertainty in UAV navigation decision-making," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 44, no. 1, pp. 295–313, Jan. 2008.

Jie Chen (M'09–SM'12) received the B.S., M.S., and Ph.D. degrees in control theory and control engineering from the Beijing Institute of Technology, Beijing, China, in 1986, 1993, and 2000, respectively.

He is currently a Professor of Control Science and Engineering with the Beijing Institute of Technology. His current research interests include complicated system multiobjective optimization and decision, intelligent control, constrained nonlinear control, and optimization methods.



Xing Zhang received the bachelor's degree from the University of Science and Technology Beijing, Beijing, China, in 2009. He is currently pursuing the Ph.D. degree with the School of Automation, Beijing Institute of Technology, Beijing.

His current research interests include intelligent optimization, path planning, and multivehicle systems.

Bin Xin (S'09–M'10) received the B.S. degree in information engineering and the Ph.D. degree in control science and engineering, both from the Beijing Institute of Technology, Beijing, China, in 2004 and 2012, respectively.

He is currently a Lecturer with the School of Automation, Beijing Institute of Technology. His current research interests include search and optimization, evolutionary computation, operations research, and combinatorial optimization.

Hao Fang (M'15) received the B.S. degree from the Xi'an University of Technology, Xi'an, China, in 1995, and the M.S. and Ph.D. degrees from the Xi'an Jiaotong University, Xi'an, in 1998 and 2002, respectively.

He held two Post-Doctoral appointments at the INRIA/France Research Group of COPRIN and at the LASMEA (UNR6602 CNRS/Blaise Pascal University, Clermont-Ferrand, France). Since 2011, he has been a Professor with the Beijing Institute of Technology, Beijing, China. His current research interests include all-terrain mobile robots, robotic control, and parallel manipulators.