

# DART: Diversity-enhanced Autonomy in Robot Teams

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## Abstract

This paper defines the research area of Diversity-enhanced Autonomy in Robot Teams (DART), a novel paradigm for the creation and design of policies for multi-robot coordination. While current approaches to multi-robot coordination have been successful in structured, well understood environments, they have not been successful in unstructured, uncertain environments, such as disaster response. **While robot hardware has advanced significantly in the past decade, the way we solve multi-robot problems has not.** Even with significant advances in the field of multi-robot systems, the same problem-solving paradigm has remained: assumptions are made to simplify the problem, and a solution is optimized for those assumptions and deployed to the entire team. This results in brittle solutions that prove incapable if the original assumptions are invalidated. This paper introduces a new multi-robot problem-solving paradigm which uses a diverse set of control policies that work together synergistically within the same team of robots. Such an approach will make multi-robot systems more **robust** in unstructured and uncertain environments, such as in disaster response, environmental monitoring, and military applications, and allow multi-robot systems to extend beyond the highly-structured and highly-controlled environments where they are successful today.

## Keywords

Multi-robot systems, Multi-agent systems

## 1 Introduction

The field of multi-robot systems (MRS) is growing at a rapid pace. Research in MRS spans many different areas, including automated delivery (Agha-mohammadi et al. (2014); Lonsdorf (2017); Sung et al. (2013)), surveillance (Glaser (2017)), and disaster response (Schurr et al. (2005); Jennings et al. (1997)). There have also been many successful demonstrations of increasing numbers of robots (Chung et al. (2016); Glaser (2016); Hauert et al. (2011); Kushleyev et al. (2013); Preiss et al. (2017); Rubenstein et al. (2012)). MRS have also been successfully deployed in the field including in warehousing (D'Andrea and Wurman (2008)), manufacturing (Hagerty (2015)), and entertainment (Barret (2016)). While these outcomes show the promise of MRS, the environments in which MRS have been successful are highly controlled, and some are highly instrumented, enabling precise tuning of controllers and nearly perfect knowledge of environmental conditions.

Many environments where MRS could be beneficial are not highly controlled or equipped with the extensive infrastructure often necessary to coordinate large teams of robots with state-of-the-art algorithms. For example, containing wildfires, searching collapsed buildings, patrolling borders, monitoring infrastructure, and containing oil spills all occur in highly dynamic and unique environments (no two collapsed buildings are the same), with high uncertainty and little control over other non-robot agents in the environment. One of the most desirable benefits of MRS is *robustness*, wherein robots can compensate for loss of capabilities by **relying on other robots in the team. However, the uncertainty**

of many real-world environments renders current state-of-the-art algorithms and controllers, even those designed for robustness, ineffectual. **While robot hardware has advanced significantly in the past decade, the way we solve multi-robot problems has not.** Many control policies are so specialized and optimized for specific capabilities and conditions that they **do not empower robots to cope with uncertainty. Incorporating diversity, in the form of an ensemble of control policies that work synergistically across the team, can help to realize the true benefits of robustness in the face of uncertainty for teams of robots. Single robot systems can also benefit from ensembles of control policies, from which they can draw when faces with control failure.**

## 2 Motivation

In disaster response alone, the potential impact of autonomous MRS is substantial: 60,000 people die each year in natural disasters, mostly in developing countries (Kenny (2009)). This makes robots an ideal tool for disaster response. In fact, DJI announced that *one* properly equipped drone can find a missing person more than *five times faster* than traditional search methods (DJI (2016)). However, most robots used in search and rescue today are teleoperated (Liu and Nejat (2013)), requiring trained operators which may not be nearby. Autonomous robots equipped for disaster response that can *automatically* synthesize control policies without the need for an expert operator can reduce response time and save many more lives, especially when a trained operator may be hours away.

The potential applications of autonomous MRS go well beyond disaster response, including military, agriculture,

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transportation, manufacturing, and fulfillment applications. However, current solutions for MRS have not successfully transitioned from controlled environments such as laboratories or warehouse facilities to the inherently high uncertainty in these complex environments. Without infrastructure that provides communication and localization, and without knowledge of or control over the environment, current state-of-the-art methods fail.

