

Chapter 1

A Taxonomy of Multirobot Systems

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1.1 Why a Taxonomy is Important

A key difficulty in the design of multi-agent robotic systems is the size and complexity of the space of possible designs. In order to make principled design decisions, an understanding of the many possible system configurations is essential. In Dudek et al. [DJMW96] we presented a taxonomy that classifies multi-agent systems according to communication, computational and other capabilities. In this chapter we update the taxonomy developed in the early 1990's and place a number of recent multirobot systems within it.

Task oriented behaviour by groups of agents is ubiquitous in nature. How and why should multiple mobile robots be used for a task? Although most mobile robotic systems involve a single robot operating alone in its environment, a number of researchers have considered the problems and potential advantages involved in having an environment inhabited by a group of robots which cooperate in order to complete some required task. For some specific robotic tasks, such as exploring an unknown planet [AB98], pushing objects [Par94b, MNS95, RDJ95], or cleaning up toxic waste [Par98], it has been suggested that rather than sending one very complex robot to perform the task it would more effective to send a number of

smaller, simpler robots. Such a collection of autonomous agents is sometimes described as a *swarm* [BW89], a *colony* [DMC96], or as a *collective* [KZ93], or the robots may be said to exhibit *cooperative behaviour* [Par93]. Using multiple robots rather than a single robot can have several advantages and leads to a variety of design tradeoffs. Collectives of simple robots may be simpler in terms of individual physical design than a larger, more complex robot, and thus the resulting system *may* be more economical, more scalable and less susceptible to overall failure.

There is a continuum of possible collective designs. A collective might consist of a collection of completely autonomous agents which only communicate by pairwise transfer of information. A collective might consist of a number of remotely controlled appendages so that the entire collective might more properly be described as a single large robot with distributed actuators. Both of these extremes exist in the literature. Although this later extreme might be considered as a collective, the more interesting case occurs when the elements of the collective lack any functionally relevant, permanent physical connectivity. We thus distinguish between a single, complex and possibly distributed robot R and a collective of robots $\{r_i\}$ which lack a functionally relevant, permanent physical connection.

Collectives offer the possibility of enhanced task performance, increased task reliability and decreased cost over more traditional robotic systems. Although they have this potential, many possible collective designs are neither more efficient, nor more reliable, nor more robust than a comparable single (more complex) robot. In order for a collective to have these advantages the collective must be designed with these issues in mind.

In addition to having these properties, it is essential that the collective have an overall behaviour or set of actions that accomplishes the same behaviour or action that was required of the single more complex robot. For a collective to exhibit cooperative intelligent behaviour, the members of the collective must be able to communicate with each other. This communication may take place directly via an explicit communication channel or indirectly through one robot sensing a change in other robots in its environment. Michaud and Vu [MV99] present an interesting example of agents communicating via an external light that allows robots to communicate motivations. Intra-collective communication presents difficulties in terms of collective efficiency, fault tolerance, and cost.

Interactions between natural organisms such as birds, ants, termites, wasps, primates, fish or wolves have been examined in the context of ethology [Tin51, Tin72, McF89]. Observations from biology and ethology have provided inspiration for developments ranging from subsumption architectures for single robots to inter-robot communication strategies for groups of robots [Bro91, AD91]. Canonical issues for biological groups include the

maintenance of an appropriate distance between members of a school or flock, often via purely local communications [Par82], or the communication of the location of a goal such as a food source. While the specific behaviours used by animals have been examined rigorously, the alternative design options for inter-agent communication has been less extensively examined.

How Task Impacts Team Organization

The next chapter addresses multirobot tasks in detail. Here we discuss the issue briefly in order to consider how task and robot team organization interrelate.

Traffic Control, Box Pushing and Foraging have been proposed as multiple robot tasks. Although these tasks have been addressed by robotic collectives, are they appropriate tasks for this type of approach? Some tasks seem ideally suited to multiple robotics. Gage [Gag92] identifies a number of military applications such as mine deployment, carrier deck foreign object disposal, etc., as potential applications for robotic collectives. These tasks are typified by the high potential for damage to individual collective elements, and thus it is the expendability of collective elements which is identified as the major reason for proposing robot collectives for the task, rather than any particular computational efficiency or reliability requirement. Although expendability is certainly a strong argument for collections of inexpensive robots over a single more complex expensive robot, are there computational reasons why a collective of robots should be preferred? Given a particular task T , which can be solved with either one very complex robot R , or with a collective of robots $\{r_i\}$, under what conditions should R be chosen over $\{r_i\}$?

