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Foraging Robots

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Article Outline

Glossary

Autonomy In robotics autonomy conventionally refers to the degree to which a robot is able to make its own decisions about which actions to take next. Thus a fully autonomous robot would be capable of carrying out its entire mission or function without human control or intervention. A semi-autonomous robot would have a degree of autonomy but require some human supervision.

Behaviour-based control Behaviour-based control describes a class of robot control systems characterised by a set of conceptually independent task achieving modules, or behaviours. All task achieving modules are able to access the robot's sensors and when a particular module becomes active it is able to temporarily take control of the robot's actuators [2].

Braitenburg vehicle In robotics a Braitenburg vehicle is a conceptual mobile robot in which simple sensors are connected directly to drive wheels. Thus if, for instance, a front-left-side sensor is connected to the right-side drive wheel and vice-versa, then if the sensors are light sensitive the robot will automatically steer towards a light source [11].

Finite State Machine In the context of this article a finite state machine (FSM) is a model of robot behaviour which has a fixed number of states. Each state represents a particular set of actions or behaviours. The robot can be in only one of these states at any given instant in time and transitions between states may be triggered by either external or internal events.

Odometry Odometry refers to the technique of self-localisation in which a robot measures how far it has travelled by, for instance, counting the revolutions of its wheels. Odometry suffers the problem that wheel-slip leads to cumulative errors so odometric position estimates are generally inaccurate and of limited value unless combined with other localisation techniques.

Robot In this article the terms *robot* and *mobile robot* are used interchangeably. A mobile robot is a man-made device or vehicle capable of (1) sensing its environment and (2) purposefully moving through and acting upon or within that environment. A robot may be fully autonomous, semi-autonomous or tele-operated.

Swarm Intelligence The term swarm intelligence describes the purposeful collective behaviours observed in nature, most dramatically in social insects. Swarm intelligence is the study of those collective behaviours, in both natural and artificial systems of multiple agents, and how they emerge from the local interactions of the agents with each other and with their environment [8, 19].

Tele-operation A robot is said to be tele-operated if it is remotely controlled by a human operator.

1 Definition

Foraging robots are mobile robots capable of searching for and, when found, transporting objects to one or more collection points. Foraging robots may be single robots operating individually, or multiple robots operating collectively. Single foraging robots may be remotely tele-operated or semi-autonomous; multiple foraging robots are more likely to be fully autonomous systems. In robotics foraging is important for several reasons: firstly, it is a metaphor for a broad class of problems integrating exploration, navigation and object identification, manipulation and transport; secondly, in multi-robot systems foraging is a canonical problem for the study of robot-robot cooperation, and thirdly, many actual or potential real-world applications for robotics are instances of foraging robots, for instance cleaning, harvesting, search and rescue, land-mine clearance or planetary exploration.

2 Introduction

Foraging is a benchmark problem for robotics, especially for multi-robot systems. It is a powerful benchmark problem for several reasons: (1) sophisticated foraging observed in social insects, recently becoming well understood, provides both inspiration and system level models for artificial systems. (2) Foraging is a complex task involving the coordination of several - each also difficult - tasks including efficient exploration (searching) for food or prey, physical collection (harvesting) of food or prey almost certainly requiring physical manipulation, transport of the food or prey, homing or navigation whilst carrying the food or prey back to a nest site, and deposition of the food item in the nest before returning to foraging. (3) Effective foraging requires cooperation between individuals involving either communication to signal to others where food or prey may be found (e.g. pheromone trails, or direction giving) and/or cooperative transport of food items too large for a single individual to transport.

There are, at the time of writing, very few types of foraging robots successfully employed in real-world applications. Most foraging robots are to be found in research laboratories or, if they are aimed at real-world applications, are at the stage of prototype or proof-of-concept. The reason for this is that foraging is a complex task which requires a range of competencies to be tightly integrated within the physical robot and, although the principles of robot foraging are now becoming established, many of the sub-system technologies required for foraging robots remain very challenging. In particular, sensing and situational awareness; power and energy autonomy; actuation, locomotion and safe navigation in unknown physical environments and proof of safety and dependability all remain difficult problems in robotics.

This article therefore focusses on describing and defining the principles of robot foraging. The majority of examples will necessarily be of laboratory systems not aimed at solving real-world applications but designed to model, illuminate and demonstrate those principles. The article proceeds as follows. Section 3 describes an abstract model of robot foraging, using a finite state machine (FSM) description to define the discrete sub-tasks, or states, that constitute foraging. The FSM method will be used throughout this article. The section then develops a taxonomy of robot foraging. Section 4 describes the essential design features that are a requirement of any foraging robot, whether operating singly or in a multi-robot team, and the technologies currently available to implement those features; the section then outlines a number of examples of single-robot foraging, including robots that are commercially available. Section 5 then describes the development and state-of-the-art in multi-robot (collective) foraging; strategies for cooperation are described including information sharing, cooperative transport and division of labour (task allocation), the section then reviews approaches to the mathematical modelling of multi-robot foraging. The article concludes in section 6 with a discussion of future directions in robot foraging and an outline of the technical challenges that remain to be solved.

3 An Abstract model of Robot Foraging

Foraging, by humans or animals, is the act of searching (widely) for and collecting (or capturing) food for storage or consumption. Robot foraging is defined more broadly as searching for and collecting *any* objects, then returning those objects to a collection point. Of course if the robot(s) are searching for energy resources for themselves then robot foraging will have precisely the same meaning as human or animal foraging. In their definitive review paper on cooperative mobile robotics Cao *et al* state simply "In foraging, a group of robots must pick up objects scattered in the environment" [14]. Østergaard *et al* define foraging as "a two-step repetitive process in which (1) robots search a designated region of space for certain objects, and (2) once found these objects are brought to a goal region using some form of navigation" [54].

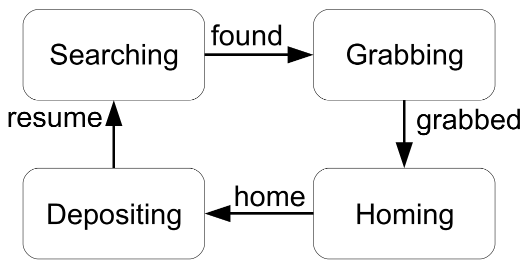

Figure 1: Finite State Machine for Basic Foraging

Figure 1 shows a Finite State Machine (FSM) representation of a foraging robot (or robots).

In the model the robot is in always in one of four states: *searching*, *grabbing*, *homing* or *depositing*. Implied in this model is, firstly, that the environment or search space contains more than one of the target objects; secondly, that there is a single collection point (hence this model is sometimes referred to as central-place foraging), and thirdly, that the process continues indefinitely. The four states are defined as follows.

1. Searching. In this state the robot is physically moving through the search space using its sensors to locate and recognise the target items. At this level of abstraction we do not need to state how the robot searches: it could, for instance, wander at random, or it could employ a systematic strategy such as moving alternately left and right in a search pattern. The fact that the robot has to search at all follows from the pragmatic real-world assumptions that either the robot's sensors are of short range and/or the items are hidden (behind occluding obstacles for instance); in either event we must assume that the robot cannot find items simply by staying in one place and scanning the whole environment with its sensors. Object identification or recognition could require one of a wide range of sensors and techniques. When the robot finds an item it changes state from searching to grabbing. If the robot fails to find the target item then it remains in the searching state forever; searching is therefore the 'default' state.

2. Grabbing. In this state the robot physically captures and grabs the item ready to transport it back to the home region. Here we assume that the item is capable of being grabbed and conveyed by a single robot (the case of larger items that require cooperative transport by more than one robot will be covered later in this article). As soon as the item has been grabbed the robot will change state to homing.

