A Survey of Distributed Intelligence and Its Applications in Multi-Robot Ensembles

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Abstract

This article gives a general outline of distributed intelligence and the reasons why this field needs further study. We next classify common DIS systems according to the interactions they often exhibit, as the interaction type is important to the solution paradigm. We provide three common models of distributed intelligence and illustrate how they might be applied to systems including several robots. Among these frameworks are the ontological, knowledge-based, and bio-inspired ones, as well as the organizational and social ones. Next, we take a look at the work allocation problem, which is common in multi-robot systems, and show how different problem abstraction paradigms lead to different solutions. We draw the conclusion that the two models are distinct and that the constraints and requirements of a given application should be considered while making a selection. System designers need more information to determine the appropriate abstraction (or paradigm) for each problem.

Introduction

information dispersed over a system Teams of living things that are able to learn, reason, plan, solve problems, understand ideas and language, and think abstractly are called systems with "distributed intelligence." Any intelligent being, whether it a human, a machine, a piece of code, or a physical object, might be considered a "entity" in this sense. Multiple players in such a system often take turns directing different aspects of the activity. Because our species has always thrived in collaborative settings, we are all used to using the expertise of other individuals. Management teams in corporations sometimes consist of individuals with titles such as chief executive officer, chief operating officer, chief financial officer, chief information officer, etc. Cancer patient care teams include of experts in several subspecialties such as medical oncology, surgical oncology, plastic and reconstructive surgery, pathology, and associated professions. Special operations units are only one example of how the military uses disseminated intelligence. Team A.polish your abilities in the domains of combat, engineering, healthcare, and speech. Catapult crews, landing signal officers, ordnance men, plane handlers, etc. are all examples of components that could be present on a military aircraft carrier. People have plainly figured out that these teams can do complex tasks much faster by using specialists that collaborate well. Cohesive systems including software agents, robotics, sensors, computers, and even people and animals (such as search and rescue dogs) are the aim of distributed intelligence in computer science and related fields. Urban search and rescue, transportation and logistics, computer security, gaming technology and simulation, military network-centric operations, and many more challenges might be solved by such systems.

A Field Concerned With Distributed Intelligence

Many different paradigms are being considered by researchers as potential approaches to distributed intelligence. These models aren't always the best fit for dispersed intelligence. That is why it is so important to study the many kinds of distributed intelligence that could arise in different settings. One way to learn more about the domain space is to look at all the potential interactions between the entities in a distributed intelligence system. Figure 2 shows three dimensions along which we think about interactions: the goals at play, the degree to which the entities engaged are aware of one another, and the extent to which each entity's actions contribute to the team's overall performance. Differentiating between systems is as simple as looking at whether their individual components work toward shared or independent goals. Along the axis of other people's awareness, the systems are categorized as either aware or unaware. In this context, "conscious" means that an entity may think about how its teammates act and what drives them. While non-aware robots can do things like detect adjacent items and maneuver to avoid them, they can't understand or predict what their coworkers are going to do next. The foundation of the functioning of several "un aware" systems is the idea of stigmergy, whereby objects interact with one other without exchanging direct signals. As a last step, we divide systems into two camps: yes, when individual actions boost collective performance, and no, when they have no such effect (no). A floor-cleaning robot, working in tandem with other such robots, is an example of a thing whose actions serve to enhance the goals of other entities. One robot's floor cleaning efforts help the other robots in the team avoid re-cyling. Although these domain space divides are obviously approximations, we nonetheless find them helpful for understanding the most typical interactions in the actual world. A distributed intelligence system's numerous possible interactions are shown in this subspace. Conventional means of expression include:

- Collective
- Cooperative
- Collaborative
- Coordinative

We go into more into about these kinds of interactions in the paragraphs that follow. Collective interactions are among the most basic forms of human contact; in these, members of the team work together toward a common objective while remaining oblivious to one another. Swarm robotics, which has been the subject of several studies (e.g., McClurkin 2004; Matara's 1995), is one example of such an intervention in MRS.

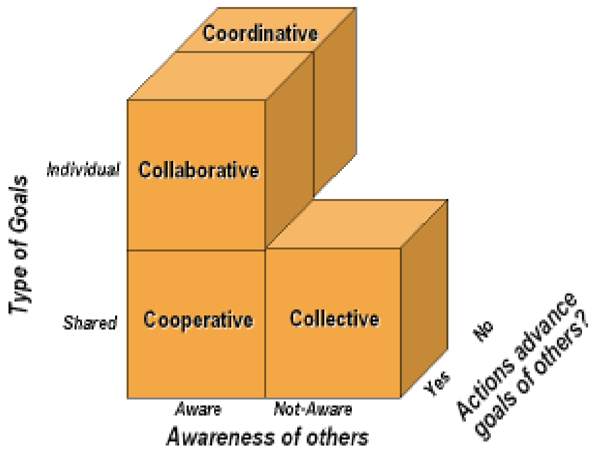

Figure 1: Categorization of types of interactions in systems of distributed intelligence.

