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Multirobot Control Strategies for Collective Transport

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Abstract

One potential application of multirobot systems is collective transport, a task in which multiple robots collaboratively move a payload that is too large or heavy for a single robot. In this review, we highlight a variety of control strategies for collective transport that have been developed over the past three decades. We characterize the problem scenarios that have been addressed in terms of the control objective, the robot platform and its interaction with the payload, and the robots' capabilities and information about the payload and environment. We categorize the control strategies according to whether their sensing, computation, and communication functions are performed by a centralized supervisor or specialized robot or autonomously by the robots. We provide an overview of progress toward control strategies that can be implemented on robots with expanded autonomous functionality in uncertain environments using limited information, and we suggest directions for future work on developing such controllers.

1. INTRODUCTION

In many applications that are suitable for robotic systems, in that they involve repetitive actions or take place in hazardous or remote locations, an object must be transported to a new location, manipulated into a new configuration, or accelerated to a target velocity. Examples of such applications include construction, manufacturing, assembly in space and underwater, transportation and delivery, search-and-rescue operations, disaster response, mining, and even biomedical applications at the micro/nanoscale (1, 2). When the payload is too large, bulky, or heavy to be moved by a single robot, a group of robots can be deployed to achieve the desired objective by exerting forces on the payload simultaneously or in quick succession, as illustrated in **Figure 1**. This task is described in the literature as transport or manipulation, with the modifiers collective, cooperative, coordinated, collaborative, or group used to indicate that the payload's movement is produced by the efforts of multiple robots. In this review, we refer to the task as collective transport or cooperative manipulation.

Controllers for cooperative object manipulation were first designed in the late 1980s and early 1990s for two or three stationary robotic manipulators with multiple degrees of freedom (DOFs). The accelerated development of mobile robots in the mid-1990s led to research on control of collective transport by groups of mobile robots. The proposed controllers often required reference inputs (such as a target payload location or trajectory) and information about the system parameters and state (such as geometric and inertial properties of the payload and measurements of its position and velocity) that the robots can only obtain from an external observer or a specialized teammate, i.e., a centralized node. These requirements limit the robots' ability to operate autonomously during transport using their own sensor data and computations and enforce their dependence on potential single points of failure.

In this review, we provide an overview of control strategies for collective transport that have been developed over the past three decades in terms of the extent of autonomous functionality that they implement in the robot transporters. The organization of the literature from this

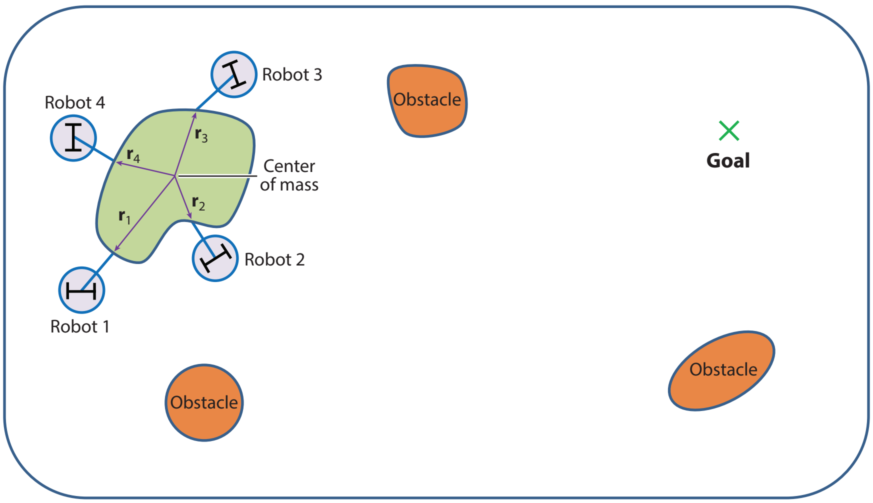

Figure 1

A planar collective transport task performed by four robots in a bounded domain containing obstacles. Each robot is attached to the payload with a one-degree-of-freedom manipulator.