Tasks that *require* multiple agents

Does there exist a task T which can be solved by $\{r_i\}$ but for which no R can be found? Consider the following (missile launch) example;

There are two keys which are a large distance apart which must be turned at the same time.

Note that this task does not necessarily require multiple robots to solve it. If the keys are not too far apart then a single *large* robot can be used to solve the problem. If the keys can be turned within some small time interval of each other then a single *fast* robot R can solve the problem. In order to exclude solutions which are based on a single robot R , the task must involve spatially separate tasks which require some sort of synchronization. This synchronization implies inter-robot communication. The robots must either

have their clocks synchronized initially (which requires communication) and then plan to turn their keys at precisely the same time, or they must be able to communicate with each other in order to indicate that it is time to turn the key. A more prosaic example is a multi-robot scene exploration system that uses the motion of shadows in a scene to compute spatial occupancy. In this case, one robot uses a camera to examine the scene while a second robot moves a light source about the scene to cast appropriate shadows [LDZ95].

Tasks that are traditionally multiagent

Many modern transportation, industrial, agricultural, and fishing related tasks are currently performed by a group of effectively autonomous agents. The tasks that they perform are typically parallelized with small amounts of coordinating communication at either the start (for truck delivery) or at the end (forestry). In these tasks each element of $\{r_i\}$ operates independently for the most part, utilizing inter-agent communication either initially, to parcel up the expected workload in an efficient manner, or penultimately, just before dealing with any work that was not covered during the parallel portion of the processing. From a robotic collective point of view, the computational processing is relatively straightforward due to the inherent parallelism of the tasks.

Elements of these collectives operate in effective ignorance of each other. Similar strategies have been proposed in robotic collectives work. For example, the *ignorant swarms* of Mataric [Mat92] and the *communication-less swarms* of Dudek *et al* [DJMW93a] propose to solve simple, highly parallel tasks by having a number of robots solve a problem in parallel without communication. Although this approach may maximize reliability, it fails to maximize performance as members of the collective cannot be directed to uncompleted work which they cannot sense directly. If elements of the collective do not communicate at all then task completion can become probabilistic and while a probabilistic solution may be acceptable for some problems it is not in general. For some foraging or search tasks, such as finding lost children, a probabilistic solution is not appropriate and inter-robot communication must occur.

Tasks which are inherently single agent

There exist tasks which do not benefit from the use of additional agents in order to solve them. Task and environment can combine to remove any benefit of the use of multiple agents. A single task at a single location does not benefit from the use of multiple robots, as a single robot is both

necessary and sufficient.

Tasks that may benefit from the use of multiple agents

Between these extremes exist tasks which could be performed faster, or more reliably with a collective $\{r_i\}$ rather than with a single robot R .

Consider the issue of speed. Perhaps the collective $\{r_i\}$ can perform a particular task faster than a single robot R . A typical task in this class is that of finding a particular object in a finite region. If there are n elements of $\{r_i\}$, then one should expect a speedup of at most n if we assume that each element of $\{r_i\}$ can do no more work per unit time than can R . Note that in order to obtain a speedup near n the work performed by each collective member must be well coordinated and each element of $\{r_i\}$ must have abilities near those of R . If this is not the case then there will be a loss of speedup as multiple robots will search the same area or individual elements of $\{r_i\}$ will search less efficiently. Once again, a high level of inter-robot communication is required.

It is also unlikely that individual elements of $\{r_i\}$ will be able to do the same amount of work per unit time that can be accomplished by R . Indeed, given a task T in which the only advantage of a collective is speed, then it might be worthwhile improving the performance of R , rather than constructing a reliable collective of $\{r_i\}$ to accomplish the same task.

Reliability (redundancy) is one performance measure for which collectives easily exhibit performance over that of a single robot. Failure of a single element of $\{r_i\}$ may not result in task failure. Failure of R guarantees task failure. What sort of design features should be included in $\{r_i\}$ so that the swarm exhibits reliability?

The communication mechanism utilized by the collective is critical to its practicality, efficiency and reliability. The need for effective communication is made quite clearly by Parker [Par95] who performed various tasks with collectives whose members could and could not communicate with other collective members. She found that global awareness of the state of the collective members improves task efficiency. Rus *et al* [RDJ95] describes furniture moving experiments using centralized and distributed control, and also an experiment where communication takes place through the task itself.