(Kuba and Zhang, 1993). Biologically relevant tasks like foraging, traveling in big groups, herding animals, keeping a formation, etc., are the focus of this work's robotic system creation efforts. As the number of robots in a system increases, the global goal becomes an emergent feature of the local interactions, and the robots in the system commonly carry out very simple control rules at the local level. The second kind of contact is cooperative interaction, which happens when all parties engaged are aware of one other, share goals, and work together to achieve them. In multi-robot systems, for instance, robots might work together to transport a package (e.g., (Gerkey &Matari'c 2002)), tidy up a construction site (e.g., (Parker 1998)), perform a rescue mission (e.g., (Murphy 2000)), or even uncover the secrets of other planets (e.g., (Stroup et al., 2006)). Robots in such a system may have to coordinate their actions in the shared workspace to ensure that they don't block each other's path to the system's ultimate goal. Still, most of the time, the robots are working together to complete a common task.There is a third kind of interaction in distributed intelligence systems provided by autonomous robots that know what their teammates are up to and how their actions fit into the bigger picture. In the collaborative subset of the domain space, entities work together to achieve their distinct but complementary goals. Here, we differentiate between cooperative do main space and entities' capacities to cooperate in order to help each other accomplish their goals more effectively. Collaborative efforts are common in human research teams since everyone brings something unique to the table. Team members are all pulling in the same direction (doing their assigned study), but when they collaborate with individuals who have different backgrounds and experiences, their individual strengths will complement one another. It is possible for any organization to become cooperative by looking at the larger picture and reassessing its goals; in fact, the majority of these partnerships are cooperative as well. An example of collaborative cooperation would be a group of robots working together to accomplish common objectives. If a robot's sensors aren't able to get it where it needs to go, it might be able to work with others to accomplish what it needs to by sharing resources and improving each other's sensors. (Parker & Tang 2006; Vig& Adams 2006) demonstrate such an alliance. The last and fourth kind of interaction in distributed intelligence is coordinated interaction. Even if they are aware of one another, the entities in these systems aren't cooperating to achieve a common goal, and their actions aren't helping the team succeed. When many robots are operating in close proximity to one another, collisions like this are common. It is crucial that the robots work together so that they don't interfere with each other. A number of methods for traffic management and multi-robot route planning have been developed for application in such settings, including (Kloser&

Hutchinson 2006; Guo & Parker 2002) and (Asama et al. 1991; Yuta & Pre mute 1992; Wang 1991). Additionally, we may have expanded our domain space by a third dimension to categorize systems based on whether they (1) aid other entities in achieving their objectives, (2) have no effect on other entities' ability to accomplish their objectives, or (3) hinder other entities' ability to achieve their objectives. This would let us create a new sort of interaction where each player acts in their own self-interest, is aware of the other participants, and still manages to obstruct the other participants' goals. This is the core of the hostile domain, where things collude to harm one another. Kitano et al. (1997), Browning et al. (2005), Veloso, Stone, & Han (1999), and Stone & Veloso (1999) are just a few of the many works that address this issue within the framework of multi-robot systems, and more especially multi-robot soccer. The military value of such collaboration is undeniable.

Theories of Distributed Intelligence

Different types of interactions in distributed intelligence systems need a wide variety of models for generating distributed intelligence. System designers may learn about successful ways to solve problems by looking at the problem space through the lens of each paradigm, which offers a different degree of abstraction. Similarities between human communities and ant colonies are a common theme in these models. Although paradigms may be helpful, they can't be applied to every interaction scenario. This section presents a synopsis of several popular models of distributed intelligence, focusing on their applicability to multi-robot systems. Remember that a major challenge with all of these models is determining how to achieve global coherence via the interaction of objects at the local level. Approaches to solve this problem that are complimentary are revealed at different levels of problem abstraction.

The three most popular approaches to developing distributed intelligence systems are the knowledge-based, ontological, and semantic paradigms; the organizational and social paradigms; and the bioinspired, emergent swarms' paradigm.