perspective distinguishes this review from previous reviews, which classify collective transport strategies according to the type of controller employed (3) or the interaction mechanisms between the robots and the payload, such as pushing, grasping, and caging (4, 5). In Section 2, we characterize collective transport problems in terms of the control objective, the type of robot platform, kinematic constraints between the robots and the payload, and assumptions about the robots' capabilities and information about the payload and environment. We review control strategies that have been developed to address these problems in Section 3, categorizing the controllers according to the degree to which their sensing, computation, and communication functions are centralized. In Section 4, we discuss the state of the art in work toward controller design for collective transport in uncertain, unstructured environments, which requires more autonomous functionality by the robot transporters. We conclude in Section 5 with potential directions for future research on control strategies for such environments.

2. PROBLEM DESCRIPTION

Controllers for multirobot collective transport have been designed for different problem scenarios, which we characterize here in terms of the control objectives of the transport task, the type of robot platform used in the transport team, the kinematic constraints on the composite robot–payload system, the robots' sensing and communication capabilities, and the robots' information about the payload and the environment.

2.1. Transport Control Objectives

Prior works on control strategies for collective transport have generally focused on achieving one or more of the following objectives. Common primary objectives include stabilizing the payload's configuration and/or velocity to specified reference values (e.g., moving the payload to a target location) and driving these variables to track reference trajectories. Secondary objectives, which enable the robots to complete the primary objectives, include regulating or minimizing the interaction forces between the robots and the payload in order to prevent excessively large forces that could damage the payload or the robots and avoiding collisions with obstacles in partially or fully unknown environments. In the case where the control strategy requires explicit interrobot communication, another secondary objective may be the maintenance of a connected communication network among the robots.

2.2. Type of Robot Platform

Collective transport control strategies have been developed predominantly for nonholonomic wheeled mobile robots, which have nonholonomic constraints between their rotational and translational motion. In some works, the robots move the payload by pushing against it with their mobile bases, while in others, the robots are each equipped with a one-DOF gripper or pincer that they use to grasp the payload. Many works propose controllers for mobile manipulators, which are composed of a mobile base with a multi-DOF manipulator mounted on top. Mobile manipulators are designed to have sufficient redundancy in their DOFs to control the configuration and velocity of the robots and the payload as well as regulate the interaction forces between each robot and the payload. More recently, mobile robots with three or four omnidirectional wheels and a pincer or multi-DOF manipulator have been used for collective transport. Such omnidirectional robots have unconstrained kinematics. In addition to ground robots, collective transport strategies have been designed for aerial robots (6), surface vehicles (7, 8), and underwater robots (9, 10).

2.3. Kinematic Constraints Between the Robots and the Payload

The robots' attachment to the payload introduces kinematic constraints on the motion of the composite robot–payload system. The type of attachment determines the number of DOFs of the entire system and governs the motion of the robots with respect to the payload. Early works on cooperative object manipulation by stationary manipulators typically assumed a rigid grasp between each end effector and the payload, for which the end effector's position and orientation relative to the payload's configuration remain constant. Each attachment of this type eliminates six DOFs from the total number of DOFs of the robot–payload system in its configuration space, and thus the manipulators must be highly redundant in order to perform the task while avoiding deadlock configurations. Given this limitation, researchers considered another type of attachment called a point grasp, for which the end effector's position relative to the payload's center of mass remains constant while its relative orientation about one axis can change; i.e., the end effector is connected by a pin joint at a unique point. This type of attachment is used mostly for planar manipulation tasks rather than for manipulation in three-dimensional space.

To simplify the controller design and analysis, robots performing collective transport are often modeled as point masses with double-integrator dynamics. For robots represented as point masses, a point contact models a rigid attachment of a robot to the payload. In some collective transport control strategies, particularly ones designed for large populations of expendable, interchangeable robots called robotic swarms, the robots repeatedly attach to and detach from the payload, changing the composition of the transport team over time. Due to these transient contacts with the payload, time-invariant kinematic constraints on the robot–payload system cannot be derived.