3. Homing. In this state the robot must move, with its collected object, to a home or nest region. Homing clearly requires a number of stages, firstly, determination of the position of the home region relative to where the robot is now, secondly, orientation toward that position and, thirdly, navigation to the home region. Again there are a number of strategies for homing: one would be to re-trace the robot's path back to the home region using, for instance, odometry or by following a marker trail; another would be to home in on a beacon with a long range beacon sensor. When the robot has successfully reached the home region it will change state to depositing.

4. Depositing. In this state the robot deposits or delivers the item in the home region, and then immediately changes state to searching and hence resumes its search.

There are clearly numerous variations on this basic foraging model. Some are simplifications: for instance if a robot is searching for one or a known fixed number of objects then the process will not loop indefinitely. Real robots do not have infinite energy and so a model of practical foraging would need to take account of energy management. However, many variations entail either complexity within one or more of the four basic states (consider, for instance, objects that actively evade capture - a predator-prey model of foraging), or complexity in the interaction or cooperation between robots in multi-robot foraging. Thus the basic model stands as a powerful top-level abstraction.

3.1 A Taxonomy of Robot Foraging

Oster and Wilson classify the foraging strategies of social insects into five types, summarised in table 1 [53]. Hölldobler and Wilson describe a more comprehensive taxonomy of insect foraging as a combination of strategies for (1) hunting, (2) retrieval and (3) defense [30]. However, since we will not be concerned in this article with defensive robot(s), then Oster and Wilson's classification is more than sufficient as a basis for consideration of robot foraging.

Type	Description
I	solitary insects find and retrieve prey singly
II	as I except that solitary foragers signal the location of food to other insects
III	foragers depart the nest and follow 'trunk trails' before branching off to search unmarked terrain
IV	as II except that a group of insects assaults or retrieves the prey en-masse
V	multiple insects forage as groups

Table 1: Oster and Wilson's classification of insect foraging

In robotics several taxonomies have been proposed for multi-robot systems. Dudek *et al* define seven taxonomic axes: collective size; communications [range, topology and bandwidth]; collective reconfigurability; processing ability and collective composition [21]. Here collective size may be: single robot, pair of robots, limited (in relation to the size of the environment) or infinite (number of robots $N_r >> 1$); communications range may be: none (i.e. robots do not communicate directly), near (robots have limited range communication) or infinite (any robot may communicate with any other). Collective reconfigurability refers to spatial organisation and may be: static (robots are in a fixed formation); coordinated (robots may coordinate to alter their formation) or dynamic (spatial organisation may change arbitrarily). Processing ability refers to the computational model of individuals, here Dudek *et al* make the distinction between the general purpose computer which most practical robots will have, or simpler models including the finite state machine. Collective composition may be: identical (robots are both physically and functionally identical), homogenous or heterogeneous. Dudek *et al* makes the distinction — highly relevant to foraging robots — between tasks that are *traditionally single-agent*, tasks that are *traditionally multi-agent*, tasks that *require* multiple agents, or tasks that *may benefit* from multiple agents.

In contrast to Dudek's taxonomy which is based upon the characteristics of the robot(s), Balch characterises tasks and rewards [3]. Balch's task taxonomy is particularly relevant to robot foraging because it leads naturally to the definition of performance metrics. Balch articulates six task axes: time; criteria; subject of action; resource limits; group movement and platform capabilities. Time and criteria are linked; time may be: limited (task performance is determined by how much can be achieved in the fixed time); minimum (task performance is measured as time taken to complete the task); unlimited time, or synchronised (robots must synchronise their actions). Criteria refers to how performance is optimised over time; it may be finite (performance is summed over a finite number of time steps); average (performance is averaged over all time) or discounted (future performance is discounted geometrically). Subject of action may be: object- or robot-based, depending upon whether the movement or positioning of objects or robots, respectively, is important. Balch's fourth criterion is again relevant to foraging: resource limits which may be: limited (external resources, i.e. objects to be foraged, are limited); energy (energy consumption must be minimised); internally competitive (one robot's success reduces the likelihood of success of another), or externally competitive (if, for instance, one robot team competes against another). See also [24] for a formal analysis and taxonomy of task allocation.

Østergaard *et al* [54] develop a simple taxonomy of foraging by defining eight characteristics each of which has two values:

1. number of robots: single or multiple;
2. number of sinks (collection points for foraged items): single or multiple;
3. number of source areas (of objects to be collected): single or multiple;
4. search space: unbounded or constrained;
5. number of types of object to be collected: single or multiple;
6. object placement: in fixed areas or randomly scattered;
7. robots: homogeneous or heterogeneous and
8. communication: none or with.

This taxonomy maps more closely (but not fully) onto the insect foraging taxonomy of table 1, but fails to capture task performance criteria, nor does it specify the strategy for either searching for, physically collecting or retrieving objects. Tables 2 and 3 propose a more comprehensive taxonomy for robot foraging that incorporates the robot-centric and task/performance oriented features of Dudek *et al* and Balch, respectively, with the environmental features of Østergaard *et al*, whilst mapping onto the insect foraging classification of Oster and Wilson. The four major axes are Environment, Robot(s), Performance and Strategy. Each major axis has several minor axes and each of these can take the values enumerated in the third column of tables 2 and 3. The majority of the values are self-explanatory, those that are not are annotated. Table 3 suggests a mapping of Oster and Wilson's classification onto robot foraging strategies.

Following Balch [3], we can formalise successful object collection and retrieval as follows:

$$F(O_i, t) = \begin{cases} 1 & \text{if object } O_i \text{ is in a sink at time } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

If the foraging task is performance time limited (Performance time = fixed) and the objective is to maximise the number of objects foraged within fixed time T, then we may define a performance metric for the number of objects collected in time T,

$$P = \sum_{i=1}^{N_o} F(O_i, t_0 + T) \tag{2}$$

where N_o is the number of objects available for collection and t_0 is the start time. A metric for the number of objects foraged per second is clearly, $P_t = P/T$. P as defined here is independent of the number of robots. In order to measure the performance improvement of multi-robot foraging, for example the benefit gained by search or homing with trail following, recruitment or coordination (assuming the task can be completed by a single robot, grabbing = single and transport = single), then we may define the performance of a single robot P_s as defined in equation 2 and use this a baseline for the normalised performance P_m of a multi-robot system,

$$P_m = \frac{P}{N_r} \tag{3}$$

where N_r is the total number of robots. The efficiency of multi-robot foraging is then the ratio P_m/P_s.

Major Axis	Minor Axis	Value	Notes
Environment	search space	unbounded	
		constrained	
	source areas	single limited	fixed number of objects
		single unlimited	objects ‘re-grow’
		multiple	
	sinks	single	home, nest or collection point
		multiple	
	object types	single static	one type of static object, food or ‘prey’
		multiple static	
		single active	one type of prey which evades capture
	object placement	fixed known locations	
		uniform distribution	
		clustered	
Robot(s)	number	single	
		multiple	
	type	homogeneous	
		heterogeneous	
	object sensing	limited	short-range sensing
		unlimited	unlimited-range sensing
	localisation	none	
		relative	
		absolute	
	communications	none	
		near	
		infinite	
	power	limited	robot can run out of energy
		forage	robot forages for own energy
		unlimited	

Table 2: A taxonomy of robot foraging, part A

Major Axis	Minor Axis	Value	Notes
Performance	time	fixed	objects foraged per second
		minimum	minimise time to forage
		unlimited	
	energy	fixed	objects foraged per Joule
		minimum	minimise energy used
		unlimited	
Strategy	search	random wander	
		geometrical pattern	
		trail following	type III
		follow other robots	
		in teams	type V
	grabbing	single	
		cooperative	type IV
	transport	single	
		cooperative	type IV
	homing	self-navigation	
		home on beacon	
		follow trail	
	recruitment	none	type I
		direct	type II
		indirect	
	coordination	none	type I
		self-organised	types II-V
		master slave	
		central control	

Table 3: A taxonomy of robot foraging, part B

Consider now that we wish instead to minimise the energy cost of foraging (Performance energy = minimum). If the energy cost of foraging object i is E_i, then we may define a performance metric for the number of objects foraged per Joule of energy,

$$P_e = \frac{N_o}{\sum_{i=1}^{N_o} E_i} \tag{4}$$

then seek the foraging strategy that achieves the highest value for P_e.