The requirements of practicality, efficiency and reliability are typically at odds with one another. Sophisticated inter-robot communication can maximize performance for many tasks, yet such communication requirements often leads to reduced reliability. If there are fixed communication topologies (e.g. [UFA92]) or controller robots (e.g. [HB92]), or other fragile communication mechanisms, then failure of these fixed links in the communications network will cause the entire collective to fail. In order to maxi-

mize the reliability of the collective, the communication mechanism between elements of $\{r_i\}$ must survive the worst possible destruction of collective elements. Communication, like action, should be distributed throughout the collective. Balch and Arkin [BA94] describe a number of simulation experiments of various tasks (forage - look for things, consume - look for things and then do work there removing it, graze - consume everything). Simulations were constructed using different levels of communication between the various elements of the collective, including no communication, state communication (robots communicate information concerning their current internal state to each other), and goal communication (robots communicate information concerning goals to each other). The work is plainly impacted by the implementation of the robots, and details of the simulation. General findings are the following: (a) communication improves performance significantly in tasks with little implicit communication, (b) communication appears unnecessary in tasks for which implicit communication exists, (c) more complex communication strategies offer little benefit over basic communications. They define goal communication as more complex than state communication.

Many different collective architectures have been proposed. The behaviour based control strategy proposed by Brooks [Bro91] has become established as one possible approach for collections of simple independent robots, particularly for simple tasks. Other authors have considered how a collection of simple robots can be used to solve complex problems. Ueyama *et al* [UFA92] propose a scheme whereby complex robots are organized in tree-like hierarchies with communication between robots limited to the structure of the hierarchy. Hackwood and Beni [HB92] propose a model in which the robots are particularly simple but act under the influence of “signpost robots”. These signposts can modify the internal state of the swarm units as they pass by. Under the action of the signposts, the entire swarm acts as a unit to carry out complex behaviours.

Mataric [Mat92] describes experiments with a homogeneous population of actual robots acting under different communication constraints. The robots either act in ignorance of one another, informed by one another, or intelligently (cooperating) with one another. As intra-collective communication improves, more and more complex behaviours are possible. In the limit, in which all of the robots have complete communication, then the robots can be considered as appendages of a single larger robot (or robotic “intelligence”). One major goal of many robotic collectives is to distribute not only the sensing (and possibly actions) of the robots, but also the intelligence. What sort of processing can be accomplished by a collection of robots that cannot be accomplished by a single one? What effects do limits on communications and unit processing capabilities have

on the potential actions of the collective? How do we compare the structure of various possible collectives?

The information processing ability of a collective is dependent upon a large number of factors including the number of units, their sensing abilities, and their communication mechanisms (see [AH92, NA93]). In order to understand more fully the properties of various designs of collectives, it is instructive to group collectives into classes and to determine the capabilities of each class. It may be the case that certain collective organizations have more potential processing ability than others, and that some collective organizations may be similar to existing parallel models of computation.

1.2 Dimensions of Robot Collective Taxonomies

There have been a number of efforts to develop descriptive categories or taxonomies for describing robot collectives. Dudek *et al* [DJMW93a, DJMW93c, DJMW96] and independently Cao *et al*. [CFK97] have proposed the classification of *swarm*, *collective* or *robot collaboration* research by defining a taxonomy or collection of axes. Cao *et al* [CFK97] define five research axes for collectives:

- Group Architecture.
 - Centralized/Decentralized.
 - Differentiation - heterogeneous vs. homogeneous.
 - Communication Structures (interaction via environment, via sensing, and via communications).
 - Modelling of Other agents.
- Resource Conflicts - how members deal with resource conflicts (communication).
- Origins of Cooperation - how cooperation is motivated and achieved.
- Learning - how the collective adapts to the task, primarily using evolutionary techniques, such as reinforcement learning, neural network controllers, genetic algorithms, and genetic programming.
- Geometric Problems - how path planning is addressed in collectives.

These axes are highly interdependent, as they focus on problems and solutions, and very broad making it difficult to identify isolated sample points within the taxonomy. The paper has an extensive set of references, and it is an excellent survey of research up to 1997.

Yuta and Premvuti [YP92] subdivided collectives based on the interactions of collective elements; do individual elements work towards a common objective or do they work independently. Arkin *et al* [ABN93] also examined different collectives along several dimensions but only in terms of a particular task. The objective of each of these taxonomies is both to clarify the strengths, constraints and tradeoffs of various designs, and also to highlight various design alternatives. Whereas Dudek *et al* [DJMW93a, DJMW93c, DJMW96] concentrated on defining a taxonomy within which different robot collectives could be compared and contrasted, Cao *et al* [CFKM95] expands the axes of comparison to include learning and the geometric structure of the problem. Following Dudek *et al* this paper concentrates on the more restrictive taxonomic comparison.

