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Complex Adaptive Systems Modeling

REVIEW

Open Access

Multi-Agent Foraging: state-of-the-art and research challenges

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Abstract

Background: The foraging task is one of the canonical testbeds for cooperative robotics, in which a collection of robots has to search and transport objects to specific storage point(s). In this paper, we investigate the *Multi-Agent Foraging* (MAF) problem from several perspectives that we analyze in depth.

Results: First, we define the *Foraging Problem* according to literature definitions. Then we analyze previously proposed taxonomies, and propose a new foraging taxonomy characterized by four principal axes: *Environment, Collective, Strategy* and *Simulation*, summarize related foraging works and classify them through our new foraging taxonomy. Then, we discuss the real implementation of MAF and present a comparison between some related foraging works considering important features that show extensibility, reliability and scalability of MAF systems

Conclusions: Finally we present and discuss recent trends in this field, emphasizing the various challenges that could enhance the existing MAF solutions and make them realistic.

Keywords: Multi-agent foraging, Foraging taxonomies, Swarm intelligence, Swarm robotics

Background

Swarm intelligence provides the design and implementation of systems composed of many simple individuals who interact locally and produce remarkable behavior as a whole (Dudek et al. 1996). It provides multiple benefits such as robustness where the performance of the system is not affected significantly with the failure of individuals, simplicity of computational and perceptual capabilities of individuals but still allowing global complex behaviors and scalability of the control mechanism that does not depend on the number of agents (Mitton and Simplot-Ryl 2014). The application of swarm intelligence to collective robotics is identified as *Swarm Robotics* in El Zoghby et al. (2014). Many artificial systems such as distributed computing systems and artificial intelligence systems are characterized by complex behaviors that emerge as a result of the nonlinear spatio-temporal interactions among a large number of system components at different levels of organization. These systems are known as *Complex Adaptive Systems* (CAS) as stated by Lansing (2003). Holland (2006) also considers CAS as dynamic systems able to adapt in and evolve with a changing environment. MAF problem is a benchmark problem for swarm robotics. It can be seen as a CAS and defined like in Niazi and Hussain

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(2012) as a system made up of multiple simple individuals which interact in a nonlinear fashion, thereby giving rise to global and often unpredictable behaviors. A good way to understand a CAS is to study them in special cases, thus to simulate dedicated behavior from particular perspectives. Holland (2006) states that the analysis of CAS is done through a combination of applied, theoretical and experimental methods (e.g. mathematics and computer simulations). Authors in Fortino and North (2013) state that *Agent-Based Modeling* (ABM) has proven to provide an effective set of tools for modeling and simulating different types of CAS. MAF was widely studied through ABM, computer simulation before real experiments to explain and understand it.

MAF constitutes a metaphor for a broad class of problems including robotic exploration, navigation, object identification, manipulation and transport. Cleaning, harvesting, search and rescue, land-mine clearance and planetary astrobiology are real world applications that could be considered as instances of foraging robots. Even if the sophisticated foraging observed in social insects provides both inspiration and system level models for artificial systems, foraging remains an active research problem for various reasons: most of the developed foraging systems are adapted to real world problems, they are in research laboratories for validation and mostly studied through simulation in Multi-Agent platforms like Netlogo used by Wilensky (1997) and Starlogo used by Resnick (1996), in robotic-based platforms like Swarmanoid of Dorigo et al. (2013) or through real robots with ARGoS in Pinciroli et al. (2012). The high complexity of foraging which requires a large number of skills tightly integrated within the physical robot, as stated by Winfield (2009).

One goal of our works is to discover foraging algorithms inspired from the biological principles of self-organization (e.g. ants) and physical dynamics in nature (e.g. vortex). We proposed and simulated a variety of algorithms to solve different configurations of the foraging problem in order to: (1) Allow cooperative behaviors in Zedadra et al. (2015). (2) To study scalability of the proposed approach in Zedadra et al. (2016). (3) To allow the execution of our algorithms even with limited energy of agents in Zedadra et al. (2015) and in Zedadra et al. (2016). Our goal here is to analyze and survey the MAF problem: defining the problem, summarizing the existing taxonomies, presenting a new taxonomy of foraging, discussing the real implementation of MAF and listing challenges and open issues regarding MAF.

The paper is organized as follows: we present a definition of foraging in "Foraging definition" section. In "Foraging taxonomies" section we deal with foraging taxonomy; specifically, in "Existing taxonomies" section, we describe the existing taxonomies for robotic systems and foraging problem. We propose in "Proposed taxonomy" section a new taxonomy for foraging. In "Foraging related works" section, we synthesize a collection of foraging works including our works and classify them through the proposed taxonomy. We discuss in "Real robotic implementation of foraging agents" section, the real robotic implementation of the foraging problem and we present a comparison table of some of the related works with simulated and real experiments. We highlight in "Future directions" section, further research questions and challenges which can help in treating new aspects of foraging that could be realistic in real world. We finish with a conclusion in "Conclusion" section.

Foraging definition

Foraging consists in searching and collecting items in an environment and move them to storage point(s). Ostergaard et al. (2001) define the foraging as a two-step task known as searching and homing, where robots have to find as quick as possible items in the environment and return them to a goal region. While Winfield (2009) defines the foraging with a four state machine (*searching, grabbing, homing* and *depositing*), many variations can be derived from this basic point of view to define some special cases like dealing with energy limitations. However, most of the literature that works on foraging consider the two tasks *searching* and *homing*, since the two others are more related to robot design. As scalability is an important factor in nowadays applications, we believe that cooperation (over communication) is an important factor to consider in the conception of a foraging system. Therefore, we define foraging as the conjunction of the two tasks (searching and homing) with consideration of communication:

- *Searching* Robots inspect the search space for targets (or food). While the random walk is the most adopted strategy of search in unknown environments, several other search strategies can be used according to the environment structure and the amount of information provided to robots.
- *Homing* Robots have to return home with the collected food by using prior information and/or on-board sensors, following a pheromone trail or even exploiting specific tools (e.g. compass).
- *Communication* The cooperation between robots either in searching or in homing tasks can improve the group performance by accelerating the search when avoiding already visited regions or in homing when exploiting together found food. In several other problems cooperation can be achieved without communication, as in Feinerman et al. (2012). However, communication routine is necessary to share and receive information between agents in the swarm directly via transmitting messages or indirectly via the environment.

We present the *Finite State Machine* (FSM) of a foraging robot in Fig. 1. In the model, agents start all from the default state *searching*. They move in the environment (randomly or using a more complex strategy) using their sensors to locate objects. As soon as objects are located they change to state *homing* where they grab a limited quantity of objects and return home. When home is reached, they deposit objects and resume their search. Agents transit to *avoiding obstacle* state from the two other states whenever an

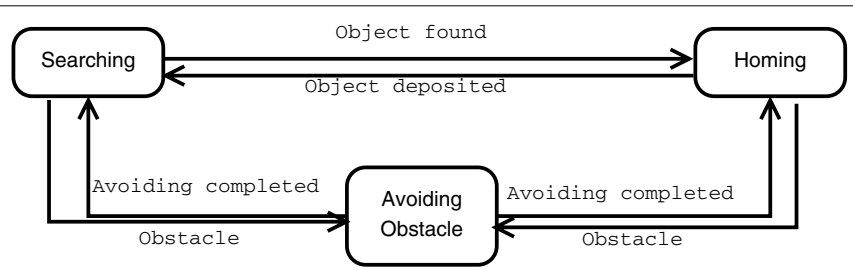


Fig. 1 Finite state machine of a foraging robot

obstacle is encountered. The finish time of foraging is when all objects are located and transported to the home.