4 Single Robot Foraging

The design of any foraging robot, whether operating alone or as part of a multi-robot team, will necessarily follow a similar basic pattern. The robot will require one or more *sensors*, with which it can both sense its environment for safe navigation and detect the objects or food-items it seeks; *actuators* for both locomotion through the environment and for physically collecting, holding then depositing its prey, and a *control system* to provide the robot with — at the very least — a set of basic reflex behaviours. Since robots are machines that perform work, which requires energy, then *power management* is important; if, for instance, the robot is foraging for its own energy then balancing its energy needs with the energy cost of foraging is clearly critical. Normally, a *communication* transceiver is also a requirement, either to allow remote tele-operation or monitoring or, in the case of multi-robot collective foraging, for robot-robot communications. A foraging robot is therefore a complex set of interconnected sub-systems and, although its system-level structure may follow a standard pattern, the shape and form of the robot will vary significantly depending upon its intended environment and application.

This section will review approaches and techniques for sensing, actuation, communications and control, within the context of robot foraging and with reference to research which focusses on advancing specific capabilities within each of these domains of interest. Then a number of examples of single robot foraging are given, including real-world applications.

4.1 Sensing

Obstacle avoidance and path planning There are many sensors available to designers of foraging robots and a comprehensive review can be found in [22]. A foraging robot will typically require short or medium range proximity sensors for obstacle avoidance, such as infra-red return-signal-intensity or ultrasonic- or laser-based time-of-flight systems. The most versatile and widely used device is the 2D or 3D scanning laser range finder which can provide the robot with a set of radial distance measurements and hence allow the robot to plan a safe path through obstacles [64].

Localisation All but the simplest foraging robots will also require sensors for localisation, that is to enable the robot to estimate its own position in the environment. If external reference signals are available such as fixed beacons so that a robot can use radio trilateration to fix its position relative to those beacons, or a satellite navigation system such as the Global Positioning System (GPS), then localisation is relatively straightforward. If no external infrastructure is available then a robot will typically make use of several sensors including odometry, an inertial measurement unit (IMU) and a magnetic compass, often combining the data from all of these sensors, including laser scanning data, to form an estimate of its position. Simultaneous Localisation and Mapping (SLAM) is a well-known stochastic approach which typically employs Kalman filters to allow a robot (or a team of robots) to both fix their position relative to observed landmarks and map those landmarks with increasing confidence as the robot(s) move through the environment [18].

Object detection Vision is often the sensor of choice for object detection in laboratory experiments in foraging robots. If, for instance, the object of interest has a distinct colour which stands out in the environment then standard image processing techniques can be used to detect then steer towards the object [31]. However, if the environment is visually cluttered, unknown or poorly illuminated then vision becomes problematical. Alternative approaches to object detection include, for instance, artificial odour sensors: Hayes *et al* demonstrated a multi-robot approach to localisation of an odour source [28]. An artificial whisker modelled on the Rat mystacial vibrissae has recently been demonstrated [56], such a sensor could be of particular value in dusty or smoky environments.

4.2 Actuation

Locomotion The means of physical locomotion for a foraging robot can take many forms and clearly depends on the environment in which the robot is intended to operate. Ground robots typically use wheels, tracks or legs, although wheels are predominantly employed in proof-of-concept or demonstrator foraging robots. An introduction to the technology of robot mobility can be found in [63]. Flying robots (unmanned air vehicles - UAVs) are either fixed- or rotary-wing; for recent examples of work towards teams of flying robots see [13] (fixed-wing) and [51] (rotary-wing). Underwater robots (unmanned underwater vehicles - UUVs) generally use the same principles for propulsion as submersible remotely operated vehicles (ROVs), [70]. Whatever the means of locomotion important principles which apply to all foraging robots are that robot(s) must be able to (1) move with sufficient stability for the object detection sensors to be able to operate effectively and (2) position themselves with sufficient precision and stability to allow the object to be physically grabbed. These factors place high demands on a foraging robot's physical locomotion system, especially if the robot is required to operate in soft or unstable terrain.

Object manipulation The manipulation required of a foraging robot is clearly dependent on the form of the object and the way the object presents itself to the robot as it approaches. The majority of foraging experiments or demonstrations have simplified the problem of object manipulation by using objects that are, for instance, always the right way up (metal pucks or wooden sticks protruding from holes) so that a simple gripper mounted on the front of the robot is able to grasp the objects with reasonable reliability. However, in general a foraging robot would require the versatility of a robot arm (multi-axis manipulator) and general purpose gripper (hand) such that — with appropriate vision sensing — the robot can pick up the object regardless of its shape and orientation. This technology is well developed in tele-operated robots used for remote inspection and handling of dangerous materials or devices, see [66, 62].

4.3 Communications

Communications is of fundamental importance to robot foraging. Only in the simplest case of a single robot foraging autonomously would communications be unnecessary. For single robot tele-operation radio communication between operator and robot is clearly an essential requirement. In multi-robot foraging robot-robot communication is frequently employed to improve multi-robot performance; all six axes of strategy in the taxonomy of table 3: search, grabbing, transport, homing, recruitment and coordination may require some form of robot-robot communication. Arai *et al* point out the important distinction between *explicit* and *implicit* communication [1].

Explicit communication Explicit communication applies when robots need to exchange information directly. The physical medium of communication is frequently (but not necessarily) radio, and wireless local area network (WLAN) technology is highly appropriate to terrestrial multi-robot systems, not least because a spatially distributed team of wireless networked robots naturally forms an *ad-hoc* network, which — providing the team maintains sufficient connectivity — allows any robot to communicate with any other via multiple hops, [69]. A method for linking wireless connectivity to locomotion in order to maintain connectivity is described in [52]; work that falls within the framework of *situated* communications proposed by Støy. Situated communication pertains when "both the physical properties of the signal that transfers the message and the content of the message contribute to its meaning" [65].

Implicit communication Implicit communication applies when robots communicate not directly but via the environment, also known as *stigmergic* communications. Thus one robot changes the environment and another senses the change and alters its behaviour accordingly. Beckers *et al*, in one of the first demonstrations of self-organised multi-robot puck clustering, show that stigmergic communication alone can give rise to the desired overall group behaviour [6]. However, in their study on multi-robot communication, Balch and Arkin show that while stigmergy may be sufficient to complete the task, direct communication can increase efficiency [4]. Trail following, in which a robot follows a short-lived trail left by other(s), is an example of implicit communication [59, 60].

4.4 Control

From a control perspective the simplicity of the finite state machine for basic foraging, in figure 1, is deceptive. In principle, a very simple foraging robot could be built with basic hard-wired reflex actions such as obstacle avoidance and taxis toward the attractor object; such a robot is known as a Braitenberg vehicle, after his landmark work [11]. However, even simple foraging requires a complex set of competencies that would be impractical to implement except as a program on one or more embedded computers (microprocessors) in the robot. There are clearly many ways of building such a control program, but in the field of mobile robotics a number of robot control architectures have been defined. Such architectures mean that robot designers can approach the design of the control system in a principled way.