In the next chapter of this book Balch presents two highly focussed taxonomies of multirobot systems. The first is a taxonomy of the features of the task to be accomplished. The second is a taxonomy of rewards, assuming a reinforcement learning framework.

Parker [Par00] presents a survey of research areas in distributed mobile robot systems, and identifies open research questions and challenges. It is claimed that biological influences, as emulations of known biological systems, on simple tasks involving cooperation and/or competition are well understood, whereas biological approaches to complex tasks such as robot soccer and especially their learning aspects are still wide open. Parker includes references to more recent hardware implementations (up to 2000).

Stone and Veloso (Chapter ?? in this book) propose a taxonomy along what are believed to be the most important aspects of agents, namely degree of heterogeneity and degree of communication, with a focus on learning issues that arise because of the presence of multiple interacting agents. Other issues touched upon include whether agents have global or local view, whether an agent alters the environment so as to either affect the sensory input or the effects of another agent's actions. Machine learning techniques involve reinforcement learning, genetic programming, or case-based reasoning (where agents store negative cases so as to avoid them in the future). Interesting questions surveyed are:

- Whether explicit cooperation and commitment is better than totally self-interested agents. In certain simplified predator-prey environments is no, but yes in more complex domains.
- What is communicated (goal information or state information, goal is generally better).
- Open problem for agents is how to learn for themselves what to communicate and how to interpret it.

- Simulated soccer domain has been a successful testbed for testing multiagent designs, including machine learning. A survey of recent research results in robotic soccer is presented.
- Layered learning (by the authors) is useful when learning a direct mapping from sensing to actuators is intractable. Layered learning consists in a hierarchical task decomposition and learning of mappings between successive layers.

1.3 A Taxonomy of Robot Collectives

There are several natural dimensions along which robotic collectives can be naturally classified. These dimensions address the characteristics of the collective as a whole rather than the architectural characteristics of individual robots. The dimensions follow, with key points along each dimension noted with symbolic labels. Table 1.1 summarizes the axes of the taxonomy.

By size of the collective:

The number of robots in the environment.

SIZE-ALONE 1 robot. The minimal collective

SIZE-PAIR 2 robots. The simplest group.

SIZE-LIM Multiple robots. The number n is small relative to the size of the task or environment.

SIZE-INF $n \gg 1$ robots. There is effectively an infinite number of robots.

Two robots can, of course, succeed at tasks that are impossible with a single robot. Almost any operation involving simultaneity or near simultaneity of events (such as turning two keys at the same time), is impossible with a single spatially limited robot. Multiple robots can be used to obtain speedups in terms of task performance subject to robot task synchronization.

The distinction between SIZE-LIM and SIZE-INF is a property of the size of the task. A number of robot collectives assume that the number of robots available for the task is unbounded (SIZE-INF) and this provides a number of simplifications in terms of probabilistic task completion. As a simple example, consider the task of searching a bounded environment for a lost child or robot (this is known as the “find robbie” task). Provided that the collective is SIZE-INF then one algorithm is given by flood filling the environment with the robots. Eventually every location will either be filled

with a robot (robbie wasn't there) or one of the robots will find robbie. Note that the robots do not have to communicate with each other to complete this task - they just need sufficient sensing in order to be able to determine if they have found robbie and to navigate to flood the environment. For any finite sized collective (SIZE-LIM) this same algorithm is only probabilistic.

By communication range:

In most systems there are limits to the range of direct communication for any single robot. This is a function both of the communications medium and the robot distribution. We list three key classes for this dimension.

COM-NONE Robots cannot communicate with other robots directly.

It is possible for robots to communicate with each other *indirectly* by observing their presence, absence or behaviour (as many animals seem to). In order to have truly "ignorant robots" [Mat92], the robots must not only not communicate with each other they must not try to signal each other through behaviour.

COM-NEAR Robots can only communicate with other robots which are sufficiently nearby.

This corresponds to the communication mechanism proposed by Hackwood and Beni [HB92]. Distance, in this context, can be interpreted either topologically or in a Euclidean sense. A limited communication distance can occur due to physical communication constraints. For example, the power of the communication signal is often limited not only for local design reasons, but also to allow non-overlapping use of the same channel (a scarce resource) by agents in different geographical areas.

COM-INF Robots can communicate with any other robot. This is a classical assumption, which is probably impractical if $n \gg 1$. The distinction between COM-NEAR and COM-INF is analogous to the distinction between SIZE-LIM and SIZE-INF. From a practical point of view, the collective may be considered to be COM-NEAR if the communication range is smaller than the maximum separation of the robots during their execution of the task of interest, and COM-INF if the communication range is greater than this maximum separation. We identify these two points in the communication range continuum to highlight the qualitative difference in the constraints imposed on the solution of a problem as the result of differences in communication range.