Existing variants of foraging are defined according to multiple features such as the type of items to be collected that are identical or different [known as *multi-foraging*; Balch investigates in Balch (1999) the impact of diversity on performance in multi-robot foraging], delivering the items to a unique central location [known as *central place foraging*, this latter is presented in depth in Orians and Pearson (1979)], to multiple locations as described by Debout et al. (2007) or destroying them when found [defined as *destructive foraging* by Bartumeus et al. (2005)].

Foraging taxonomies

Taxonomies offer some benefits to researchers: (1) summarize and describe in a simple manner the literature works; (2) offer guidance and perspectives when engaged in similar works; (3) help them in situating and comparing their works with existing ones. The understanding of the many possible system configurations via taxonomies helps in making principled design decisions. In the domain of swarm intelligence several taxonomies have been proposed for Multi-Agent Systems, each with different focus. We summarize in "Existing taxonomies" section existing robotic and foraging taxonomies, present a new foraging taxonomy in "Proposed taxonomy" section, overview and classify existing foraging works through the proposed taxonomy in "Foraging related works" section.

Existing taxonomies

Figure 2, illustrates graphically the taxonomy proposed by Cao et al. (1997) to classify existing works on cooperative tasks such as box pushing, traffic control and foraging. This taxonomy contains five principal axes: *Group Architecture*, *Resource Conflicts*, *Origins of Cooperation*, *Learning* and *Geometric Problems*. Each axis is described by multiple features. The axis *Group Architecture* is explained by: *Organization* of the control ,*Difference* between teammates, *Communication* medium, *Modeling of Teammates*. The axis *Resource Conflicts* is explained by the *Source* of conflict. The axis *Origins of Cooperation* is explained by the *Motivation* to execute a cooperation. The axis *Learning* is explained by *Evolutionary Techniques* used to learn automatically without human intervention. The axis *Geometric Problems* is explained by a collection of *Applications* which consider geometrical problems.

The taxonomy of Cao et al. shown by Fig. 2 is general. Axes of the taxonomy are highly interdependent and very broad making it difficult to identify isolated sample points within the taxonomy. It fails to capture task performance criteria, nor to specify the strategy for either searching or collecting objects.

Ostergaard et al. (2001) define eight characteristics of a foraging task. The defined characteristics identify a set of parameters that qualify the complexity of the problem. Three principal axes are used to classify works: *Robot*, *Environment* and *Communication*. Each axis is explained by a set of properties. The axis *Robot* is explained by: the *Number* of agents and the *Difference* in functionalities and modeling between them. The axis *Environment* is explained by: *Sinks Number* which is the number of storage points used to store food, *Boundaries* of the environment, *Source* of food available in the environment, each source contains a quantity of items, *Items* which are featured by: *Number*

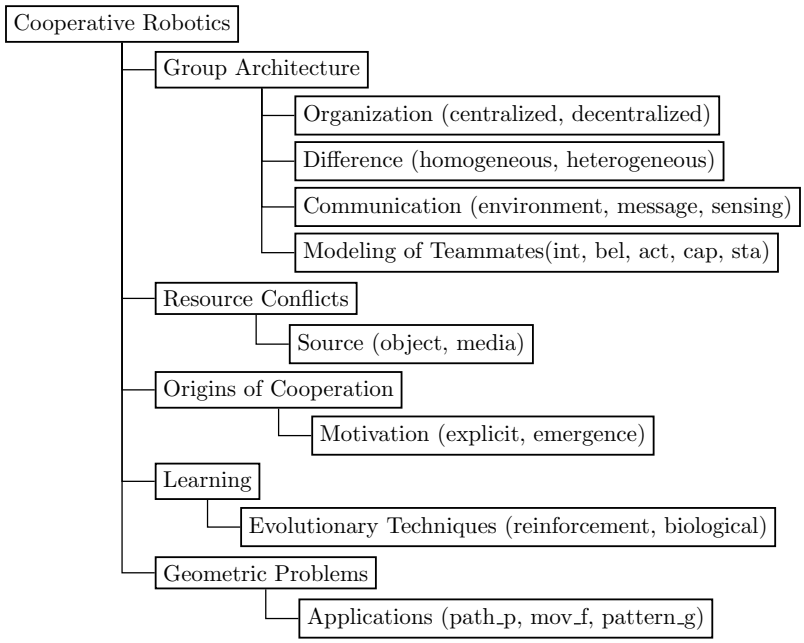


Fig. 2 A graphical representation of Cao et al. taxonomy (Cao et al. 1997), with five axes: *Group Architecture, Resource Conflicts, Origins of Cooperation, Learning, Geometric Problems*. Where: intentions (*int*), beliefs (*bel*), actions (*act*), capabilities (*cap*), states (*sta*), Path planning (*path_p*), moving to formation (*mov_f*) and pattern generation (*pattern_g*)

of items in a source and *Initial Position*. The axis *Communication* is explained by the feature *Presence* of communication to show whether a communication exists or not. We summarize and graphically represent the characteristics of *Ostergaard* with the three axes in Fig. 3.

The parameters defined in *Ostergaard's* taxonomy are very limited and interesting properties of Multi-Agent Foraging systems were neglected such as: capacity of robots in sensing and transport, how cooperation and coordination are achieved, which information an agent can communicate to others, how exploration and homing are achieved.

Balch (2002) was interested in features of the task the team of agents must accomplish. He proposes a taxonomy for *Multi-Robot Systems* (MRS). This taxonomy focuses on three principal axes: *Task Environment*, *Robotic Platform* and *Performance*. The axis *Task Environment* is featured by: *Subject of Action*, *Group Movement* and *Resource Limits*. The axis *Robotic Platform* is described by: *Number* of robots, *Position* of robots, *Sensors* range, *Communication* if it exists between robots. The axis *Performance* is explained by: elapsed *Time* constraints, *Criteria* or performance metrics. We synthesize and graphically represent the textual description of *Balch* taxonomy (Balch 2002) by Fig. 4.

Balch taxonomy adds new features to describe and evaluate tasks, not considered in the previous taxonomies (under axes *Task Environment* and *Performance*). However, it does not state any axes or features about coordination and cooperation strategies unless the presence or the absence of communication which constitute key features to compare works.

Dudek et al. (2002) present a taxonomy which classifies Multi-Agent Systems according to communication, computational and other capabilities such as size, difference and