A widely adopted robot control architecture, first proposed and developed by Brooks, is the layered *subsumption* architecture known generically as behaviour-based control [12]. Behaviour-based control is particularly relevant to foraging robots since, like foraging, it is biologically inspired. In particular, as Arkin describes in [2], the principles of behaviour-based control draw upon ethology — the study of animal behaviour in the natural environment. Essentially behaviour-based control replaces the functional modularity of earlier robot control architectures with task achieving modules, or behaviours. Matarić uses Brooks' behaviour language (BL) to implement a set of basic behaviours for multi-robot foraging, as described in more detail below in section 5, [46, 47]. Refer to [14] for a comprehensive review of group control architectures for multi-robot systems.

Figure 2 shows the subsumption architecture for basic foraging (from figure 1), with the addition of *avoidance* for safely avoiding obstacles (including other robots in the case of multi-robot foraging). Each behaviour runs in parallel and, when activated suppresses the output of the layer(s) below to take control of the robot's actuators.

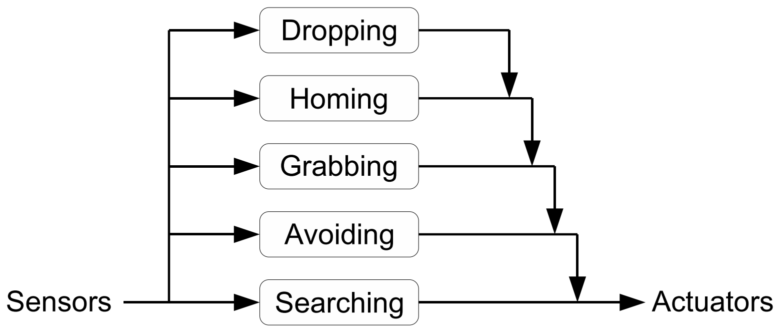

Figure 2: Subsumption control architecture for basic foraging

4.5 Examples of Single Robot Foraging

4.5.1 A Soda-can collecting Robot

Possibly the first demonstration of autonomous single-robot foraging is Connell's soda-can collecting robot *Herbert*, [15]. Herbert's task was to wander safely through an office environment while searching for empty soda-cans; upon finding a soda-can Herbert would need to carefully grab the can with its hand and 2 degrees-of-freedom arm, then return to a waste basket to deposit it before resuming the search. Herbert therefore represents an implementation of exactly the basic foraging model of figures 1 and 2. However, two of the behaviours are not so straightforward. Both searching and homing require the robot to be able to navigate safely through a cluttered and unstructured 'real-world' environment, while grabbing is equally complex given the precision required to safely reach and grab the soda-can. Thus Herbert's control system required around 40 low-level behaviours in order to realise foraging.

4.5.2 A Robot Predator

Figure 3: The Slugbot: a proof-of-concept robot predator

Arguably the first attempt to build a robot capable of actively predating for its own energy is the *Slugbot* of Holland and co-workers, [33, 26]. The Slugbot (figure 3) solved the difficult problems of finding and collecting slugs in an energy efficient manner by means of, firstly, a long but light articulated arm which allows the robot to scan (in spiral fashion) a large area of ground for slugs without having to physically move the whole robot (which is much more costly in energy). Secondly, the special purpose gripper at the end of the arm is equipped with a camera which, by means of reflected red light and appropriate vision processing, is able to reliably detect and collect the slugs. An evolution of the Slugbot, the *Ecobot*, uses microbial fuel cell (MFC) technology to generate electrical energy directly from unrefined biomass [49].

4.5.3 Real-world foraging robots

Autonomous crop harvesting is an obvious real-world application of single-robot foraging. The Demeter system [57] has successfully demonstrated automated harvesting of cereal crops. Demeter uses a combination of GPS for coarse navigation and vision to sense the crop-line and hence fine-tune the harvester's steering to achieve a straight and even cut of the crop. The vision processing is challenging because it has to cope with a wide range of lighting conditions including — in conditions of bright sunlight — shadows cast onto the crop line by the harvester itself. In the field of automated agriculture a number of proof-of-concept robot harvesters have been demonstrated for cucumber, tomato and other fruits [34, 35].

Robot lawn mowers and vacuum cleaners can similarly be regarded as simple forms of foraging robot and are notable because they are the only form of autonomous foraging robot in commercial production; in both cases the search task is simple because the grass, or dirt are not discrete objects to be found. The search problem for robot lawn movers and vacuum cleaners thus becomes the problem of energy efficient strategies for (1) safely covering the whole search space while avoiding obstacles and (2) homing and docking to a re-charging station. Robot lawn mowers typically require a wire to be installed at the perimeter of the lawn, thus delimiting the robot's working area, see [29] for a survey of commercial robot lawn mowers. A short account of the development of a vacuum cleaning robot is given in [58].

Although technically an *off-world* application, the planetary rover may be regarded as an instance of single-robot foraging in which the objects of interest (geological samples) are collected and analysed within the robot. Autonomous sample-return robots would be true foragers [61]. The proof-of-concept robot astrobiologist *Zoë* forages - in effect - for evidence of life [67].

5 Multi-robot (collective) Foraging

Foraging is clearly a task that lends itself to multi-robot systems and, even if the task can be accomplished by a single robot, foraging should — with careful design of strategies for cooperation — benefit from multiple robots. Swarm intelligence is the study of natural and artificial systems of multiple agents in which there is no centralised or hierarchical command or control. Instead, global swarm behaviours emerge as a result of local interactions between the agents and each other, and between agents and the environment, [8]. Swarm robotics is concerned with the design of artificial robot swarms based upon the principles of swarm intelligence, thus control is completely distributed and robots, typically, must choose actions on the basis only of local sensing and communications, [7, 16]. Swarm robotics is thus a sub-set of multi-robot systems and, in the taxonomy of table 3 the strategy: coordination = self-organised.

Foraging is therefore a benchmark problem within swarm robotics, not least because of the strong cross-over between the study of self-organisation in social insects and their artificial counterparts within swarm intelligence [19]. This section will therefore focus on examples of multi-robot foraging from within the field of swarm robotics. Three strategies for cooperation will be outlined: information sharing, physical cooperation and division of labour. The section will conclude with an outline of the problem of mathematical modelling of swarms of foraging robots.

5.1 Without cooperation

Balch and co-workers describe the winners of the 'Office Cleanup Event' of the 1994 AAAI Mobile Robot Competition: a multi-robot trash-collecting team [5]. The robots were equipped with a vision system for recognition and distance estimation of trash items (primarily soda cans) and differentiation between trash items, wastebaskets and other robots. The robots did not communicate, but employed a collective strategy in which robots generate a strong repulsive force if they see each other while searching, and a weaker (but sufficient for avoidance) repulsive force while in other states; this had the effect of causing the robots to spread-out and hence search the environment more efficiently. Interestingly, Balch *et al.* found that the high density of trash in the competition favoured a 'sit-and-spin' strategy to scan for trash items rather than the random wander approach of the original design. The FSM was essentially the same schema as shown in figure 1 except that since there could be a number of wastebaskets at unknown locations then 'homing' becomes 'search for nearest wastebasket'.