Note that we have deferred issues related to having multiple robots (autonomous agents) communicating (writing) to a single robot (memory location). This is a classic problem in parallel computation [FRW88]. As minor modifications in the communication design of parallel machines can result in major changes in the power of the resulting machine [Boa89], we also partition the taxonomy by considering the topology of the inter-unit communication strategy utilized by the collective.

Cao *et al* [CFKM95] identify the communication structure as one of their taxonomic axes, and identify interaction via the environment, sensing and communications as three critical structures. The taxonomy presented here provides a finer granularity in terms of communications in order to highlight the importance of different communication strategies on the overall capability of the collective.

By communication topology:

Robots may not be able to communicate with an arbitrary element of the collective regardless of its proximity. Robots may only be allowed to communicate within a particular hierarchy [UFA92], or with specific controller robots [HB92]. Individual robots may have names and messages may be sent to them directly, or messages may be broadcast to all robots. Some key variations are:

TOP-BROADCAST Broadcast. Every robot can communicate with all of the other robots.

It is not possible to send a message only to a particular element of the collective.

TOP-ADD Address. Every robot can communicate with any arbitrary robot by name or address.

TOP-TREE Tree. Robots are linked in a tree and may only communicate through this hierarchy. This communication topology is utilized in systems with controlling robots or supervisors such as in the FIRST system [CP95].

TOP-GRAPH Robots are linked in a general graph.

This is a more general connectivity scheme than the tree and is more robust since redundant links can prevent the entire collective from becoming disconnected.

Communication strategies based on either tree-like or address based communication topologies are likely to be highly sensitive to failure of particular robots in the collective. Failure of a particular robot will isolate

robots on either side of the failed node in the hierarchy. Addressing implies distinctive roles for individuals; resulting in reduced interchangeability, unless the robots' roles change dynamically based on actions or failures of other members of the collective. Note that the actual set of robots that can communicate directly at any time is a function both of this dimension and of the communication range and robot distribution in space.

By communication bandwidth:

Communication may be inexpensive in terms of the robots' processing time, in that the robot has a special channel for communication, or it may be expensive in that the robot is prevented from doing other work while communicating. Sample points along this dimension include;

BAND-INF Communication is free.

The communication bandwidth is sufficiently high that the communication cost and overhead can be ignored. This is a common assumption in theoretical computational models and can lead to robots that behave as if there was a central intelligence.

BAND-MOTION Communication costs of the same order of magnitude of the cost of moving the robot between locations.

This can be thought of as being similar to the mechanism by which bees communicate by performing an intricate dance that is observed by other bees in the neighborhood. Systems such as the block moving algorithm of Brown and Jennings [BJ95] and some of the furniture moving approaches of Rus *et al* [RDJ95] use the task to signal communication. Although these may appear to be classified as **BAND-ZERO** (described below), they are more correctly classified as **BAND-MOTION** as the pushing action (motion) of one robot is communicated through the object being pushed to other robots in the collective.

BAND-LOW Very high cost. Communication costs much more than the cost of moving from one location to another.

This suggests very independent robots.

BAND-ZERO No communication.

Robots are unable to sense each other. As mentioned earlier, this is probably an impractical case if coordinated collective behaviour is desired.

Note that low bandwidth may be acceptable if the primary reason for using multiple robots is redundancy rather than efficiency.

Axis	Description
Collective Size	The number of autonomous agents in the collective.
Communication Range	The maximum distance between two elements of the collective such that communication is still possible.
Communication Topology	Of the robots within the communication range, those which can be communicated with.
Communication Bandwidth	How much information elements of the collective can transmit to each other.
Collective reconfigurability	The rate at which the organization of the collective can be modified.
Processing Ability	The computational model utilized by individual elements of the collective.
Collective Composition	Are the elements of the collective homogeneous or heterogeneous.

Table 1.1: Summary of the taxonomic axes

Collective reconfigurability:

The rate at which the collective can spatially re-organize itself; roughly equivalent to the rate at which members can move with respect to one another. For example, bees can presumably reconfigure their spatial layout with respect to one another very quickly while soldiers marching in lock-step or cars on a highway cannot. This dimension is closely related to the communication range of members of the collective. Changes in topology, however, will alter the nearest-neighbor relationships and thus are not equivalent to simple scaling of the communication range. In practice, there may be topological constraints to the allowed reconfigurations. For example, if the members of a robotic collective drive on roads, then only certain topological changes are allowed irrespective of member velocity. This can be seen in the work of Aguilar *et al* [AAF⁺95]. Here global control of a collective operating within a roadway-like environment utilizes controllers at intersections to communicate with robots adjacent to and heading towards the intersection as well as other controllers. Another issue that determines reconfigurability is the possible presence of non-holonomic motion constraints on collective members: non-holonomic robots can reduce the rate of reconfiguration due to complex maneuvering that may be required, or they may render some configurations unattainable.