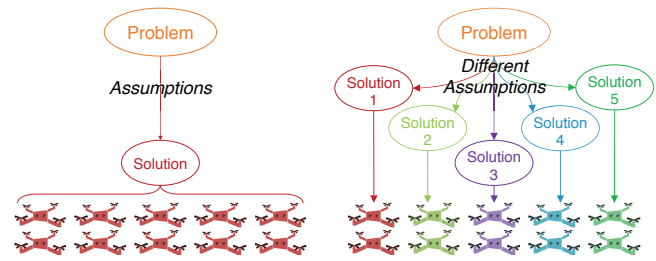
While the field of MRS has advanced significantly, the same problem-solving paradigm has remained. First, the problem is defined. Next, complexity is reduced by making several assumptions to simplify the problem, such as terrain and communication range. Finally, an optimal solution to that specific problem is designed and applied to all the robots in the team. This paradigm, pictured in Fig. 1(L), limits the capability of MRS to cope with real-world environments. The solutions are brittle, as the assumptions made are easily invalidated and the optimized controller is not designed for real environments. In the best case, the controller is able to overcome these challenges, but it is not **the best solution to the problem, defeating the purpose of optimization**. In the worst case, the controller cannot cope, **potentially** causing mission failure, loss of high-value assets, and casualties; after all, if the **environment violates the assumptions and the same ill-equipped controller** is applied to all robots, **it is possible that all of them will fail**.

## 2.1 Leveraging Diversity

Instead of applying the same controller to all robots, a new approach leveraging diversity in policies within the robot team can allow MRS to better cope with uncertain environments. Using an ensemble of diverse control policies to accomplish a coordinated task within a single team of robots can enable the team to adjust to different conditions. For example, with two unmanned aerial vehicles (UAV) on a large security task, a natural result of using an ensemble of controllers is for one UAV to position itself high, to view the entire area, while the other UAV takes a closer look at areas of interest. **Diversity allows the robots to perceive and respond to failure as they encounter it in the environment**.

**2.1.1 Diversity in Human Workgroups** Diversity is well established as a way to improve the performance of human workgroups: studies have shown repeatedly that diverse groups outperform homogeneous groups (Hoffman (1978); Hoffman and Maier (1961); Nemeth (1986); Jackson (1992)). While diverse groups do have a higher likelihood of conflict (Steiner (1972); O'Reilly and Flatt (1989); Ancona and Caldwell (1992)), that conflict can be productive. In studies where conflict due to diverse skill sets was purposely introduced into the workgroup, it was shown to consistently lead to higher-quality solutions (Jehn (1995); van de Vliert and de Dreu (1994); de Wit et al. (2012)).

**2.1.2 Diversity in Insect and Animal Behavior** Heterogeneity has also been studied extensively in insect and animal behavior. Jandt et al. (2014) study personality at multiple levels with regard to behavioral syndromes and insect societies, discussing fitness consequences of intra-colony behavioral variation. Specifically, under varying environmental conditions, maintaining a mixture of individuals with different behavioral types may be more effective than



**Figure 1.** (L) The current MRS problem-solving paradigm is linear, making the same assumptions and deploying the same solution to all robots in the team. (R) The proposed novel paradigm takes advantage of diversity in controllers to handle various scenarios. **Varying** assumptions are made, and a complementary ensemble of control policies is deployed across the team.

individuals switching between behavioral types, which might be costly and inefficient. Slower, more accurate individuals can bring large quantities of food back to the colony when good abundance is constant, whereas faster “sloppier” individuals might be more efficient at exploiting resources in more frequently changing environments (Chittka et al. (2009)). Burns and Dyer (2008) found that ant colonies that maintain a mixture of different foraging types within a group allows colonies to respond more quickly to environmental fluctuation. In certain species, groups with a mixture of aggression types tend to have higher fitness than groups with only one type (Modlmeier and Foitzik (2011); Pruitt and Riechert (2011)). On the other hand, maintaining a mixture of *inflexible* behavioral types can incur costs to the colony, such as overly aggressive types being aggressive to their own nestmates (Crosland (1990)).