5.2 Strategies for cooperation

5.2.1 Information sharing

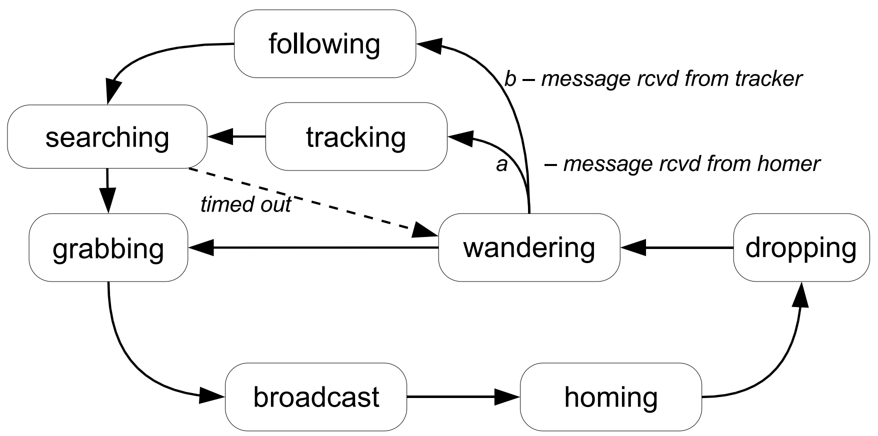

Figure 4: Finite State Machine for multi-robot foraging with recruitment - adapted from [47]

Matarić and Marjanovic provide what is believed to be the first description of a multi-robot foraging experiment using real (laboratory) robots in which there is no centralised control [47]. They describe a system of 20 identical 12" 4-wheeled robots, equipped with: a two-pronged forklift for picking up, carrying and stacking metal pucks; proximity and bump sensors; radio transceivers for data communication and a sonar-based global positioning system. Matarić and Marjanovic extend the basic five state foraging model (wandering, grabbing, homing, dropping and avoiding), to introduce information sharing as follows. If a robot finds a puck it will grab it but also broadcast a radio message to tell other robots it has found a puck. Meanwhile, if another robot in the locale hears this message it will first enter state *tracking* to home in on the source of the message, then state *searching* - a more localised form of wandering. The robot will return to wandering if it finds no puck within some time out period. Furthermore, while in state *tracking* a robot will also transmit a radio signal. If nearby robots hear this signal they will switch from wandering into *following* to pursue the tracking robot. Thus the tracking robot actively recruits additional robots as it seeks the original successful robot (a form of secondary swarming, [48]); when the tracking robot switches to searching its recruits will do the same. Figure 4 shows a simplified FSM. Within the taxonomy of table 3 Strategy : recruitment = direct and indirect.

5.2.2 Physical cooperation

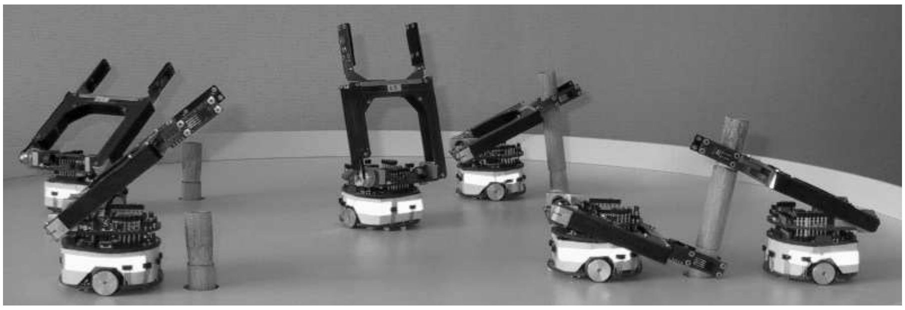

Figure 5: Cooperative grabbing: Khephera robots engaged in collective stick-pulling. With kind permission of A. Martinoli.

cooperative grabbing Consider the case of multi-robot foraging in which the object to be collected cannot be grabbed by a single robot working alone, in table 3 this is Strategy: grabbing = cooperative. Ijspeert *et al* describe an experiment in collaborative stick-pulling in which two robots must work together to pull a stick out of a hole [32, 44]. Each *Khephera* robot is equipped with a gripper capable of grabbing and lifting the stick, but the hole containing the stick is too deep for one robot to be able to pull the stick out alone; one robot must pull the stick half-way then wait for another robot to grab the stick and lift it clear of the hole, see figure 5. Ijspeert and co-workers describe an elegant minimalist strategy which requires no direct communication between robots. If one robot finds a stick it will lift it and wait. If another finds the same stick it will also lift it, on sensing the force on the stick from the second robot the first robot will let go, hence allowing the second to complete the operation.

cooperative transport Now consider the the situation in which the object to be collected is too large to be transported by a single robot, in table 3 Strategy: transport = cooperative. Parker describes the ALLIANCE group control architecture applied to an example of cooperative box-pushing by two robots [55].

Arguably the most accomplished demonstration of cooperative multi-robot foraging to date is within the *swarm-bot* project of Dorigo and co-workers [20]. The *s-bot* is a modular robot equipped with both a gripper and a gripping ring, which allows one robot to grip another [50]. Importantly, the robot is able to rotate its wheelbase independently of the gripping ring so that robots can grip each other at any arbitrary point on the circumference of the grip ring but then rotate and align their wheels in order to be able to move as a single unit (a *swarm-bot*). Groß*et al* describe cooperative transport which uses visual signalling [27]. s-bots are attracted to the

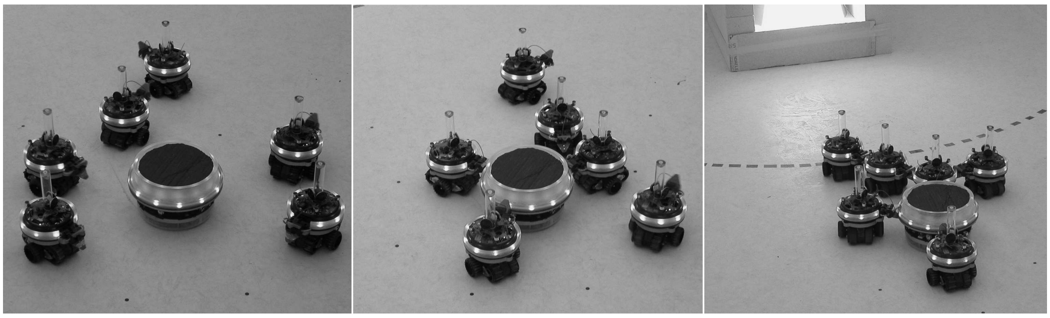

Figure 6: Cooperative transport by s-bots. (Left) s-bots approach the attractor object, (middle) s-bots start to grab the object, (right) s-bots collectively drag the object toward a beacon. With kind permission of M. Dorigo.

(large) object to be collected by its ring of red LEDs. The s-bot's LEDs are blue, but when an s-bot finds and grabs the attractor object it switches its LEDs to red. This increases the red light intensity to attract further s-bots which may grab either the object, or arbitrarily a robot already holding the object. The s-bots are then able to align and collectively move the object.

5.2.3 Division of labour

In multi-robot foraging it is well know that overall performance (measured, for instance, as the number of objects foraged per robot in a given time interval), does not increase monotonically with increasing team size because of interference between robots (overcrowding), [4, 25, 38]. Division of labour in ant colonies has been well studied and in particular a response threshold model is described in [9] and [10]; in essence a threshold model means that an individual will engage in a task when the level of some task-associated stimulus exceeds its threshold.

For threshold-based multi-robot foraging with division of labour figure 7 shows a generalised finite state machine for each robot. In this foraging model the robot will not search endlessly. If the robot fails to find a food-item because, for instance, its searching time exceeds a maximum search time threshold T_s, or its energy level falls below a minimum energy threshold, then it will abandon its search and return home without food, shown as *failure*. Conversely *success* means food was found, grabbed and deposited. Note, however, that a robot might see a food-item but fail to grab it because, for instance, of competition with another robot for the same food-item. The robot now also has a *resting* state during which time it remains in the nest conserving energy. The robot will stop resting and leave home which might be according to some threshold criterion, such as its resting time exceeding the maximum rest time threshold T_r, or the overall nest energy falling below a given threshold.