ARR-STATIC Static arrangement.

The topology is fixed.

ARR-COMM Coordinated rearrangement.

Re-arrangement with members that communicate. In interesting example of this is the formation control work of Balch *et al* [BA95] where the group of robots can sometimes change to a specified alternative topology.

ARR-DYN Dynamic arrangement.

The relationship of members of the collective can change arbitrarily.

Static collective arrangement is likely to result in very fragile collectives.

The centralization/decentralization axis of Cao *et al* [CFKM95] includes aspects of the collective reconfigurability and collective topology axes. Cao *et al* distinguish between collectives in which there is a single controlling agent and those which do not, while the design space presented here places less emphasis on this particular dichotomy, in contrast with other options.

By processing ability of each collective unit:

Each unit of the collective has a particular model of computation. It may be useful to model individual members of the collective with a computational model that is simpler, and therefore weaker, than that of a Turing Machine. For example, if individual members of the collective are modelled as finite state machines [HU79] (operating as a function of their sensors, the current communication input, and some finite number of internal states) then it will be possible to provide formal bounds on the execution of an individual member of the collective. It is interesting to note that, even if individual members of the collective have a particular limited computational model, the entire collective may have an overall computational ability that is considerably more powerful. Thus, there exists the attractive possibility of having collectives where the computational power of individual units is deliberately restricted, in order to allow formal reasoning about their behaviour for example, but where the collective as a whole exhibits very general computational abilities.

For simplicity, we deal only with the common simple sequential computational models. Note that this is a non-continuous dimension.

PROC-SUM Non-linear summation unit [HKP91].

This very simple unit is used in constructing a simulated neural network but may be too simple to be a realistic model for a single robot although it illustrates the near-extremum of this dimension.

PROC-FSA Finite state automaton.

This is the computational model preferred by the subsumption architecture computational systems [Bro86]. Finite state models are also used for many communication protocols to facilitate proofs of correctness [Tan88]. It should be noted that individual units may in fact be general-purpose processors, *programmed to behave as FSAs* in order to simplify reasoning concerning their behaviour.

PROC-PDA Push-down automaton.

PROC-TME Turing machine equivalent.

The computational model assumed by most robotic systems.

By collective composition:

Even an ensemble of robots that is homogeneous in terms of physical structure may be differentiated by programming or behaviour. Thus, heterogeneity could be subdivided into both a physical component and a software component, implemented using physically homogeneous robots. However, we do not distinguish robots with identical software from those with non-identical software since even identical software can act in very different ways as a result of environmental stimuli or explicit negotiation. Thus, a collective may be:

CMP-IDENT Identical.

The collective is made up of units that are homogeneous in both form and function (hardware and software). Note that this does not preclude differentiation in the roles assumed by members of the group based on environmental or stochastic factors. Note, further, that assigning unique labels to elements of the collective is consistent with this classification since it could be achieved procedurally, as it is in some computer networks.

CMP-HOM Homogeneous.

The collective is made up of units all with essentially the same physical characteristics.

CMP-HET Heterogeneous. The collective is made of of units that are not physically uniform. In general, this also implies difference at the behavioral level.

Balch (Chapter ?? in this book) treats the degree of homogeneity as a result rather than an initial condition. He defines the notion of hierarchic social entropy and uses it as a continuous measure for defining hierarchic

clustering based on behavioural characteristics. Reinforcement learning is used to associate actions with state, experiments with various reward functions, including both individual rewards and group rewards, and rewards upon delivery or progressive rewards as task gets accomplished. For two tasks, soccer and multi-foraging, the diversity of the evolved team is measured and correlated with performance. It was found that local rewards lead to greater homogeneity in both domains. In soccer, higher diversity is associated with higher performance, whereas in multi-foraging, higher diversity is associated with lower performance.

The value of the taxonomy as a language of discourse concerning swarm robotics is twofold. First, it provides for the succinct description of systems and results in the literature. Second, it maps out the space of possible designs for a collective, giving the researcher guidance and perspective when engaged in any theoretical or practical work. To illustrate the descriptive power of the taxonomy, the following section provides the full taxonomic labelling of some sample collectives from the literature.