2.4. Robot Sensing and Communication Capabilities

The robots' onboard sensors and communication devices, as well as any measurements that they can obtain from external instruments, are key specifications in the formulation of collective transport problems. In this section, we summarize common assumptions in prior work about the capabilities of the robots.

Feedback controllers are used to stabilize the position, orientation, translational velocity, and angular velocity of a mobile robot to reference values or trajectories. The time evolution of these state variables is given by the solution of a dynamical model describing the robot's motion, for which several candidates are described in the previous subsection. To execute these controllers, the robot must obtain measurements or estimates of the current values of these variables. One approach is to receive this information from an external localization system, such as GPS or an indoor positioning system. For example, in indoor settings, the robots and payload can be localized by tagging them with identification markers and tracking the markers in real time using an overhead camera and image-processing algorithms. Another approach is for the robots to measure or estimate the variables using their onboard sensors and computational devices. Mobile robots can use odometry sensor measurements (e.g., from wheel encoders) fused with data from inertial measurement units to improve the accuracy of their estimated configuration. Robotic manipulators can use encoders and tachometers to measure their joint angles and joint rates, respectively, in order to determine the position and velocity of their end effector with respect to their base, which is a mobile robot in the case of a mobile manipulator. Moreover, mobile manipulators can measure interaction forces using a force sensor at the robot's attachment point on the payload.

Many collective transport strategies require the robots to explicitly communicate information to one another using a wireless ad hoc network or a central router that establishes connections between the robots. This information often consists of the robots' configurations and velocities, and can include estimates of the payload's state variables and geometric and dynamic parameters if they are unknown and are needed to implement the robots' feedback control laws. Using communication protocols that are designed to achieve consensus (11), the robots can arrive at a common estimate of the payload's position, velocity, mass, and other properties. Additionally, interrobot communication can be introduced to improve the stability properties of adaptive control strategies for collective transport (12).

2.5. Information About the Payload and Environment

Most works on collective transport assume that the robots have prior information about the dynamics and geometry of the payload or that they obtain this information during transport through sensor measurements or communication. The payload's mass and moment of inertia are commonly assumed to be known to the robots. Many transport strategies that employ centralized control require that all robots know the magnitude and orientation of the vector from the payload's center of mass to the attachment point of each robot on the payload (the vectors $\mathbf{r}_i$ in **Figure 1**), e.g., in order to compute the grasp matrix (13). In works where the control objective is trajectory tracking by the payload, it is common to assume that the robots regularly receive measurements of the position and velocity of the payload's center of mass and the payload's orientation and angular velocity during transport. These measurements are usually transmitted to the robots by a global observer or a leader robot.

Information about the environment, in particular a map of the free space where the transport team can travel, is implicitly assumed in most research on collective transport. In many works, reference trajectories for the configuration and velocity of the robots and/or payload are computed offline by a motion planner, which generates collision-free, reachable trajectories based on prior information about obstacles and inaccessible regions in the environment. In a few works, the transport team includes a leader robot that has this prior information (whereas the other robots do not) and assumes the role of the motion planner. The leader robot is given the reference trajectory offline, or in some cases computes this trajectory online while the transport team moves the payload. The leader explicitly communicates the next waypoint on the trajectory to the follower robots, or it conveys this information through implicit communication, in which the followers estimate the leader's intended motion using their local sensor measurements. A few recent works have considered scenarios in which none of the robots are assigned desired trajectories for the robots or payload, as discussed in Section 4.

3. EXISTING CONTROL APPROACHES

In this section, we review control strategies for collective transport that have been developed for the problem scenarios characterized in Section 2. The control strategies can be broadly classified according to their degree of reliance on a single component of the system for the following functions: acquisition of sensor measurements, computation of control commands based on this sensor feedback, and communication of these commands to the robots' actuators to move the payload. In a given control strategy, each of these functions may be centralized, meaning that it is performed by a single stationary or mobile unit, or decentralized (also called distributed), meaning that each robot performs the function independently using its own onboard resources, possibly incorporating information that is explicitly shared by other robots within its local communication range. Centralized functions may be performed by a supervisory agent (14) that does not physically participate in the transport (i.e., operates externally to the transport team) or by a member of the transport team called a leader robot, which has particular sensing, computation, communication, and/or actuation capabilities that the other team members—the follower robots—lack. In the second case, the control strategy is called a leader–follower controller.