Let us consider the special case of multi-robot foraging in which robots are foraging for their own energy. For an individual robot foraging costs energy, whereas resting conserves energy. We can formally express this as follows. Each robot consumes energy at A units per second while searching or retrieving and B units per second while resting, where $A > B$. Each discrete food item collected by a robot provides C units of energy to the swarm. The average food item retrieval time, is a function of the number of foraging robots x, and the density of food items in the environment, ρ, thus $t = f(x, \rho)$.

If there are N robots in the swarm, E_c is the energy consumed and E_r the energy retrieved, per second, by the swarm then

$$E_c = Ax + B(N - x) \tag{5}$$

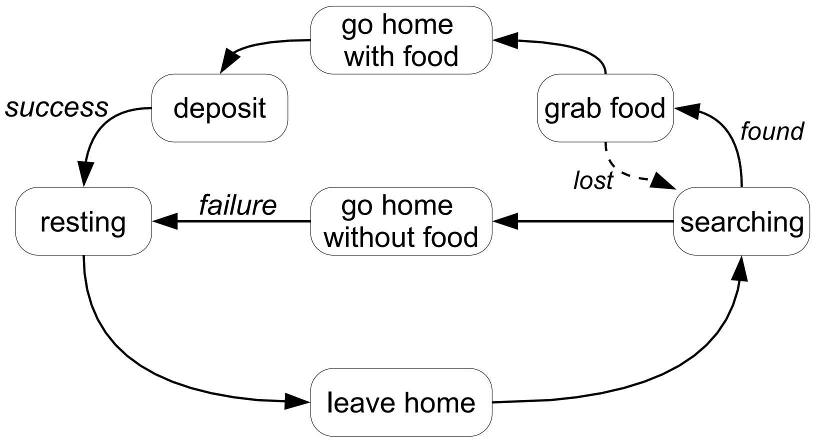

Figure 7: Finite State Machine for Foraging with Division of Labour

$$E_r = Cx/t = \frac{Cx}{f(x,\rho)} \tag{6}$$

The average energy income to the swarm, per second, is clearly the difference between the energy retrieved and the energy consumed,

$$E = E_r - E_c = (\frac{C}{f(x,\rho)} - (A-B))x - BN \tag{7}$$

Equation 7 shows that maximising the energy income to the swarm requires either increasing the number of foragers x or decreasing the average retrieval time $f(x,\rho)$. However, if we assume that the density of robots in the foraging area is high enough that interference between robots will occur then, for constant ρ, increasing x will increase $f(x,\rho)$. Therefore, for a given food density ρ there must be an optimal number of foragers x^*.

Krieger ad Billeter adopt a threshold-based approach to the allocation of robots to either foraging or resting; in their scheme each robot is allocated a fixed but randomly chosen activation threshold [36]. While waiting in the nest each robot listens to a periodic radio broadcast indicating the nest-energy level E; when the nest-energy level falls below the robot's personal activation threshold then it leaves the nest and searches for food. It will continue to search until either its search is successful, or it runs out of energy and returns home; if its search is successful and it finds another food-item the robot will record its position (using odometry). On returning home the robot will radio its energy consumption thus allowing the nest to update its overall net energy. Krieger and Billeter show that team sizes of 3 or 6 robots perform better than 1 robot foraging alone, but larger teams of 9 or 12 robots perform less well. Additionally, they test a recruitment mechanism in which a robot signals to another robot waiting in the nest to follow it to the food source, in tandem. Krieger's approach is, strictly speaking, not fully distributed in that the nest is continuously tracking the average energy income E; the nest is — in effect — acting as a central coordinator.

Based upon the work of [17] on individual adaptation and division of labour in ants, Labella *et al* describe a fully distributed approach that allows the swarm to self-organise to automatically find the optimal value x^* [37]. They propose a simple adaptive mechanism to change the ratio of foragers to resters by adjusting the probability of leaving home based upon successful retrieval of food. With reference to figure 7 the mechanism works as follows. Each robot will *leave home*, i.e. change state from resting to searching, with probability P_l. Each time the robot makes the *success* transition from deposit to resting, it increments its P_l value by a constant Δ multiplied by the number of consecutive successes, up to a maximum value P_{max}. Conversely, if the robot's searching time is up, the transition *failure* in figure 7, it will decrement its P_l by Δ times the number of consecutive failures, down to minimum P_{min}. Interestingly, trials with laboratory robots show that the same robots self-select as foragers or resters — the algorithm exploits minor mechanical differences that mean that some robots are better suited as foragers.

Recently Liu *et al* have extended this fully distributed approach by introducing two additional adaptation rules [43]. As in the case of Labella *et al* individual robots use internal cues (successful object retrieval), but Liu adds environmental cues (collisions with team mates while searching), and social cues (team mate success in object retrieval), to dynamically vary the time spent foraging or resting. Furthermore, Liu investigates the performance of a number of different adaptation strategies based on combinations of these three cues. The three cues increment or decrement the searching time and resting time thresholds T_s and T_r as follows (note that adjusting T_r is equivalent to changing the probability of leaving the nest P_l):

1. Internal cues. If a robot successfully finds food it will reduce its own rest time T_r; conversely if the robot fails to find food it will increase its own rest time T_r.

2. Environment cues. If a robot collides with another robot while searching, it will reduce its T_s and increase its T_r times.

3. Social cues. When a robot returns to the nest it will communicate its food retrieval success or failure to the other robots in the nest. A successful retrieval will cause the other robots in the nest to increase their T_s and reduce their T_r times. Conversely failure will cause the other robots in the nest to reduce their T_s and increase their T_r times.

In order to evaluate the relative effect of these cues three different strategies are tested, against a baseline strategy of no cooperation. The strategy/cue combinations are detailed in table 4.

	internal cues	social cues	environment cues
S_1 (baseline)	×	×	×
S_2	✓	×	×
S_3	✓	✓	×
S_4	✓	✓	✓

Table 4: Foraging swarm strategy - cue combinations

Figures 8 and 9, from [43], show the number of active foragers and the instantaneous net swarm energy, respectively, for a swarm of eight robots. In both plots the food density in the environment is changed at time $t = 5000$ and again at time $t = 10000$ seconds. Figure 8 shows the swarm's ability to automatically adapt the number of active foragers in response to each of the step changes in food density. The baseline strategy S_1 shows of course that all eight robots are actively foraging continuously; $S_2 - S_4$ however require fewer active foragers and strategies with social and environmental cues, S_3 and S_4, clearly show the best performance. Notice, firstly that the additional of social cues — communication between robots — significantly improves the rate at which the system can adapt the ratio of foragers to resters and, secondly, that the addition of environmental cues — collisions with other robots — brings only a marginal improvement. The rates of change of net swarm energy in figure 9 tell a similar story. Interestingly, however, we see very similar gradients for $S_2 - S_4$ when the food density is high (on the RHS of the plot), but

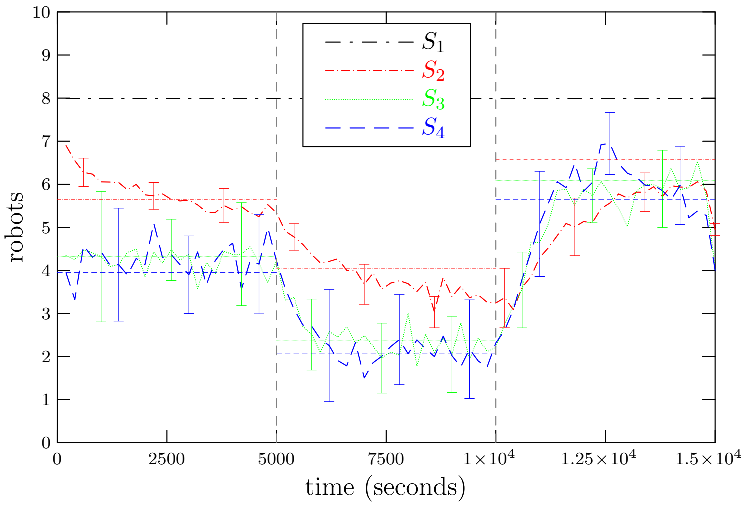

Figure 8: Number of foraging robots x in a foraging swarm of $N = 8$ robots with self-organised division of labour. S_1 is the baseline (no cooperation strategy); S_2, S_3 and S_4 are three different cooperation strategies (see table 4). Food density changes from 0.03 (medium) to 0.015 (poor) at $t = 5000$, then from 0.015 (poor) to 0.045 (rich) at $t = 10000$. Each plot is the average of 10 runs.