These results in insect and animal behavior studies point strongly to behaviorally heterogeneous teams with the ability to adapt to the environment and task having higher fitness in uncertain and dynamic environments, which has inspired many multi-robot approaches. However, there is a need to further **study** the use of diversity as a tool for multi-robot systems, especially in tightly-coordinated tasks, **as well as single robot systems operating in uncertain environments**.

## 2.2 A New Paradigm

Thus, *the current problem-solving paradigm in MRS may not reflect an effective approach to working in teams*. In the current paradigm, one set of assumptions is made, a single control policy is developed, and it is uniformly deployed to all robots in the team as in Fig. 1(L). Instead, an ensemble of control policies **may be able to leverage the strengths of the different control policies under different conditions** much as in human workgroups: **varying control policies should be developed using different sets of assumptions and/or different styles of interaction, and the best approaches combined synergistically within the team, as in Fig. 1(R)**. In this way, MRS **may leverage diversity much as human workgroups do, to improve robustness in uncertain environments**. **Single robot systems may also benefit from ensembles of control policies, as they would allow the system to swap policies in the case of control failure**.

### 3 Current State of the Art

Diversity of robots with different physical embodiments or capabilities has previously been studied (Parker (1998); Pimenta et al. (2008); Huang et al. (2006); Prorok et al. (2017)), but has not led to significant improvements in robustness of multirobot systems. However, controllers for those teams are developed using a similar paradigm, making the same assumptions across the entire team. There has been relatively little exploration into diversity in control policies within a single team of robots. Most research in this area is a result of studying ants that take different roles in foraging and house hunting (Dorigo et al. (2006); Sugawara et al. (2004); Berman et al. (2007)) or collective transport (Kumar et al. (2013)), and applied to similar problems in robotics. Unfortunately, in trying to model ant algorithms closely, these works do not take advantage of robot capabilities, including communication, sensing, and computation, which could expand the solution space and lead to better, more appropriate solutions for a larger set of problems.

Behavioral or control diversity in teams of robots has also been explored. In Tang and Parker’s ASyMTR architecture based on schemas, robots take different roles depending on environmental conditions (Tang and Parker (2007); Parker and Tang (2006)), but the robots are all programmed to react the same. This leaves them vulnerable to unforeseen changes in capabilities or the environment, and does not enable robots to individually adjust their approaches.

A majority of work exploring control diversity in robots exists in behavior-based systems, most notably Balch’s work in learning behavioral specialization for robot teams (Balch (1997, 2000)). Goldberg and Matarić (1997) evaluate multi-robot controllers based on the amount of interference and describe caste arbitration, where all robots have the same capabilities, but have different conditions for activating behaviors. Schneider-Fontan and Matarić (1998) conclude that adapting group behavior is a balance between minimizing interference and maximizing synergy, and interference is the key stumbling block in the way of efficient group interactions.

More recently, evolutionary robotics and agent-based systems have been appearing as a method for encouraging behavioral diversity and plasticity (individuals changing roles over time). Mouret and Doncieux (2011) review and benchmark published approaches to behavioral diversity, and show that fostering behavioral diversity substantially improves the evolutionary process in the investigated experiments, regardless of task. Pugh et al. (2016) review quality diversity algorithms, which have resulted in a new class of algorithms that return an archive of diverse, high-quality behaviors in a single run. Vassiliades and Christodoulou (2016) design behaviorally plastic agents (capable of switching between different behaviors in response to environmental changes), by taking inspiration from neuroscience, using artificial neural networks, neuromodulation, and synaptic gating. Umedachi et al. (2015) attempt to understand the underlying mechanism of the behavioral diversity of animals, then use the findings to build truly adaptive robots. However, all of these approaches focus on training agents to act independently in the environment, and thus are not directly

applicable to multi-robot problems where task completion relies on tight coordination, such as box-pushing, shape formation, wildfire containment, cooperative transport, etc. Furthermore, agents are trained in the environments where they will be used, which, especially in natural disasters, may not be possible.