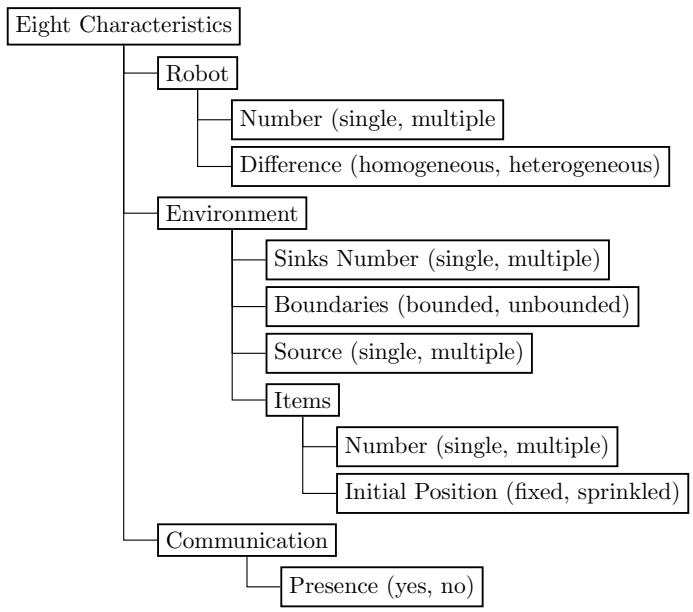


Fig. 3 A graphical representation of *Ostergaard* taxonomy (Ostergaard et al. 2001), with three axes: *Robot, Environment* and *Communication*

reconfigurability of teammates. It is composed of two axes. The axis *Collective* which is explained by features: *Size* or number of robots, *Difference* in physical and functional capabilities of robots, *Processing Ability* used to differentiate the computational model of robots, *Reconfigurability* meaning the rate at which the collective can spatially re-organize itself. The axis *Communication* is featured by: a *Range*, a *Topology* and a *Bandwidth* meaning that communication may be inexpensive in terms of the robots' processing time or it may be expensive in that the robot is prevented from doing other work while communicating. Figure 5, illustrates graphically schema of Dudek et al. taxonomy (Dudek et al. 2002).

Dudek et al. taxonomy concentrates on teammates structure and communication abilities, but does not give interest to tasks nor to strategies relays to Multi-Robot Systems or to foraging in particular. Thus, it is difficult to classify and compare works that use the same characteristics in terms of collective and communication and differ in homing or searching strategies in a foraging system which constitute fundamental factors for comparison.

Winfield (2009) proposes a more detailed taxonomy for foraging, based on the taxonomies proposed in Balch (2002), Dudek et al. (2002) and Ostergaard et al. (2001). It is composed of four major axes: *Environment, Robot, Performance* and *Strategy*. Each major axis is described by features in a minor axis and each feature can take specific values. The axis *Environment* is described by: *Sinks Number*, *Search Space*, *Source Nature* which is the number of food locations in the environment and the quantity of objects in each location, *Object Type* which is the number of food locations and whether objects are mobile or immobile, *Object Placement*. The axis *Robot* is explained by: *Number* of robots, *Difference* between robots, *Object Sensing* capabilities of a robot, *Localization*, *Communication* and *Power* which is the energy of a robot. The axis *Performance* includes

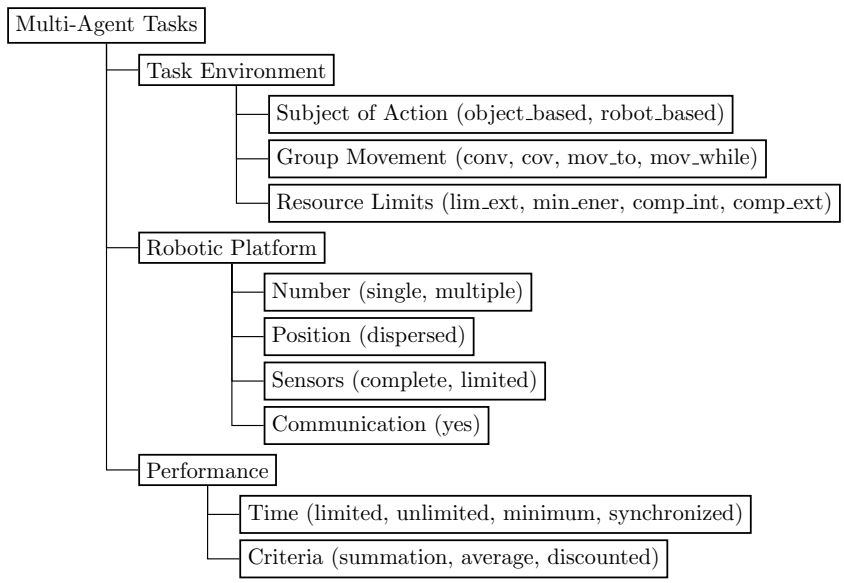


Fig. 4 A graphical representation of *Balch* taxonomy (Balch 2002), with three axes: *Task Environment*, *Robotic Platform* and *Performance*. Where: coverage (*cov*), convergence (*conv*), movement from initial to final locations (*mov_to*) or maintaining a configuration while moving (*mov_while*), limited external resources (*lim_ext*), minimum energy task (*min_ener*), competition between team members for resources *(comp_int*) and team competes with external agencies (*comp_ext*)

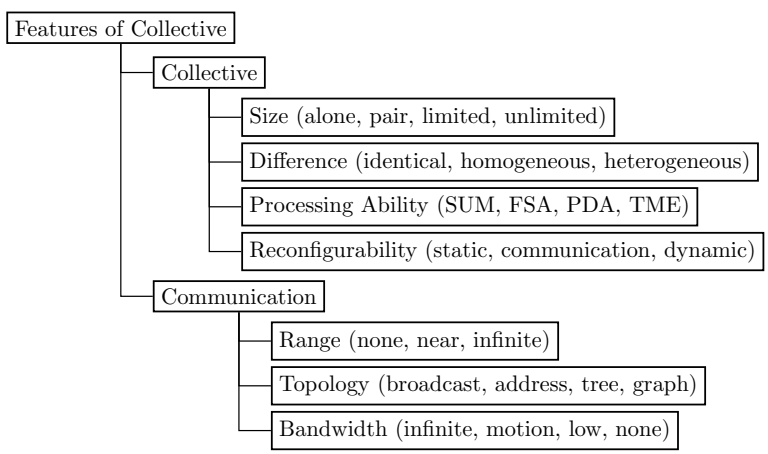


Fig. 5 A graphical representation of Dudek et al. taxonomy (Dudek et al. 2002), with two axes: *Collective* and *communication*. Where: non-linear SUMmation unit (*SUM*), Finite State Automaton (*FSA*), Push-Down Automaton (*PDA*) or Turing Machine Equivalent (*TME*)

two features: *Time* and *Energy*. *Strategy* axis represents the strategies used in the foraging including: *Search* to specify the search strategy used, *Grabbing*, *Transport*, *Homing*, *Recruitment* of other robots to existing trails, *Coordination* strategy if it exists. Figure 6 represents graphically this taxonomy.

Winfield gives a more comprehensive taxonomy for robot foraging that incorporates the robot and task/performance oriented features of Dudek et al. (2002) and Balch (2002) respectively with environmental features proposed by Ostergaard et al. (2001).