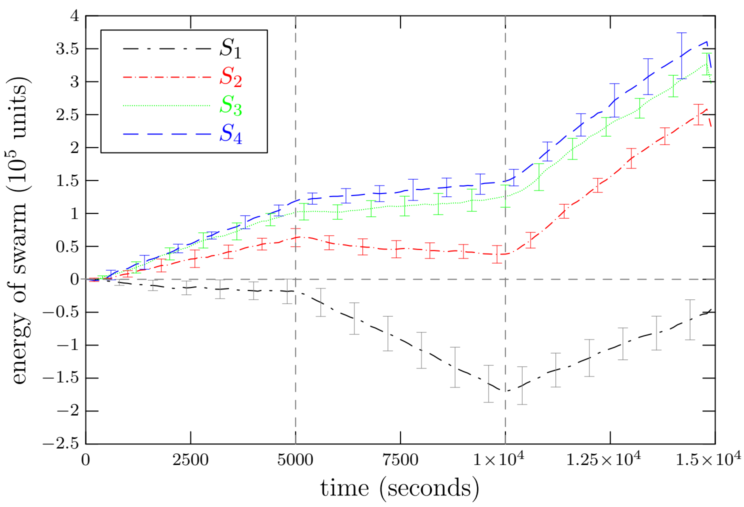

Figure 9: Instantaneous net energy E of a foraging swarm with self-organised division of labour. S_1 is the baseline (no cooperation strategy); S_2, S_3 and S_4 are three different cooperation strategies (see table 4). Food density changes from 0.03 (medium) to 0.015 (poor) at $t = 5000$, then from 0.015 (poor) to 0.045 (rich) at $t = 10000$. Each plot is the average of 10 runs.

when the food density is medium or poor the rate of increase in net energy of strategies S_3 and S_4 is significantly better than S_2. This result interestingly suggests that foraging robots benefit more from cooperation when food is scarce, than when food is plentiful.

5.3 Mathematical modelling

A multi-robot system of foraging robots is typically a stochastic non-linear dynamical system and therefore challenging to mathematically model, but without such models any claims about the correctness of foraging algorithms are weak. Experiments in computer simulation or with real-robots (which provide in effect an 'embodied' simulation) allow limited exploration of the parameter space and can at best only provide weak inductive proof of correctness. Mathematical models on the other hand, allow analysis of the whole parameter space and discovery of optimal parameters. Ultimately, in real-world applications, validation of a foraging robot system for safety and dependability will require a range of formal approaches including mathematical modelling.

Martinoli and coworkers proposed a *microscopic* approach to study collective behaviour of a swarm of robots engaged in cluster aggregation [45] and collaborative stick-pulling [32], in which a robot's interactions with other robots and the environment are modelled as a series of stochastic events, with probabilities determined by simple geometric considerations and systematic experiments with one or two real robots.

Lerman, Martinoli and co-workers have also developed the *macroscopic* approach, as widely used in physics, chemistry, biology and the social sciences, to directly describe the collective behaviour of the robotic swarm. A class of macroscopic models have been used to study the effect of interference in a swarm of foraging robots [38] and collaborative stick-pulling [39, 44]. A review of macroscopic models is given in [41]. More recently, Lerman *et al* [40] successfully expanded the macroscopic probabilistic model to study dynamic task allocation in a group of robots engaged in a puck collecting task, in which the robots need to decide whether to pick up red or green pucks based on observed local information.

5.3.1 A macroscopic mathematical model of multi-robot foraging with division of labour

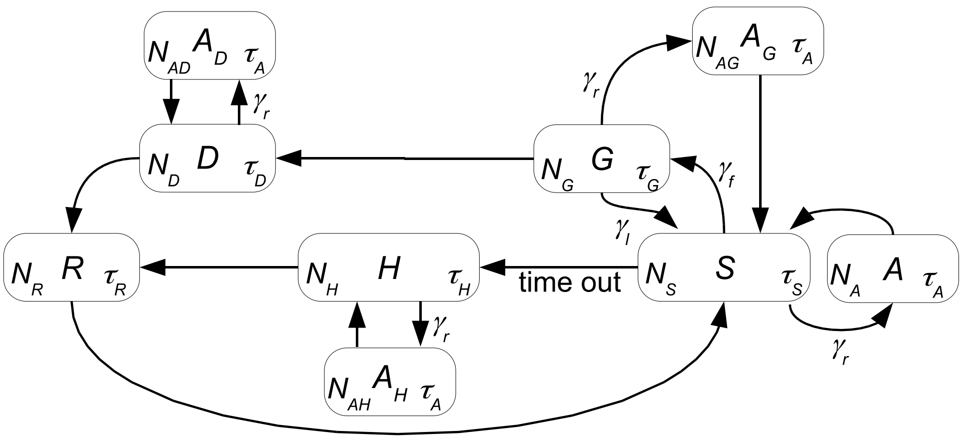

Figure 10: Probabilistic Finite State Machine (PFSM) for Foraging with Division of Labour

Recently Liu *et al* have applied the macroscopic approach to develop a mathematical model for foraging with division of labour (as described above in section 5.2.3), [42]. The finite state machine of figure 7 is extended in order to describe the probabilistic behaviour of the whole swarm, resulting in a probabilistic finite state machine (PFSM). In figure 10 each state represents the average number of robots in that state. The five basic states are S for *searching*, H for *homing*, G for *grabbing*, D for *depositing* and R for *resting*, and the average number of robots in each of these states is respectively N_S, N_H, N_G, N_D and N_R. τ_S, τ_H, τ_G, τ_D and τ_R represent the average times a robot will spend in each state before moving to the next state.

In each time step a robot in state S has probability γ_f of finding a food-item and moving to state G, in which it will move towards the target food-item until it is close enough to grab it using the gripper. Once the robot successfully grabs the food-item it will move to state D, in which the robot moves back to the 'nest' carrying the food-item and deposits it. After the robot has unloaded the food-item it will rest in state R, for τ_R seconds and then move to S to resume *searching*. Meanwhile, if the robot in state S fails to find a food-item within time τ_S, it will move to state H, and return to the 'nest' to save energy or minimise interference with other robots. Because of competition among robots more than one robot may see the same food-item and thus move towards it at the same time; clearly only one of them can grab it, a robot in state G therefore has probability γ_l to lose sight of the food-item if it has already been grabbed by another robot, which in turn drives the robot back to state S to resume its search.

In foraging interference between robots because of overcrowding, competition for food-items or simply random collisions is a key aspect of the dynamics of foraging. Thus collision avoidance is modelled as follows. Robots in states S, G, D and H will move to *avoidance* states A, A_G, A_D and A_H respectively with probability γ_r, as shown in figure 10. The avoidance behaviour then takes τ_A seconds to complete before the robot moves back to its previous state.