1.4 The Power of Robot Collectives: Case Studies

Distributed computer processing has been extensively studied by theoretical computer scientists and mathematicians, as well as by computer designers. Many models of robot collectives map onto pre-existing computational or hardware models. An example of a related computational model is PRAM (parallel random access machines) [van90], which is highly developed, but has significant differences from robot collectives, because the latter involve mobile processors.

The following case studies illustrate that there is something to be gained by using a collective in place of a single robot. We show that sufficiently sophisticated collectives can be used to solve particular problems and relate these collectives to the taxonomy given above. We outline how the performance of a collective can be provably better than that of a single robot for certain tasks such as exploration.

Turing equivalence of a collective of finite automata

An unbounded number of robots $\{A_i\}$ whose processing abilities can be modelled individually as finite automata with the ability to communicate their state to their neighbours may simulate an arbitrary Turing Machine [DJMW96]. This is notable, because this fact makes it possible in principle to construct a spatially distributed intelligence from a large collection of very simple

devices. The individual automata may be mobile (moving according to their own current state, as assigned by the distributed computation), and thus able to accomplish some interesting actions in the world. It is not our purpose to explore applications of the simulation constructed for the proof of this result, because it is undoubtedly the case that more efficient use could be made of the collective members by tailoring their behaviour to the particular problem of interest instead of a Turing machine simulation. This type of system is classified as:
(SIZE-INF, COM-NEAR, TOP-ADD, BAND-INF, ARR-STATIC, PROC-FSA, CMP-HET)

Exploration

Environmental exploration is a fundamental problem in autonomous robots. Although many different exploration algorithms have been proposed in the literature (see [DJ00] for a general introduction to the task), the vast bulk of these algorithms deal with single-robot exploration. Given the time-cost associated with exploration, it seems an almost ideal task for a robot collective. A number of different multiple-robot exploration algorithms have appeared in the literature.

Exploration using an occupancy-grid-based map

The problem of constructing an occupancy-grid-based map has been considered by Burgard *et al* [BMF⁺00]. Here two autonomous robots cooperate to construct an occupancy-grid representation of space. Each individual robot constructs a probability-based occupancy-grid representation of space. When the robots meet, data in the two grids are combined by combining the occupancy probabilities computed by the robots separately. Such a system is
(SIZE-LIM, COM-NEAR, TOP-ADD, BAND-INF, ARR-COM, PROC-TME, CMP-HOM)

Exploration using a topological map

A collective of robots can explore a graph-like (topological) environment more effectively than a single robot [DJMW96]. The collective operates by having individual robots start at a common location, and then move independently to explore parts of the graph using the pebble-based exploration algorithm described in [DJMW91]. This algorithm equips each robot with a unique marker which the robot can pick-up/put-down at the robot's current location and thus can be used to solve the "have I been here before" problem. The individual members of the collective meet on a pre-arranged schedule to merge their maps and to subdivide the remaining unexplored

portions of the graph. Various refinements of the general algorithm are presented assuming more powerful robot-to-robot communication strategies. Our taxonomy classifies this kind of system as
(SIZE-LIM, COM-NEAR, TOP-ADD, BAND-INF, ARR-COM, PROC-TME, CMP-HOM)

Exploration using a metric map

Although construction of a global metric representation may be useful for some applications of robotic collectives, it is also possible to use the collective itself to define a global representation of space. Dudek *et al* [DJMW93b] demonstrated how a collection of autonomous robots can define a mesh of local coordinate systems with respect to one another without reference to environmental positions (landmarks, markers, etc.). The approach involves a robot-based representation for the environment, in which metric information is used locally to determine the relative positions of neighbouring robots, but the global map is a graph, capturing the neighbour relations among the robots.

(SIZE-LIM, COM-NEAR, TOP-GRAPH, BAND-INF, ARR-COMM, PROC-TME, CMP-HOM)

Materials transport

Materials transport, and specifically box pushing have been considered by a number of different researchers. Kube and Zhang [KZ96] describe a box-pushing system in which a large number ($n \gg 1$) of robots find and move boxes to an indicated goal. The boxes are designed so that they cannot be moved by individual robots, but at least three robots are required in order to move them. Essentially individual robots are attracted to the box to be moved, and then push the box towards the goal. As multiple members of the collective

(SIZE-INF, COM-NONE, NA, NA, NA, PROC-FSA, CMP-HOM)

Parker (see [Par98]) has conducted a series of experiments with both homogeneous and heterogeneous teams of robots engaged in box pushing. Individual members of the teams operate under ALLIANCE – a control architecture in which a collection of motivational behaviours exist within each robot. Each of the behaviours cross-inhibits other behaviours and behaviours become more or less urgent depending upon external events. The ALLIANCE control architecture is expanded to multiple mobile robots by having individual members of the collective broadcast their current active behaviours to the other robots and hence through cross-inhibition to affect the behaviour of other members of the collective.