There is also a significant body of work on large-scale simulation of crowds, that generate realistic-appearing simulated crowds (Bera et al. (2016); Guy et al. (2010); Pelechano et al. (2007); Lee et al. (2007)). While these approaches generate diverse behaviors, diversity in crowd simulation plays a different role than the one we seek. While we seek diversity to enhance performance, diversity in crowd simulation is cosmetic.

#### 3.1 Diversity Improving Performance

Diversity has already been shown to improve performance in some scenarios. In multi-agent systems, Marcolino et al. (2013) address the problem of selecting the best possible team to accomplish a goal given limited resources. Varied agents form a team and vote on the best course of action in the computer game Go. They compare teams with the strongest individual members and teams with diverse members, and find that a team of diverse agents can outperform a uniform team of the strongest agents when individual agents outperform the overall strongest agent in certain states. It’s important to keep in mind, however, that their diverse agents combine to make a single decision, while in a multi-robot system, each agent encounters different scenarios and must make their own decision. Nonetheless, in scenarios where the team of robots encounters similar challenges, they may be able to share useful information about which actions were successful and unsuccessful with certain parameters. If this can propagate throughout the team, the entire team may be more informed and thus perform better.

In single robot systems, diversity can be provided by switching controllers. For example, Zefran and Burdick (1998) design stable control schemes for systems with changing dynamics; in their case, a different controller is activated in each dynamic regime of the system. However, to successfully design such a system, one must fully understand the dynamics of and how to stabilize the system in each regime. For a multi-robot system in an uncertain environment, it may not be possible to fully understand the dynamics of each robot under all possible environmental conditions, thus it may be difficult to know how to stabilize the system in advance. Equipping the team with varied control policies or a set of parameters enables performance observation of each control policy or parameter set *in parallel*, which can then quickly inform individuals of how to stabilize themselves.

Lyu et al. (2016) explore  $k$ -survivability in multi-robot systems. The  $k$ -survivability of  $n$  paths is the probability that “at least  $k$  out of  $n$  robots following those paths through a stochastic threat environment reach goals.” The main idea is that if the best and safest path is known, then it is still not robust for all robots to take that path, since all the robots on that path can fall to a single trap.  $k$ -survivability demonstrates that in uncertain environments, diversity can



be leveraged to improve the performance, and in this case the survivability, of a team of robots.

In swarm robotics, Li et al. (2004) study the effect of diversity and specialization in self-organizing, distributed, artificial systems, correlating the degree of specialization with the swarm's overall performance. Since not all diversity will lead to better performance, they define specialization as diversity that is evoked for better performance. They study the stick-pulling problem, where robots search an arena pulling sticks out of the ground; each stick requires two (or more, in the generalized case) robots to remove the stick from the ground, and each robot has a gripping time parameter, which can be homogeneous or heterogeneous across the team (Ijspeert et al. (2001); Martinoli et al. (2004); Martinoli and Mondada (1997)). When the number of robots was smaller than the number of sticks, this problem could lead to a deadlock situation where all robots wait for assistance for extended periods of time. In this scenario, heterogeneous swarms, in which agents had in parallel learned their own gripping time parameters, outperformed both swarms with hardwired homogeneous and learned homogeneous gripping time parameters, due to the specialization of the agents.

## 4 Some Open Problems in Diversity-enhanced Autonomy for Robot Teams

Much as human workgroups, as well as insects and animals, benefit from diversity in composition of the group, such variation of behavior would be beneficial for teams of robots operating in uncertain and unstructured environments. Thus, it is natural to consider enhancing multi-robot autonomy with diverse control policies designed to work synergistically together. There exist many open problems in DART; some of the challenging open problems that must be addressed by the community are described here.