Constructing the mathematical model requires two further steps. Firstly, writing down a set of difference equations (DEs) describing the change in the average number of robots in each state from one time step to the next and, secondly, estimating the state transition probabilities. Expressing the PFSM as a set of DEs is relatively straightforward. For instance, the change in the average number of robots N_A in state A from time step k to $k+1$ is given as:

$$N_A(k+1) = N_A(k) + \gamma_r N_S(k) - \gamma_r N_S(k - T_A) \quad (8)$$

where $\gamma_r N_S(k)$ is the number of robots that move from the search to the avoidance state A and $\gamma_r N_S(k - T_A)$ is the number of robots that return to S from state A after time T_A (note T_A is τ_A discretised for time step duration Δt). The full set of DEs is given in [42]. Clearly, the total number of robots in the swarm remains constant from one time step to the next,

$$N = N_S(k) + N_R(k) + N_G(k) + N_D(k) + N_H(k) + N_A(k) + N_{A_h}(k) + N_{A_g}(k) + N_{A_d}(k) \quad (9)$$

Estimating state transition probabilities can be challenging but if we simplify the environment by placing the 'nest' region at the centre of a circular environment in which the food growing area is bounded by two concentric rings in a bounded arena, as shown in figure 11, then a purely geometrical approach can be used to estimate γ_f, γ_r and γ_l together with the average times for grabbing, depositing and homing τ_G, τ_D and τ_H. Clearly τ_R and τ_S are the design parameters we seek to optimise, while τ_A is determined by the physical design of the robot and its sensors.

Figure 12, from [42], plots the average number of robots, from both simulation and the mathematical model, in states *searching*, *resting* and *homing* for the swarm with $\tau_r = 80$. The average number of robots in each state predicted by the probabilistic model quickly settles to a constant value. In contrast, but as one would expect, the average number of robots from simulation oscillates over time but stays near the value predicted by the model.

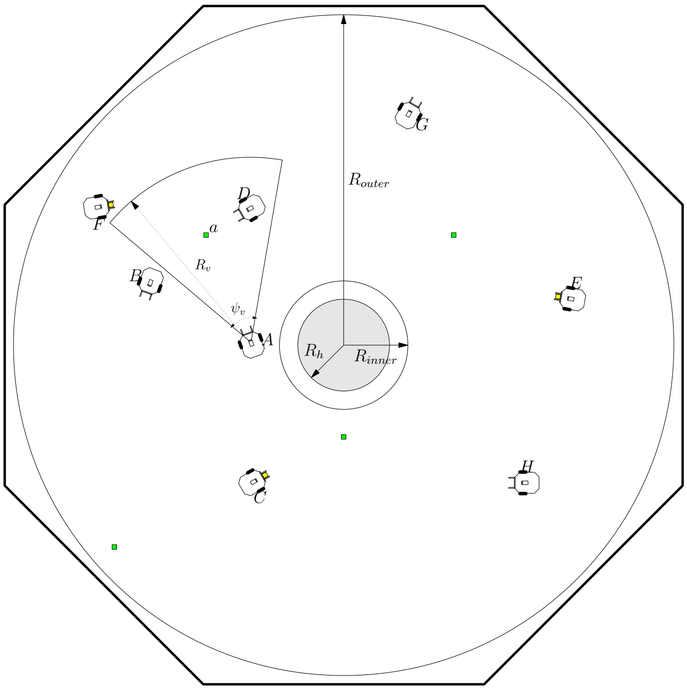

Figure 11: Foraging environment showing 8 robots labelled $A - H$. The nest region is the grey circle with radius R_h at the centre. Robot A is shown with its arc of vision in which it can sense food items; robots C, E and F have grabbed food items and are in the process of returning to the nest to deposit these. Food items, shown as small squares, 'grow' in order to maintain uniform density within the annular region between circles with radius R_{inner} and R_{outer}.

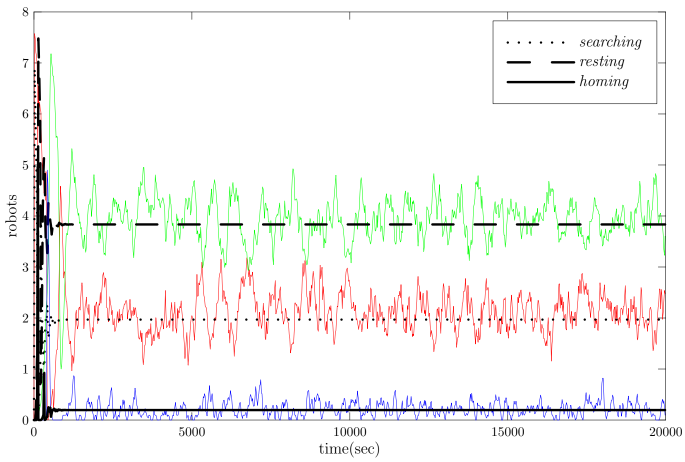

Figure 12: The number of robots in states *searching*, *resting* and *homing* for the swarm with $\tau_r = 80$ seconds. The horizontal black dashed lines are predicted by the mathematical model; coloured graphs show the instantaneous number of robots measured from simulation.

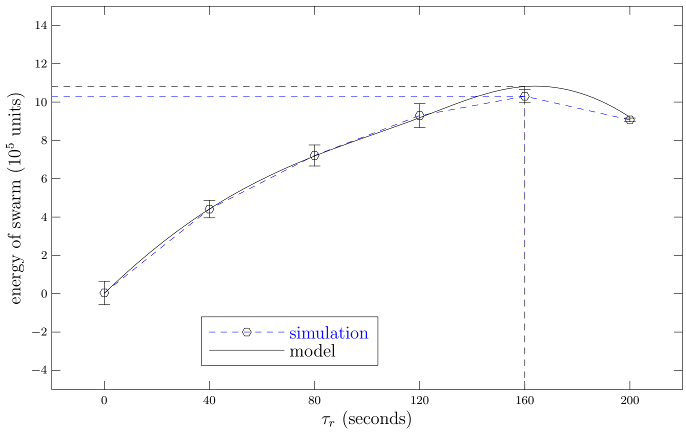

Figure 13: The net energy of the swarm for different values of the resting time parameter τ_r The black curve is the prediction of the mathematical model; the dashed curve with error bars is measured from simulation.

Figure 13 compares the predicted value of net swarm energy from the mathematical model, with the measured value from simulation, for resting time parameter τ_r increasing from 0 to 200s. The two curves show, firstly a good match between measured and predicted curves therefore validating the mathematical model and, secondly, that there is indeed an optimal value for τ_r (at about 160 seconds). We thus have confirmation that a mathematical model can be used to analyse the effect of individual parameters on the overall performance of collective foraging.

6 Future Directions

This article has defined robot foraging, set out a taxonomy and described both the development and state-of-the-art in robot foraging. Although the principles of robot foraging are well understood, the engineering realisation of those principles remains a research problem. Consider multi-robot cooperative robot foraging. Separate aspects have been thoroughly researched and demonstrated, and a number of exemplars have been described in this article. However, to date there has been no demonstration of autonomous multi-robot foraging which integrates self-organised cooperative search, object manipulation and transport in unknown or unstructured real-world environments. Such a demonstration would be a precursor to a number of compelling real-world applications including search and rescue, toxic waste cleanup or foraging for recycling of materials.

The future directions for foraging robots lie along two separate axes. One axis is the continuing investigation and discovery of foraging algorithms — especially those which seek to mimic biologically inspired principles of self-organisation. The other axis is the real-world application of foraging robots and it is here that many key challenges and future directions are to be found. Foraging robot teams are complex systems and the key challenges are in *systems integration and engineering*, which would need to address:

1. Principled design and test methodologies for self-organised multi-robot foraging robot systems.

2. Rigorous methodologies and tools for the specification, analysis and modelling of multi-robot foraging robot systems.

3. Agreed metrics and quantitative benchmarks to allow comparative evaluation of different approaches and systems.

4. Tools and methodologies for provable multi-robot foraging stability, safety and dependability [23, 68].

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