The dependence of a controller on centralized functions reduces its robustness to errors, failures, and disturbances, since a component that performs such a function is a potential single point of failure; its loss would render the entire system inoperative. Decentralized functions introduce redundancy into the system's operation, thereby improving its robustness properties. Moreover, decentralized functions can be performed by robots with local sensing and communication capabilities and are scalable with the number of robots, making them particularly suited to implementation on robotic swarms. These advantages have motivated the development of collective transport controllers with decentralized functions.

The following subsections group existing controllers for collective transport into three categories, depending on whether their sensing, computation, and communication functions are centralized or decentralized. If the three functions are all centralized or all decentralized, then we refer to the controller as fully centralized or fully decentralized, respectively. If at least one of the functions is decentralized and the other(s) are centralized, we refer to the controller as partially decentralized. We note that the robot control laws in the fully decentralized strategies may require a reference input that is provided offline, such as the target payload position or velocity.

3.1. Fully Centralized Controllers

Fully centralized control schemes rely on models of the kinematics and dynamics of the robots and payload and measurements of their configurations and velocities, and possibly the interaction forces between the robots and the payload. A supervisory agent obtains these measurements and uses them to compute control commands, which it then transmits to the robots. The first controllers for cooperative manipulation, developed for stationary robotic manipulators in the late 1980s and early 1990s, were fully centralized. One of the earliest works extended a hybrid position/force controller, originally designed for a single manipulator, to multiple manipulators (15). Feedback linearization via a nonlinear feedback control law, which was motivated by the widely used computed torque method, was frequently applied to obtain decoupled linear closed-loop dynamical models for the robots and the payload (16, 17).

Schneider & Cannon (18) proposed a cooperative manipulation strategy based on impedance control of the payload, in which the manipulators control the payload's motion such that it tracks a specified impedance behavior as it converges to a desired configuration. Multiple impedance control, proposed by Moosavian & Papadopoulos (19), is a modification of this technique that controls the impedance behavior of the manipulators as well as the payload for improved stability properties. Chang et al. (20) presented the augmented object model, an equivalent model for the dynamics of the composite manipulator–object system that inherits the configuration space of the object. A controller that is designed to achieve a desired objective in the augmented object model, such as position regulation, trajectory tracking, or impedance control, will impose the same behavior on the manipulated object. Nikou et al. (21) presented a centralized nonlinear model predictive controller for cooperative manipulation. This controller requires a mathematical model of the kinematics and dynamics of every robot and the robot–payload system, as well as information about the location and geometry of each obstacle in the environment. The energy-optimal controller developed by Verginis & Dimarogonas (22) is based on a centralized strategy that minimizes the internal forces, which are the components of the interaction forces that do not contribute to the payload's motion.

Centralized control approaches have also been proposed for collective transport by robotic swarms. Becker et al. (23) used a single input signal to steer a swarm of robots around an environment and push an object encountered by the swarm to a target configuration. Another example is the controller presented by Shahrokhi et al. (24), where an external observer (a human or a central computer) tracks the mean position and mean velocity of the robots in the swarm and communicates appropriate control commands to the robots in order to push the payload toward a target location.

3.2. Partially Decentralized Controllers

Leader–follower controllers with decentralized components began to be developed in the late 1990s and early 2000s. Many works delegated certain functions of the central supervisory unit to one or more leader robots, which, unlike the follower robots, may have information about the transport team, the payload, and the environment. Some leader–follower control schemes employ centralized sensing and communication with decentralized computation: The leader acquires data (through its own measurements) on the payload's position and velocity and transmits this information to the followers, which calculate and execute the control commands using their onboard processors. Other leader–follower strategies use decentralized sensing with centralized computation and communication: Each follower collects data with its onboard sensors and transmits these measurements to the leader, which then calculates the control commands and sends them back to the followers to execute.