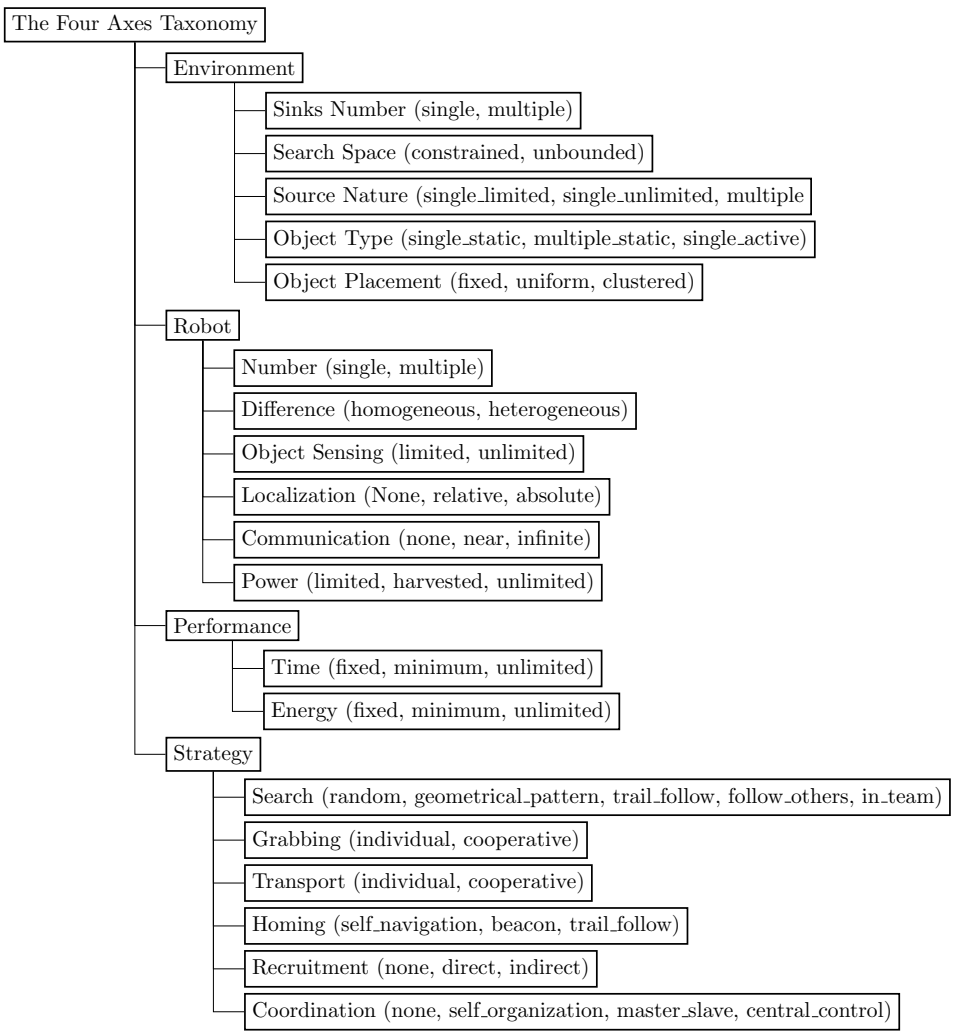


Fig. 6 A graphical representation of Winfield taxonomy (Winfield 2009), with four axes: *Environment, Robot, Performance* and *strategy*

It seems to be complete, since it combines axes from previous taxonomies. However, it neglected some determinant features. More complex foraging systems can exist but classified unfairly because of the lack of those features.

Multiple features are common between the existing taxonomies (e.g. collective architecture, environment structure, presence of communication...), while a large number of features is specific to each taxonomy. Winfield taxonomy (Winfield 2009) is a general taxonomy that combines features from other taxonomies but did not consider some important features (i.e. processing ability $\langle reactive, cognitive, hybrid \rangle$, communication $\langle range, communication\ pattern, bandwidth \rangle$, search space $\langle continuous, grid, obstacle\text{-}free, obstacle \rangle$) and simulation parameters (performance metrics and type of simulations). Such features are determinant to represent the complexity of the foraging problem and to show the simplifications considered on environment and robots. *Winfield* taxonomy: (1) does not show the difference between MAF algorithms. Taking for example two MAF algorithms; the first uses bounded, grid and obstacle-free

environment and the second uses bounded, continuous and obstacle environment. A comparison with *Winfield* taxonomy shows that the works are similar while the two are different in definition; (2) the complexity degree of MAF algorithms can't be concluded from the existing features. Taking the same example in (1) the second work is more difficult than the first while *Winfield* taxonomy shows them with the same complexity degree; (3) does not show the simplifications considered in MAF algorithms. Unfortunately, the taxonomies discussed in this paper do not consider the aforementioned features, and it will be unfair to classify and compare works through such taxonomies. We propose in this paper a new foraging taxonomy which gathers the most important features from different taxonomies and adds new important ones. We therefore believe that our taxonomy will support a more effective and thorough analysis and comparison of foraging works.

Proposed taxonomy

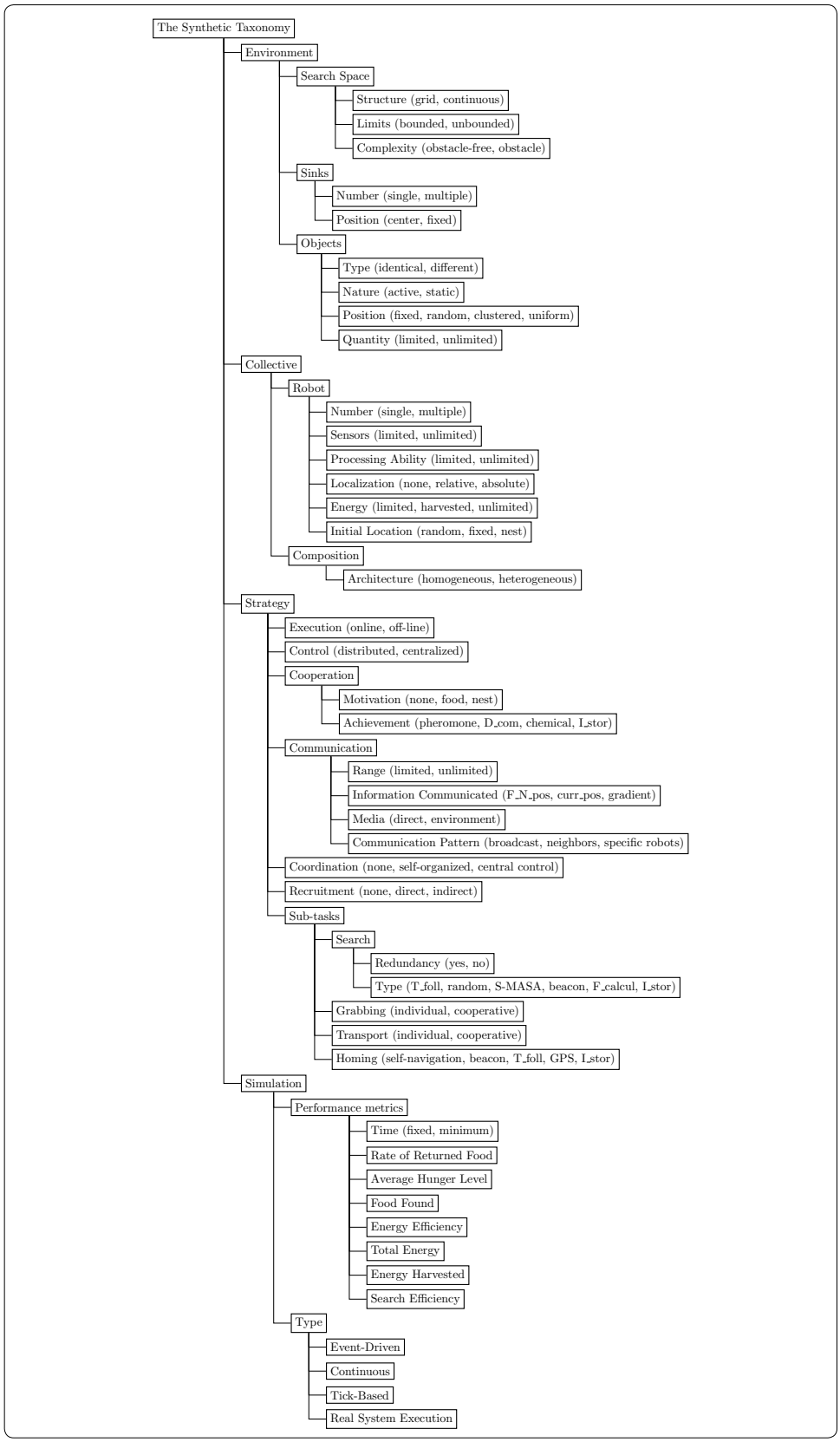
Winfield 2009 taxonomy is rigid and oriented to a portion of works only. As an extension to Winfield taxonomy and using the same style, we add a set of descriptive tags that identify the main features of environment, collective, strategy and simulation. The added features represent different aspects of a foraging system. They are inspired from the previous taxonomies unless the one of simulation which differentiate computer simulated systems and those with real world experiments. The proposed taxonomy can be supplied into two parts, each one of them addresses an aspect of the system. Axes *environment* and *collective* can address the problem definition to determine the complexity of the proposed MAF. While *strategy* and *simulation* axes address the problem solution aspect. *Strategy* axis represent features to describe the proposed solution and *simulation* axis represent features used to evaluate the solution (performance metrics) and the type of simulation used. The proposed taxonomy can be applied to real or simulated robots since we do not purposely consider the design characteristics of robots. To evaluate the taxonomy, we applied it for the analysis of some of the most diffused foraging systems.