### 4.1 Learning for MRS

In order to learn from humans, or to learn directly from simulations, new machine learning tools must be developed for many-agent systems. Multi-agent learning is an area that is not yet well represented in the literature, save for several works (Matignon et al. (2012); Foerster et al. (2016); Lowe et al. (2017); Peshkin et al. (2000)), most of which cannot handle more than a few agents. Other works focus on tasks that can be learned and completed alone (Mataric (1994); Recchia et al. (2013)). Tight coordination between a large team of agents, for example in wildfire containment, currently presents a significant computational challenge for existing multi-agent learning tools. Those that are suitable for tightly coordinated tasks for a few (2-3) agents are intractable for tasks that require tight coordination among large numbers of agents (Buffet et al. (2007); Amato et al. (2014, 2015)). *Given tightly coordinated multi-robot tasks, such as pattern formation, border patrol, or wildfire containment, automatically learn sets of control policies for individual robots that enable a teams of robots, equipped with one or more of those control policies, to complete those tasks.*

**4.1.1 Multi-Robot Learning from Humans** Humans provide a pool of diverse resources that can be tapped to develop diverse controllers that work well together. However, due to differences in human and robot capabilities (communication, locomotion, sensing, etc.), it is difficult to learn controllers by observing human in-person interaction. By limiting interaction to an interface (such as a mobile phone, tablet, or laptop), communication, locomotion, and sensing can be restricted to robot-like capabilities (Tavakoli et al. (2016)). A major benefit of human-inspired controllers is the ability to communicate with and easily motivate study participants, as opposed to animal-inspired controllers. However, learning from human cooperation requires multi-agent learning tools for many agents. While there is a recent interest in learning from demonstration for multi-robot systems (Martins and Demiris (2010); Freelan et al. (2015); Chernova and Veloso (2010)), these works either require a significant amount of domain knowledge, leading to potential bias in the creation of design policies, or do not apply to tightly coordinated tasks. *New approaches to learning are necessary in order to learn truly novel behaviors from demonstration. Given data generated by humans completing a coordinated task, find a set of control policies that, when deployed on a team of agents, produce qualitatively and quantitatively similar results.* In order to produce functional behaviors, this requires automatic solutions to the correspondence problem, which would eliminate designer bias and pave the way for novel behaviors; the agents to understand both the state of the human as well as the goal of the behavior; and measures of behavioral similarity between humans and agents.

**4.1.2 Automatic Correspondence** In learning from humans or other animals, it is necessary to solve the mapping between demonstrators and imitators automatically. Using primitive behaviors that are hand-coded, as has traditionally been done, limits the behavior space of the team of robots to those determined by the system designer, which can lead to a biased set of behaviors. *Given demonstrative data generated by a human or animal completing a coordinated task, find automatically, without hand-coding, a set of robot behaviors that produce qualitatively similar results to the demonstrator.*

### 4.2 Automatic Abstractions for Complex Observations

With large numbers of agents interacting in a space, and a very rich set of possible observations or features (potentially millions or more), it is necessary to use abstractions for the observation or feature space of each agent. For example, variations of regular or polar grids can be used with occupancies or sampling can be utilized. Abstractions can simplify the decision making process, but their utility depends on encoding relevant information, which can be task-specific. Thus, developing useful abstractions, whether automatic or hand-coded, is imperative; if done automatically, one can avoid the use and potential bias of expert knowledge. *Given a large number of agents interacting in a space, find efficient representations for the agents' observable state that enable decision making in individual agents. With respect to learning from demonstration, find efficient representations*

of the observable state of the demonstrator that enable computer-controlled agents to mimic the behaviors of the demonstrator. Efficiency can be measured by how much information is encoded in the representation, and how quickly it can be accessed and shared if necessary.

### 4.3 Measures of Behavioral Similarity

It is necessary to measure quantitatively how similar two behaviors are, whether comparing between two computer-generated behaviors or a demonstrator-imitator pair. *Given two behavioral policies, develop metrics that measure their similarity.*

### 4.4 Measures of Diversity

Taking inspiration from the study of behavioral diversity in social insect colonies, there is a need for understanding the impact of behavioral diversity on MRS in tightly coordinated tasks, and, if learning from demonstration, to measure the diversity in the demonstrators' behaviors and the resulting imitators' behaviors. This is distinct from measuring behavioral similarity, as similarity compares a pair of behaviors while diversity pertains to the team as a whole. To that end, measures of diversity and must be developed that apply to MRS, such as the Hierarchic Social Entropy of Balch (2000) or the diversity metric of Prorok et al. (2017). *Given an ensemble of agent behaviors or control policies, find a metric that quantifies the diversity of the team in a way that meaningfully differentiates between agents. As in the social science literature, diversity of a robot team can be measured in many different ways. Thus, the word meaningful here can be subjective: there are many possible measures, and perhaps different measures would be useful for different tasks, for example, depending on whether a team with small differences in parameters that do not lead to significant differences in behavior should be considered diverse.*