As part of our discussion of collective interactions in the preceding section, we delved into principles of the bioinspired swarms' paradigm. Assuming that entities can perceive meaningful information in their immediate environs (i.e., staggery) significantly reduces the necessity for communication between entities in this paradigm. To achieve the intended group behavior, these issues' application requirements permit basic action protocols, sometimes called control rules, that are the same for each entity. One local control rule that might lead to the agents' or robots' aggregation (like a swarm) under this scenario is

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Aggregate:
  If agent is outside aggregation
      distance
  then turn toward aggregation
      centroid and go.
  Else
     stop.
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For applications that can execute the same task in a distributed setting without complex entity-entity interactions and with generic entities, this paradigm works well. The first problem, predicting global behavior from a set of local control rules, and the second, determining local control rules given a desired global behavior, both provide substantial research challenges. Distributed applications like as flocking, schooling, foraging, chaining, searching, sorting, herding, aggregation, condensation, dispersion, confinement, formations, harvesting, deployment, and coverage might all be improved by adopting this model. Complex frameworks are required, however, to solve a wide range of interactions.

Competition between Robot Models for Task Assignment in a Multi-Robot Setting

We will examine three distinct methods of distributed intelligence systems and then compare and contrast how they handle a common issue in multi-robot systems: task distribution. Job allocation is a typical issue in multi-robot applications when the team's aim is divided into distinct jobs, as previously mentioned. From one job to another, diverse robots are up to the challenge. Although separate tasks may be worked on concurrently, dependent tasks must be finished in a certain sequence to take their interdependencies into consideration. After the tasks are determined, the next step is to determine the best strategy to allocate robots to each task in order to maximize an objective function. Splitting up tasks like this is a problem. Gerkey and Matara (2004) demonstrated that finding the best solution to the general problem of job allocation is NP-hard. This problem is so often addressed by using approximations that are practical and acceptable. Think about how the aforementioned paradigms may solve the multi-robot work allocation challenge. Before anything else, the bioinspired approach to task allocation often assumes a large number of similar robots. Any robot in the immediate area that is aware of the requirement to complete a task may be assigned that duty if it volunteers to do so. In order to avoid using direct communication, robots may use staggery to determine what to do. Robots may be replaced if they malfunction. For optimal performance, all robots should adhere to this principle. Second, roles may be used to organize the allocation of jobs, similar to what we stated before for multi-robot soccer. Each job has its own set of specific tasks, and robots choose roles according to their strengths. Robots in this setting don't have to be standardized in terms of their sensing, computation, and effector abilities.As an alternative method of running the business, the market-based approach to allocation was also put out. Robots use these techniques to bargain for employment by being transparent about their skills and making offers based on what they can bring to the table. It is common practice to allocate tasks to the robot with the highest potential efficiency. Because it was the first protocol to address the question of how agents may contract to fulfill a set of tasks collectively, the Contract Net Protocol (Smith, 1980) is important here. According to Botelho and Alami (1999), the M+ architecture pioneered the use of a market-based technique to assign work to many robots. Every robot in the M+ approach comes up with its own plan to achieve its goal. Afterwards, they make use of social conventions that permit the slow merging of plans as they bargain with other team members to progressively modify their actions such that they optimally benefit the team overall. Last but not least, multi-robot teams employ the knowledge-based approach to distribute tasks by simulating the abilities of each team member. One of the several possible variations is the ALLIANCE approach (Parker, 1998), where robots mimic human team members' abilities to do system tasks by observing how well team members work and gathering crucial job quality data, such the amount of time it takes to complete a task. Based on these models, the robots then determine which tasks would benefit the team the most. Using this approach, assigning duties does not need direct communication. Additional approaches become possible with the use of trained models of teammates' abilities. As these examples of task distribution demonstrate, the abstraction paradigm used determines the number of viable solutions to a specific problem in multi-robot systems. In different situations, each paradigm has its own set of advantages and disadvantages. The constraints and requirements of the application determine the best paradigm to use.

Conclusions

We have covered the various potential interactions between distributed systems, presented several important ideas in distributed intelligence, and highlighted some of the most common techniques to obtaining distributed intelligence in this article. We have shown the different interactions and paradigms using examples from the field of multi-robot systems so that you can better grasp the challenges. This round of arguments has shown us that the details of each application determine which paradigm is best suited to solve a particular issue. We also note that in complex systems, several robot paradigms may coexist. One way to define roles for the high-level abstraction is through an organizational paradigm. Another way is to deploy mobile networks using a knowledge-based modeling approach. Lastly, when creating a mobile sensor network, one can take a bio-inspired approach (Howard, Parker, &Sukhumi, 2006). System designers are tasked with creating and implementing paradigms that are customized to meet the specific needs of each application.

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