The proposed taxonomy represented graphically by Fig. 7, is composed of four major axes: *Environment, Collective, Strategy* and *Simulation*. Each major axis is described by features in a minor axis and each feature can take specific values.

The major axis *Environment* is described by: *Search Space*, *Sinks* and *Objects*. Each of its minor axes is explained by a set of features. *Search Space* is defined by *Structure*, *Limits* and *Complexity* contains or not obstacles. *Sinks* is explained by *Number* and *Position*. *Objects* is explained by *Type*, *Nature*, *Position* and *Quantity*.

The major axis *Collective* is represented by minor axes: *Robot* and *Composition*. *Robot* is characterized by *Number* of agents, *Sensors* range, *Processing Ability*, *Localization*, *Energy* and *Initial Location*. *Composition* axis is described by *Architecture* or differences in functional capabilities of robots.

The major axis *Strategy* is featured by minor axes: *Execution*, *Control*, *Cooperation*, *Communication*, *Coordination*, *Recruitment* and *Sub-tasks*. Each minor axis is explained by a set of features unless *Execution*, *Control*, *Coordination* and *Recruitment*. The axis *Cooperation* is explained by features: source of *Motivation* and how cooperation is achieved (*Achievement*). The axis *Communication* is explained by its *Range*, the


The Synthetic Taxonomy
Environment
Search Space
Structure (grid, continuous)
Limits (bounded, unbounded)
Complexity (obstacle-free, obstacle)
Sinks
Number (single, multiple)
Position (center, fixed)
Objects
Type (identical, different)
Nature (active, static)
Position (fixed, random, clustered, uniform)
Quantity (limited, unlimited)
Collective
Robot
Number (single, multiple)
Sensors (limited, unlimited)
Processing Ability (limited, unlimited)
Localization (none, relative, absolute)
Energy (limited, harvested, unlimited)
Initial Location (random, fixed, nest)
Composition
Architecture (homogeneous, heterogeneous)
Strategy
Execution (online, off-line)
Control (distributed, centralized)
Cooperation
Motivation (none, food, nest)
Achievement (pheromone, D_com, chemical, I_stor)
Communication
Range (limited, unlimited)
Information Communicated (F_N_pos, curr_pos, gradient)
Media (direct, environment)
Communication Pattern (broadcast, neighbors, specific robots)
Coordination (none, self-organized, central control)
Recruitment (none, direct, indirect)
Sub-tasks
Search
Redundancy (yes, no)
Type (T_foll, random, S-MASA, beacon, F_calcul, I_stor)
Grabbing (individual, cooperative)
Transport (individual, cooperative)
Homing (self-navigation, beacon, T_foll, GPS, I_stor)
Simulation
Performance metrics
Time (fixed, minimum)
Rate of Returned Food
Average Hunger Level
Food Found
Energy Efficiency
Total Energy
Energy Harvested
Search Efficiency
Type
Event-Driven
Continuous
Tick-Based
Real System Execution

(See figure on previous page.)
Fig. 7 A graphical representation of our proposed taxonomy for foraging, with four axes: *Environment, Collective, Strategy* and *Simulation*. Where: direct communication (*D_com*), exchanging stored information (*I_stor*), position of food or nest (*F_N_pos*), current position (*curr_pos*), trail following (*T_foll*), calculated force (*F_calcul*), use stored information (*I_stor*), follow other robots (*follow_O*)

Information Communicated, the *Media* of communication and *Communication Pattern*. *Sub-tasks* axis includes the different sub-tasks of a foraging, which we summarize them in: *Search*, explained by the *Redundancy* of search by revisiting already visited regions and the *Type* of strategy used for search. *Grabbing* shows the existence of cooperation in grabbing or not. *Transport* also shows whether there exists a cooperation or not in transporting objects. *Homing* includes the strategies used to return home.

The major axis *Simulation* is decomposed into two minor axes: *Performance metrics* and *Type*. *Performance metrics* includes the metrics used to test the foraging system performances: *Time*, *Rate of Returned Food*, *Average Hunger Level*, *Food Found*, *Energy Efficiency*, *Total Energy* and *Search Efficiency*. *Type* includes *Event-Driven, Continuous, Tick-Based* and *Real System Execution*.

Foraging related works

Table 1 situates the main foraging literature and places existing foraging systems within the proposed taxonomy. A detailed description of each work is provided in Table 1, where the values of each feature are given. Also Table 2 presents a description of some of the related works using other features.

Liu et al. propose in Liu et al. (2007) an ABM for foraging agents composed of three states: searching, following and homing. Authors consider three aspects: the distance of sources, the evaporation of pheromone and the number of agents.

Hoff et al. (2010) propose two decentralized foraging algorithms called *Virtual Pheromone* (VP) and *Cardinality*, inspired by ants behavior. Robots communicate with others in nearby using simple infrared ring architecture. Authors use robots like beacons to store virtual pheromones. In the VP, pheromones are floating-point numbers, they are stored in beacon robots and transmitted by them to other robots in vicinity. *Cardinality* algorithm is similar to the VP algorithm in that robots can decide to act as either beacons or walkers. It differs from VP in that the values the beacons store are integers (called cardinalities). They also propose three foraging algorithms in Hoff et al. (2013) called *gradient, sweeper* and *adaptive*. In *gradient* algorithm, agents broadcast information about gradient to nest or food, they switch from *beacons* (beacons transmit values) to *walkers* (walkers use those values to decide where to move) according to some criteria. Agents in the *sweeper algorithm* use virtual forces to form a line which sweeps the search space, when food is found, some robots remain as beacons while others act like walkers. In *adaptive algorithm* the colony switches between the two aforementioned algorithms. Robots use: gradient algorithm when food is close to nest, sweeper algorithm when food is far away and random walk when their number is not sufficient to cover the whole world. The gradient algorithm (Hoff III et al. 2010) is used by the *Tornado* algorithm proposed in Magdy et al. (2013). It is inspired by the spiral tornado