One of the earliest leader–follower controllers for collective transport, proposed by Stilwell & Bay (25), does not rely on explicit interrobot communication. In this control strategy, the leader knows the target direction of transport and applies a force to drive the payload in this direction. The followers estimate the leader's intended direction of motion through force sensor measurements at their points of contact with the payload, stabilize the payload's rotation, and move it in this direction. Kosuge et al. (26, 27) employed a similar strategy, in which the robot dynamics are modeled by a first-order differential equation under the assumption that each robot's velocity is controlled with appropriate feedback compensation. Chaimowicz et al. (28) and Sugar & Kumar (29) proposed controllers that maintain prescribed forces at the robots' attachment points on the payload. The controllers rely on explicit communication between the leader and the followers, and different robots can assume the leadership role during transport; e.g., a follower that detects an obstacle can request leadership in order to avoid it.

The leader–follower strategy used by Wang & Schwager (30, 31) is a consensus-based approach that does not rely on explicit communication between the robots. The leader knows the desired payload trajectory to the goal and can exert a torque on the payload and measure its angular velocity, and the followers use their local measurements of the payload's motion to reach a consensus on the magnitude and direction of their applied forces. In another work by the same authors (32), the leader—which could be a robot or a human teleoperator or physical teammate—applies a force to move the load over a predefined path, and the followers estimate the direction of the object movement using force measurements at their attachment points and apply forces in this estimated direction to assist the leader. Tsiamis et al. (33) employed a similar strategy, in which the leader achieves a desired trajectory tracking behavior via an impedance control law, and the followers estimate the leader's intended motion using a prescribed performance estimator and apply a similar impedance control law.

Another approach, presented by Yufka & Ozkan (34), considers the payload to be the leader; the followers (the transporting robots) use a path-planning approach to preserve their initial positions and orientations with respect to the virtual leader (the payload) during the transport. Verginis et al. (35) proposed a decentralized nonlinear model predictive control approach that relies on the leader's information about the dynamics and geometry of the payload and communication to the followers, and the followers compute their own control inputs. The decentralized impedance controller presented by Carey & Werfel (36) requires the leader to initiate the payload motion by applying a force in the direction of the target position, and does not require explicit communication or information about the physical properties of the payload.

Gabellieri et al. (37) described a control strategy that can utilize multiple leaders and does not rely on explicit communication. This work employed a force regulation scheme at each robot's attachment point on the payload and studied the effect of the number of leaders on the controller performance at stabilizing the payload to a desired configuration.

3.3. Fully Decentralized Controllers

Fully decentralized controllers for collective transport were initially developed in the mid-2000s. One of the earliest works on decentralized control of cooperating robots proposed the application of the augmented object model at each robot's grasp point (38). Dickson et al. (39) presented a decentralized impedance control scheme that avoids the need for a centralized controller—which was required in the work by Schneider & Cannon (18)—by using a decentralized algorithm to estimate external forces on the payload. The decentralized impedance control strategy developed by Pierri et al. (40), which was designed for trajectory tracking by a payload with initially unknown inertial properties, includes an initialization phase in which the robots estimate the inertia tensor of the payload. Liu et al. (41) proposed a decentralized computed torque scheme that requires a dynamical model of each robot and analyzed its efficacy for cases with and without force-sensing capabilities. Krovi and colleagues (42, 43) addressed decentralized kinematic control of cooperative payload manipulation by nonholonomic mobile manipulators.

In many fully decentralized control approaches to collective transport, all robots in the transport team are assumed to have identical hardware and controllers. The decentralized potential-based approach presented by Song & Kumar (44) requires the robots to have information about the payload's position at each time instant. The authors showed that the stability of the proposed method is affected by the robots' configuration around the payload. In the decentralized coordination algorithm proposed by Kennedy et al. (45), the robots use explicit communication with their neighbors to converge to a distribution that minimizes their interaction forces and achieves a desired wrench to move the payload. Fink et al. (46, 47) presented a decentralized control strategy for collective transport without explicit communication in a bounded domain containing circular obstacles. The positions and radii of the obstacles and the equation of the domain boundary are known to the robots, and the controller composes vector fields that guide the robots to approach the payload, surround it, and transport it to a goal location while avoiding interrobot collisions. Chen et al. (48) considered a scenario where the payload is significantly larger than the robots, and the robots push the payload only if it occludes their line of sight to the goal. Habibi et al. (49) presented four algorithms that enable the robots to estimate the centroid of the payload, rotate the payload, and transport it over certain marked points that can be recognized by a guide robot.