(SIZE-LIM, COM-NEAR, TOP-BROAD, BAND-INF, ARR-COMM, PROC-TME, CMP-HOM)

Mataric *et al* [MNS95] describe experiments in box pushing with legged robots. This system utilizes a synchronized “turn-taking” protocol to coordinate the members of the collective. A *my-turn* token is cycled through the members of the collective and only the robot who has the token is permitted to move. Their system is

(SIZE-LIM, COM-NEAR, TOP-ADD, BAND-INF, ARR-COMM, PROC-TME, CMP-HET)

Hirata *et al* [HKA⁺00] describe a multiple mobile robot system for coordinated transportation of material. A leader robot with one or more follower robots coordinate to transport a solid object. Each of the robots is assumed to be attached to the object to be moved. As the leader moves, each of the follower robots sense the force acting upon them by the motion of the leader robot and then move in the same direction. In essence the leader robot communicates to the follower robot through the object to be transported.

(SIZE-LIM, COM-NEAR, TOP-BROAD, BAND-LIM, ARR-STATIC, PROC-TME, CMP-HET)

Coordinated sensing

Jenkin and Dudek [JD00] describe a multi-robot system in which the robots in the collective coordinate to provide maximal sensor coverage of a target robot. The robots in the collective define a common coordinate system based on the target, and each robot broadcasts its pose relative to this common coordinate system. A global energy function is defined which has a minimum when sensor coverage is achieved. Each member of the collective then estimates the global energy and moves to minimize the system energy.

(SIZE-LIM, COM-NEAR, TOP-BROAD, BAND-LIM, ARR-COMM, PROC-TME, CMP-HOM)

Robot soccer

RoboCup[KAK⁺95] is an international effort to establish a set of Robot soccer leagues. One particular example is the CMUnited-97 system [VSHA98] in which, as is typical for CMP-HOM, not all robots are necessarily attempting to play the same role at any given time. The roles of the individual agents or the fixed-size team can be modified during the course of a soccer game, based on observed characteristics of the game. A single global processor performs perception and reasoning for the entire team, and hence the entire team can also be regarded as a single distributed robot, although each robot has its own “module”.

(SIZE-LIM, COM-INF, TOP-BROAD, BAND-MOTION, ARR-DYN, PROC-TME, CMP-HOM)

Moving in formation

There is considerable research interest in the task of having one autonomous vehicle follow another [DZ87, KRI⁺94, Par94a, KRI⁺94, DOK98, BA95]. The task is usually implemented as only a single robot following some other autonomous agent. (The task is often called leader-follower, and is typically implemented using heterogeneous robots.) A variety of strategies are available for implementing this type of inter-robot collaboration. It is usually assumed that the target to be followed does not actively aid in the processes but rather that the follower must attempt to track the leader as the leader undergoes possibly rapid random motion changes, although if the leader does communicate its intentions to the follower, this information can be exploited (see Dudek et al.[DJMW96]).

Desai et al.[DOK98] have developed a collection of control laws for non-holonomic robots moving in formation. They assume that the robots can sense and communicate with local robots, and develop control laws for the individual robots which converge in such a manner that the entire collective exhibits the desired behaviour. Fundamental to their control system is the ability for individual robots to establish a common coordinate system and communicate/sense within it.

(SIZE-LIM, COM-NEAR, TOP-ADD, BAND-INF, ARR-COMM, PROC-TME, CMP-HET)

Dudek et al.[DJMW96] describe leader-follower experiments in which the leader robot signals its intention to the follower robot. This signalling is performed by the leader robot making specific motions prior to the intended motion which can be easily sensed by the follower robot. This cue is then exploited by the follower robot.

(SIZE-LIM, COM-NEAR, TOP-BROAD, BAND-LIM, ARR-COMM, PROC-TME, CMP-HET)

1.5 Summary and Conclusions

A taxonomy for systems of multiple mobile robots provides a common language for the description of seemingly disparate theoretical and practical results. The taxonomy serves the dual functions of allowing concise description of the key characteristics of different collectives, and describing the extent of the space of possible designs. As a result, we have been able to provide a succinct comparative survey of the current literature.

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