Table 1 Situating some foraging works within the proposed taxonomy

axis 1	axis 2	axis 3	axis 4	[27]	[34]	[28]	[39]	[33]	[41]	[43]	[45]	[49]	[13]	[15]	[36]	[29]	[42]	[38]	[47]	[37]	[26]	[48]	[30]	[44]	[50]	[51]	[52]
Environment	Search_S	struct.	grid																								
			continue																								
		limits	yes																								
			no																								
		compl-exity	free																								
			obs																								
		number	single																								
			multiple																								
	Sinks	posit-ion	center																								
			fixed																								
	Objects	type	identical																								
			different																								
		nature	static																								
			active																								
		posit-ion	fixed																								
			rand																								
			clustered																								
			unif.																								
		qtty	limit																								
			no limit																								
Collective	Robot(s)	number	mult.																								
		sensors	limit																								
			no limit																								
		proc_A	limit																								
			no limit																								
		locali-zation	yes																								
			no																								
		energy	limit																								
			no limit																								
		init.	fixed																								
		locate	nest																								
			rand																								
	Comp	arch.	homo.																								
			hetero.																								
Strategy	Arch.	arch.	distrib.																								
			central.																								
	Coop.	motiv-ation	none																								
			food																								
			nest																								
			dist.																								
		achiev-ement	phero.																								
			direct																								
			chem.																								
			I_stor																								
	Communication	range	limit																								
			no limit																								
		info.	F_pos																								
			N_pos																								
			curr_pos																								
			grad.																								
		media	direct																								
			env.																								
		topo-logy	bcast.																								
			neighbor.																								
			spec.																								
		coord-inate	self.																								
			central.																								
	Sub-tasks	search	no-rdnd.																								
			rdnd.																								
			T_foll																								
			rand																								
			S-MASA																								
			beacon																								
			F_calcul																								
			I_stor																								
			A*																								
			follow																								
		grab.	indiv.																								
			coop.																								
		transp.	indiv.																								
			coop.																								
		homing	self																								
			beacon																								
			T_foll																								
			GPS																								
			A*																								
			I_stor																								
		recruit.	none																								
			direct																								
			indirect																								
Simulation	Performance	time	fixed																								
			min																								
			no limit																								
			rate_R_F																								
			avg_H_L																								
			food?																								
			pow_eff																								
			tot_pow																								
			pow_H																								
			srch_eff																								
	Simul	type	Continuous.																								
			Event.																								
			Tick.																								
			real.																								

motion. The algorithm provides faster foraging time when food is close to nest and slower foraging time when food is far away.

Alers et al. (2011) propose a foraging algorithm inspired by the biological bees' dance behavior. Agents share information about previous search experience as information vector (direction and distance toward food source); the other agents decide either to exploit previous search experience or to exploit their own search experience. Agents start all from the hive and use a random search procedure. They return home by following the homing vector stored in their memory. If the agent carries food then it communicates its vector of previous experience by means of a virtual dance. The hive collects these experiences and offers them to recruits. The latter work was enhanced in Alers et al. (2014) by using a swarm of robots with extended resources (see Table 2).

Table 2 Comparing some of the main related works based on their experimental characteristics

		Platform	Size and limits of the world	Number and nature of food	Max number of robots	Robot characteristics	Energy of the robot	Scalability	Performance metrics
Computer simulation									
	Hoff et al. (2013)	Own developed multi-agent simulator	10 m × 10 m continuous	One unlimited	20	E-Puck, sensors for nest, food, and obstacles in direct proximity, communicate with nearby robots, measure the range and bearing from which each transmission came. Robots do not have global position measurement or global communication	Unlimited	N/A	Food found or not, How quickly food is found, the rate at which it returned the food to the nest
	Lee et al. (2013)	Stage/Player	Circle of radius = 80 continuous	One food is generated at a random position per ten seconds	40	Agents can store information, sense locally their world and communicate with each other in unlimited range	Limited	Consider 25, 30, 35 and 40 agents	Energy efficiency
	Magdy et al. (2013)	Own developed multi-agent simulator	N/A	One limited at fixed position	50	Agents are Turing machine equivalent which can communicate with nearby robots	Unlimited	Consider 10, 20, 25, 30, 40 and 50 agents	Food found or not at limited time, speed to find food
	Pitonakova et al. (2014)	Own developed multi-agent simulator	4000 × 4000 continuous-space with periodic boundaries	Between 10 and 100 deposits with varied quality	100	Size 10 × 10 units, subsumption architecture, initially randomly oriented, carry one unit, odometry, memory to store energy efficiency of a deposits	Limited	Consider 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 agents	Proportion of collected food
	Simonin et al. (2014)	TurtleKit simulation platform	2D bounded grid of varied size 25 × 25 cells to 800 × 800 cells	20 with 10 units and 20 units each randomly distributed	160	Subsumption architecture, size of one cell, memory less, perceive the four neighboring cells, write on current cell integer value (APF value), read from cell, color trails with specific color, detect and follow trails, one cell can contain multiple agents	Unlimited	Consider 5, 10, 20, 40, 80 and 160 agents	Average foraging time

Table 2 continued

		Platform	Size and limits of the world	Number and nature of food	Max number of robots	Robot characteristics	Energy of the robot	Scalability	Performance metrics
	Zedadra et al. (2016)	Netlogo simulator	2D bounded grid of varied size 100 × 100 cells to 1200 × 1200 cells	1 to 10 sites with 500 to 1500 units	10,000	Subsumption architecture, size of one cell, memory less, perceive the four neighboring cells, deposit a pheromone on current cell, color trails with specific color, detect and follow trails, one cell can contain multiple agents	Unlimited	Consider 1 to 10000 agents	Average Foraging Time, Total Food Returned, Average Path Length
	Zedadra et al. (2016)	Netlogo simulator	2D bounded grid of varied size 100 × 100 cells to 1000 × 1000 cells	1 to 10 locations, each with 500 units	1000	Subsumption architecture, size of one cell, memory less, perceive the four neighboring cells, deposit a pheromone on current cell, color trails with specific color, detect and follow trails, one cell can contain multiple agents	Limited	Consider 100 to 1000 agents	Total energy consumed, energy efficiency
	Johnson and Brown (2016)	Enki 2.0 robot simulator	Circularly bounded 2D environment	Cylinders with a diameter of 10 cm	N/A	Enki's e-puck model which have a diameter of 7.4 cm, inter-wheel distance of 5.1 cm, and weight of 152 g	Unlimited	N/A	Cluster targets to specific location
Real experiments									
	Alers et al. (2014)	Turtlebot platform	Bounded 2D environment	One limited food	4	Turtlebot equipped with a laptop with a core-i3 CPU for computation, Kinect sensor, RGBD information used to detect and locate AR markers, wheel odometry and gyro information, six unique markers, toolkit called ALVAR, wi- with a UDP connection	Unlimited	N/A	Did robots converge to foraging
	Geuther et al. (2012)	Lego Mindstorms NXT kits	50x50 grid	Energy spots	Scouts: 25;Harvesters: 60	USB port and Bluetooth module to communicate with a central system, IR light sources, compass sensor	Unlimited	Varying scouts 5, 10, 15, 20 and 25; Varying harvesters 20, 30, 40, 50 and 60	Total energy harvested