Bai & Wen (50, 51) considered the transport of a flexible payload, modeling the reaction force between each robot and the payload as the gradient of a nonlinear potential function that describes the load deformation. In the strategy used by Bais et al. (52), the payload weight is distributed among robots with heterogeneous load-carrying capabilities, and the payload is transported along a desired trajectory. Kalat et al. (53) proposed a decentralized control approach in which each robot coordinates its actions with a virtual teammate located at the robot's mirror position with respect to the payload's center of mass. Rubenstein et al. (54) used an approach that assumes that all the robots know the target direction to the goal, and the robots' applied forces on the payload are calculated from a simple velocity feedback control law.

In the decentralized approach presented by Culbertson & Schwager (55), the robots have a common reference model for the desired payload motion and use an adaptive controller to compensate for the effect of friction on the payload. Adaptive robust control approaches have been recently proposed for planar and three-dimensional cooperative manipulation (12, 56–62). These approaches combine a stabilizing term with a regression term in the controller in order to achieve stabilization in the presence of parameter uncertainties. They require either prior information about the robots' distribution around the payload or feedback on the payload's motion.

Recently, decentralized learning schemes have also been proposed for cooperative manipulation. Li et al. (63) used a dynamic recurrent neural network to solve a quadratic program, which computes cooperative kinematic controllers for redundant manipulators using partially known information about the payload and the teammates. Ding et al. (64) used reinforcement learning to design two decentralized approaches to cooperative manipulation: one that applies Q-learning with individual reward functions, and one that utilizes game-theoretic techniques. The first approach exhibits more robustness to different reward structures than the second. Zhang et al. (65) applied deep reinforcement learning to a collective transport task in a bounded environment, where two robots must transport a slender payload through a narrow passage in the boundary of the domain.

Some decentralized methods require robots to communicate their measurements to each other in order to estimate unknown parameters of the payload (66, 67). More recently, Dohmann & Hirche (68) proposed an event-triggered communication strategy with distributed impedance control to improve the stability and robustness of cooperative manipulation of unknown payloads in unknown environments. Other approaches do not rely on communication or prior information about the payload's dynamics (69) but require a supervisor to define trajectories beforehand for the robots and the payload (33, 70, 71). The distributed optimization algorithm presented by Shorinwa & Schwager (72) employs explicit interrobot communication to guarantee convergence of the payload's tracking errors to zero and ensure that the robots avoid collisions with obstacles in the environment.

4. CURRENT PROGRESS ON OPEN CHALLENGES

A majority of the control strategies discussed in Section 3 rely on at least one of the following assumptions: predefined trajectories for the payload or robots, explicit interrobot communication, knowledge of the robots' distribution around the payload, and information about the locations, dynamics, and geometry of the robots, the payload, and any obstacles in the domain. While these assumptions may be valid for collective transport applications in known, structured environments, such as automated warehouses and factories, they may not be realistic for applications in uncertain, unstructured environments. For example, debris that the robots are deployed to clear after a disaster, or materials that the robots extract in mines, can constitute both payloads and obstacles with unknown properties. The robots may not have access to a global localization system such as GPS when they transport payloads underwater, underground, and in extraterrestrial environments. Stable multirobot communication networks may be difficult or impossible to maintain due to restricted onboard power and limited communication range and bandwidth.

Applications of collective transport under these conditions motivate the development of new control strategies that can be implemented with minimal prior information, local sensor measurements, and no explicit interrobot communication or global localization. One striking source of inspiration in nature for such control strategies is the behavior of group food retrieval by particular species of ants (73–75). The actions of ants during group retrieval are decentralized, in the sense that they are influenced by locally perceived information as they navigate back to their nest. The ants are able to transport a wide range of food items even though they do not follow predefined trajectories, use explicit communication, or have prior information about the payload, the number and distribution of ants around it, or the locations and geometries of obstacles in the environment (76).