### 4.5 Value of Diversity

Diversity alone will not solve the robustness issue; it should bring value to the team as they work on the task. Some tasks, for example where the optimal policy can be computed and all robots can execute the optimal policy, may not require diversity. In the presence of uncertainty, however, diversity can bring significant value to the team. *Given a team task, predict the value that diversity will bring to that task. This value can depend on the level of uncertainty, the size and nature of the task, and potential restrictions on robot capabilities (whether inherent or induced by the environment). Prediction is necessary in order to avoid wasting significant time and resources on developing diversity within the team.*

### 4.6 Architectures for Diversity

Diversity of behavior within the team may also lead to different architectures for cooperation. For example, it may lead to leader-followers type behavior, a hierarchy of subgroups within the team, a flat organization with each agent making independent decisions, and many other possibilities. These architectures will likely be influenced by

the nature of the task as well as the capabilities of the robots themselves (e.g., computation and communication). *Given a team of robots on a team task, determine the best architecture for cooperation among the robots.*

### 4.7 Integrating Small Group Theory

Considering potential architectures for diversity leads naturally to the problem of creating an effective mix of behaviors within the team. Outside of robotics, human workgroups have been extensively studied. Many theories have been developed on effective groups (see, for example, Poole and Hollingshead (2005), for a collection of works). These theories can be leveraged in order to better coordinate teams of robots on complex tasks. Small group theory, however, must be adapted in order to compensate for differences in human and robot capabilities. Collaboration with social scientists who study human workgroups can lead to novel methods of cooperation for MRS, but only if we understand the role diversity plays in team success. Quantify such a property, then use it to construct effective teams for completing team tasks that perform better than existing approaches. *Given a team of robots on a team task, determine the best combination of diverse behavioral types to include in the team.*

### 4.8 Adjusting Policies Online

To successfully utilize a diverse set of controllers, the team of robots must collectively reason about the role that each team member plays and automatically adjust their own roles to achieve an appropriately diverse team with an effective skill set. To do so, they must have the ability to measure the success of individual agents on a coordinated task, adjusting based on their own and others' shortcomings and successes. Evaluating an individual's performance within the team may not be straightforward. For example, the value of a defender in a soccer game cannot be quantified by the number of goals the defender's team scores. Thus, *given a robot completing part of a team task, develop a metric to evaluate its performance within that team. Once we can quantify an individual's performance, we can consider adjusting control policies within the team accordingly. Given an ensemble of control policies within a team of robots, develop methods to adjust individual agents' behaviors, either parametrically or otherwise, based on the agent's observations of itself or other agents.*

## 5 Discussion

This paper proposes DART, Diversity-enhanced Autonomy for Robot Teams, a new research thrust that represents a paradigm shift in problem-solving for multi-robot systems. The current problem-solving paradigm is linear: control policies are optimized for a specific set of assumptions and applied to the entire team. We propose a paradigm wherein an ensemble of control policies are developed, with multiple sets of assumptions or interaction strategies, and exist synergistically within a team of robots. Such diversity in control policies may better prepare the team of robots for unstructured and uncertain environments, much like diversity in the knowledge base in human workgroups leads to higher

quality solutions. Adoption of this new paradigm may lead to expanded success of multi-robot systems in the field, especially in challenging dynamic environments. [The DART philosophy can also be applied to single robot systems, by enabling individual robots to switch or adjust controllers in response to failure conditions. In this way, single robot systems may also be more successful in uncertain and unstructured scenarios.](#)

A small sample of open problems in DART were discussed, but there exist many open problems in this space. To further the reach of MRS into such environments will require collaboration of roboticists with experts in machine learning, biological and social sciences, human-computer interaction, and many other fields. By explicitly defining Diversity-enhanced Autonomy for Robot Teams, we hope to inspire the development of new tools for coping with uncertain, unstructured environments such as disaster response, precision agriculture, surveillance, and others.

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