Table 2 continued

	Platform	Size and limits of the world	Number and nature of food	Max number of robots	Robot characteristics	Energy of the robot	Scalability	Performance metrics
Pitonakova et al. (2016)	ARGoS simulation environment	Continuous space and updates itself 10 times per second, 50 m 50 m	N deposit with volume v and quality Q varied at each simulation	25	MarXbot robots, differentially steered with a diameter of 0.17 m, four color sensors pointed to the g round, 2 4 infrared proximity sensors, light sensor used for navigation towards the base, a range and b earing module, wheel-mounted sensors utilized for odometry and a ring of eight color LEDs used for debugging	Unlimited	N/A	Resource collected
Russell et al. (2015)	N/A	Continuous real world with 28 pre-deployed beacons	One food	8	Differential drive robots of authors own design, capable of grasping a single beacon, moving it from place to place, Arduino Uno micro-controller coupled with a Raspberry Pi Linux computer, outfitted with a camera, 802.11 wireless communication, USB interfaces, five Sharp IR infrared distance sensors, two simple bump sensors, two encoded wheels, an embedded gripper capable of collecting small cans, a flat push surface, and an I2C-driven display, outfitted with a Tmote Sky wireless sensor mote attached to the Raspberry Pi, sensor motes communicated over 802.15.4, channel 26, via UDP multi-cast	Unlimited	Varying 1, 2, 4, and 8 robots	Total food pellets gathered so far
Heinerman et al. (2016)	N/A	1 × 1 m arena	One target	6	Thymio II robot, seven Infra-Red (IR) proximity sensors for obstacle detection, differential drive with the maximum wheel actuators set between −500 and 500, a cam-era, wireless communication, and a high capacity battery, A WiFi dongle for communication, battery, allowing for a total experimental time of 10 hours, LEGO gripper	Limited	N/A	Number of pucks collected in ten-minute intervals

Lee et al. present in Lee et al. (2011) and in Lee et al. (2013) a honey-bee inspired model for foraging to improve the energy efficiency by dividing the search space and division of labor. Temporary stores at some fixed locations where used to store collected food. Robots can exchange food locations and they use GPS for homing.

Direct Ant Colony Foraging DACF2 and DACF3 are two ant colony foraging models proposed by Meng et al. (2012). The two models adapt (Panait and Luke 2004; Wilensky 1997) models respectively, by introducing direct interaction (via direct communication) besides indirect interaction (via pheromone). Agents record the last footmarks, the elapsed time since the ant leaves from nest or food $< tmpTime >$ and the ant's optimal evaluation value which is the minimal *tmpTime* of neighbor ants $< minTime >$.

Geuther et al. (2012) propose a dual agent Multi-Robot System for solving a foraging objective. They use scouts and harvesters to harvest energy positioned in clustered regions in the search space. Scouts use a Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) approach for searching and path planning. The Harvesters receive information from the scouts in the form of a matrix with the values of the sources at each point. Each robot uses an algorithm to check the grid to decide if it should move or stay. A centralized communication system is used.

Authors in Hecker et al. (2012) prove by computer simulations and real experiments that combining individual memory with communication can transform simple robots into effective swarms that are scalable and robust to the loss or malfunction of a few individuals. They propose an ABM which incorporates both shared and private information. It tests the ability of individual robots and teams of robots to collect RFID tags distributed randomly or in clustered locations in the environment. In Hecker et al. (2015), the algorithm is enhanced by using genetic algorithms to explore the system and to estimate the potential benefits of each of these sources of information in foraging on different distributions of food. Agents choose between pheromone trails (social information or recruitment) and private stored information to get to food locations.

Momen (2013) investigates whether the existence of biased brood carers has any impact on the performance of the colony. Agents switch between three tasks: *foraging, brood caring* and *resting* based on three thresholds. These latter are updated using two principles inspired by the behavior of many ant species used by Greene and Gordon (2007).

Chattunyakit et al. (2013) propose two decentralized foraging algorithms *Virtual Pheromone Field* (VPF) and *Sampling-Graph based Foraging* (SGF). The algorithms imitate swarm behaviors using a limited number of robots. In both algorithms, robots are equipped with extended resources. Random walk is adopted by the two algorithms at first stages of search and robots transmit at each step their current position to others. In *VPF*, robots build virtual pheromone trails when exploring and they use them for homing when a food is located. In *SGF* agents use A* algorithm and random walk to choose their path (for searching and for homing).

Letendre and Moses (2013) propose a foraging algorithm extended with a cluster-exploitation algorithm. Authors use a *Genetic Algorithm* (GA) to evolve a population of parameters that maximize the foraging efficiency. They conclude that there is synergy in the use of social and private information: ants with poor private information can

follow pheromone trails; while ants with better private information can ignore trails and instead rely on memory.

In Pitonakova et al. (2014) authors compare simulated robotic swarm of individualist and collective foragers. Authors prove that recruitment is useful when locating resources is difficult. Agents signal to each others the location of resources and return home on beacons. They use odometry to recognize their location and the food location. In Pitonakova et al. (2016) authors propose a foraging algorithm inspired by foraging bees. The environment used is divided into two regions (one is a dancing floor and the other is an unloading area). A light source is available to orient the robots towards the base. Multiple resources are in the environment and each one is surrounded by gradient color to help robots in localizing it. Robots have extended resources (see Table 2).

Simonin et al. (2014) propose a MAF algorithm called *c-marking agents*. This latter, is a parameter free, distributed and asynchronous version of the wavefront algorithm (Barraquand et al. 1992). Agents build simultaneously when exploring paths between food and the nest which results in an ascending Artificial Potential Field (APF). Agents need to revisit the same cell several times before the APF reaches its optimal value.

Improved Potential field-based PSO (IPPSO) is a foraging algorithm proposed by Cai and Yang (2014). It is applied to accomplish cooperative foraging tasks in completely unknown environments. The designed cooperation strategy can help the potential field to offer evaluation on the unexplored areas.

Bhattacharya and Vicsek (2014) treat the issue of how interactions between foragers influence their search efficiency by addressing a model for foraging in an environment highly variable in place and time. Foragers have local information about the distribution of targets and possess global information about the state of other foragers. They take initially random positions and they use random walk and targeted walks (following other agents to targets positions). As an extension to the latter work, Bhattacharya and Vicsek (2015) assume a finite interaction radius for the foragers rather than to be informed about the state of all other foragers. As a result, authors state that if the radius is small, then following other successful agents is always beneficial for a searcher. They find an optimal bound for this radius which depends on the density of agents. Exchanging information above this bound causes unnecessary aggregation in clusters of targets and reduction in efficiency.

Wireless sensor motes are tiny, low powered, wireless computers outfitted with an array of sensors and designed to run for months or years on batteries. Wireless sensor motes were used by Russell et al. (2015) as beacons that store several information (nest position, food position or wandering value). Robots can communicate with motes if they are in neighborhood, they are capable of picking up, moving and releasing a single sensor node in the environment, so to optimize them to shorten the trail between the nest and food. A robot can switch between foraging and ferrying food to nest. It updates the local gradients of all the pheromones based on new information. Authors use physical robot experiments and because of several physical limitations they also use computer simulations.

Collective behaviors such as aggregation to a target and foraging behavior achieved by a swarm of computation-free robots were investigated by Johnson and Brown (2016). They use simple robots that are memoryless, cannot perform computation and have

limited input/output capabilities. The fitness function used rewards behaviors that minimize the total distance between each object and the center of the cluster. This fitness function causes the robots to circle around targets and slowly nudge them into a central position.

Authors in Heinerman et al. (2016) investigate the ability of limited number robots to perform a foraging behavior in a limited time. Robots use a feed forward neural network controller. They communicate with all robots in the environment, can learn and communicate socially what they learn to other robots.