Thus far, efforts have been made toward developing multirobot transport strategies that exhibit this impressive robustness to uncertainty and individual failures and errors. A few works have proposed control strategies for robots with limited information about the payload and the environment. The motion-planning scheme presented by Desai et al. (77) employs a numerical optimization algorithm to produce collective transport by two mobile robots in an environment with static obstacles. The heuristic methodology of Pereira et al. (78) was one of the earliest works on collective transport in unstructured dynamic environments. The centralized kinematics controller proposed by Tanner et al. (79) was one of the first control strategies for collective transport to not require predefined trajectories; moreover, it does not require information about the payload dynamics. The positions and shapes of the obstacles are given to the robots, which apply potential-based control laws that are designed using a novel extension of navigation functions (80) to steer the payload around the obstacles without colliding with them or entering singular configurations.

Berman and colleagues (81, 82) used hybrid dynamical models of collective transport by ants, developed from experimental observations, to derive decentralized control policies for robots in obstacle-free environments. These robot controllers, as well as the controller described by Kube & Bonabeau (83), mimic the attachment–detachment behavior observed in ants, rely only on local sensor information, and do not require prior information about the payload. The decentralized controllers described in other papers by Berman and colleagues (84–86) address position and velocity control of the payload in obstacle-free environments without predefined trajectories or information about the payload geometry or dynamics. Bechlioulis & Kyriakopoulos (87) presented a leader–follower control strategy in which the leader knows the desired payload pose and the positions and shapes of obstacles in the environment. Following the gradient of a navigation function (80), the leader steers the payload around the obstacles while the followers estimate the leader's intended trajectory for the payload via prescribed performance estimation laws.

5. CONCLUSION

In this review, we have formulated problem scenarios for collective transport by multirobot systems that have commonly been addressed in the literature, and we have categorized different approaches to these problems according to the degree to which they rely on sensor information and control commands from a single centralized component. We have also discussed progress on the open challenge of developing controllers for collective transport that can be implemented on robots with limited information in uncertain environments. We conclude here with suggestions on how to approach the development of controllers for collective transport in problem scenarios that still present unsolved challenges.

It remains an open problem to design fully decentralized control strategies for collective transport in environments that contain obstacles with unknown positions and geometries where robots lack global position information and have limited onboard resources. For robots with identical capabilities and information, a possible first step is to model the robots as point masses with double-integrator dynamics, since the simplicity of the resulting dynamical model of the composite payload–robot system facilitates the controller design and analysis. A controller can first be formulated for collective transport in a bounded convex domain that contains unknown convex obstacles. The controller can be based on obstacle avoidance control schemes that require limited information about the obstacles, such as the optimization method presented by Arslan & Koditschek (88) and controllers based on navigation-like functions described by Farivarnejad (89). The main challenge in applying these methods is to derive conditions that guarantee collision avoidance and the absence of locally stable equilibrium points (local minima) that could trap the transport team.

These works do not address the elimination of local minima in domains that have a nonconvex boundary and/or contain nonconvex obstacles. A possible starting point to do so is to design a controller for a single robot in this scenario by redesigning a controller from Arslan & Koditschek (88) or Farivarnejad (89) or applying the closed-form approach for moving obstacles presented by Huber et al. (90), and then adapting the controller to collective transport tasks. Other candidate approaches include the use of deep learning and reinforcement learning algorithms or the techniques of regular extremum seeking (91) and stochastic extremum seeking (92). Controllers for point-mass robots can be extended to be implementable on mobile manipulators, whose redundancy can be utilized to achieve secondary control objectives. Such objectives can include the regulation of interaction forces between the robots and the payload; the minimization of internal forces within the payload, which do not contribute to the payload's motion and could be large enough to break it; and the resolution of deadlocks if the transport team becomes stuck between obstacles.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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