We investigated the MAF through several works. In Zedadra et al. (2012) and in Fortino et al. (2014), we used simple agents limited in sensors and processing abilities. Agents use pseudo random walk to search for food, they mark the environment with integer values while searching to build trails for homing. They cooperate through depositing pheromones when food is found to alert other agents in the neighborhood. In Zedadra et al. (2015), we proposed a MAF algorithm in which agents use Stigmergic Multi-Ant Search Area (S-MASA) algorithm proposed in Zedadra et al. (2014). They mark their search space with integer values, creating, simultaneously and synchronously while exploring, optimal paths to return home. We extended the algorithm by using dynamic marks rather than static ones in Zedadra et al. (2015). Agents use S-MASA for search and three kinds of pheromones. We extend the latter algorithm in Zedadra et al. (2015) to deal with energy limitations by providing agents with some behaviors to get home to recharge when their energy falls below a predefined threshold and we investigated the scalability of the extended algorithm in Zedadra et al. (2016).

Real robotic implementation of foraging agents

The foraging problem has been considered by lots of works. Computer simulations were frequently used due to: (1) several physical limitations on robots (battery life, sensors, memory, localization...) and on environment (size, complexity...); (2) physical experiments are too slow to gather more than a few runs per treatment, as it is discussed in Russell et al. (2015); (3) simulation before a real implementation is important in analyzing, understanding and improving the proposed approaches. Despite the proposed approaches, there have been no demonstration of autonomous multi-robot foraging in unknown or unstructured real-world environments and most of the works are to be found in research laboratories or at proof-stage.

Unfortunately, the unrealistic assumptions and the simplifications considered make the real implementation hard, as it is declared by authors in Kuyucu et al. (2012). In Beckers et al. (1994) and Svennebring and Koenig (2004) authors prove that stigmergic-based works (pheromone trails) have shown to efficiently coordinate a team of robots and to allow them to quickly explore a given terrain. Such approaches are not yet considered in real world because of the hard implementation of the pheromone. Several techniques for virtual marking have been considered [robots mark physically their trail via physical marks using: alcohol used by authors in Sharpe and Webb (1988), virtual marks proposed in Svennebring and Koenig (2004) or RFID tags used in Mamei and Zambonelli (2005), robots communicate a pheromone model using wireless network as shown inside (Vaughan et al. (2000)), robots transmit virtual pheromone using

infrared communication as in Payton et al. (2001), robots can switch to beacons or even use immobile beacons to communicate pheromone like information as used in Barth (2003)].

We compare in Table 2 some of the related works described in "Foraging related works" section. The latter ones are classified into two categories (computer simulations and real world experiments). We consider eight features to show the main differences between related works. To compare the complexity of environments we use two features (*Size* and *limits of the world*, *Number* and *nature of food*). One feature for robot capabilities and components (*Robot characteristics*), to test *Scalability* we use two features (*maximum number of robots* and *scalability*). *Energy* is a very determinant feature in robotic systems and we compare works based on this feature to show which of the works consider unlimited energy. We use *Platform* and *Performance metrics* to show which platform have been used specifically for simulation-based works and to show the gap between performance metrics used respectively. From Table 2:

- Columns two and three indicate that several configurations of the foraging problem have been considered, they are more complex in computer simulations, while in real experiments small bounded arenas have been considered and no outdoor, unknown and unstructured arenas have been considered;
- Scalability was considered also by simulation works rather than real experiments. In this latter, the maximum number of robots do not exceed 60 robot;
- In real experiments, robots are equipped with lots of idealized components (sensors, communication tools, unlimited energy...) even for simple robots;
- Each of the works (simulated or real) uses its own platform (Simulator or robot) and there exists no unified platform to be used by all of the works;
- Each of the works uses its proposed performance metrics which are different from the others. The difference between them makes the comparison of efficiency of MAF algorithms hard to do.

Heinerman et al. (2016): (1) declare that when considering multiple robots with sophisticated sensors such as cameras, simulations may actually run slower than real time, even for a group of small robots and (2) consider that experimenting with real robots encourages the researcher to review the robot's actual behavior during the experiments rather than allowing only post-facto analysis of the metrics gathered by unattended simulation runs.

Thus experimenting with real robots enhances the understanding of robot behavior. Researchers need to start experimenting on real robots in unknown and unstructured environments to prove the efficiency, the applicability and the reliability of the proposed approaches and to help in understanding the actual behavior of a swarm of robots in real world without any simplifications. Researchers can use agent programming methodologies and tools such the one proposed in Fortino et al. (2005, 2010, 2012, 2015), with PROFETA language presented in Fortino et al. (2013) to perform a rapid prototyping of their approach in order to investigate which design Band implementation choices are required before the real implementation. Also generic framework for distributed swarm computing can be used to model the swarm system as the one proposed in Bădică and

Bădică (2016). Finally, mobile agent systems (Aiello et al. 2009; Fortino et al. 1998, 2008) could be also exploited to implement real MAF systems.

Future directions

Collective foraging have been widely studied in literature. Foraging works consider two directions. The first focuses on proposing foraging algorithms (inspired from the auto-organized behavior of systems from biology and nature). The second concerns the real-world application of these algorithms. Current algorithmic approaches to Multi-Robot Systems are of a computational complexity which excludes their usage in non-trivial application scenarios. Moreover, many of these approaches are based-on unrealistic assumptions (simplifications on robot capability and environment structure). That is why the investigation and discovery of foraging algorithms still very interesting to converge to realistic solutions. Further trends to enhance the existing foraging algorithms include:

1. Stigmergy-based foraging algorithms are known to allow very efficient distributed control and optimization. The principal burden in these algorithms is the real implementation of the pheromone. Focusing and studying this latter burden, helps in deploying MAF stigmergy-based algorithms in real world.
2. Reducing the gap between simulations and real experiments by studying and addressing an approved list of platforms could help at implementing more realistic algorithms.
3. The diversity between existing foraging systems makes them difficult to carry out in a comparative study. Thus, an open foraging Framework is needed to unify the foraging systems.
4. The need for approved and agreed performance metrics to efficiently evaluate and compare the proposed systems.
5. Optimizing the Multi-Agent Foraging through a multi-objective function can produce more efficient and realistic algorithms.
6. Conventional single mode design strategies become less applicable in bio-inspiration design process and inspiring from the multi-locomotion mode of animals (helps in reducing energetic cost of locomotion, while still being capable of moving through unstructured and varied terrain) can lead to new sophisticated branch of robotic systems.

Even if there exists a collection of foraging algorithms evaluated with real robots, the need for using them on real applications or outdoor environments is important to validate them. The most challenging issue right now, is how to implement real foraging robots. Future directions or issues might include:

1. The design of the robot should inspire from the real individuals (e.g. ants). If we imitate the collective intelligent behavior of ants for example, we need to deeply study the design of ants in order to produce an Ant-like-Robot (material, shape, actuator,...) that could produce the same behavior in real world.

2. For Brooks (Brooks 1990), interactions over the real world are more difficult than reasoning in the symbolic world. Thus, it is time to start deploying the proposed foraging robots in real world in order to test their applicability and efficiency.
3. In designing micro-robots, energy and transport efficiency are of paramount importance.
4. Decentralized lightweight data mining algorithms could be fruitfully exploited to support the MAF system (Fatta et al. 2013).

Conclusion

Foraging is one of the active problems in the field of Multi-Robot Systems. It constitutes an abstraction of a large collection of real applications and can take inspiration from several domains. We are interested in this problem from several years and we proposed different foraging algorithms treating several aspects and difficulties in this problem. Phenomena and mechanisms associated with CAS include emergence, self-organization and self-assembly. One difficult question to study about CAS presented in Niazi and Hussain (2012) is how to design emergent behaviors and not a pre-programmed ones. The development of a simplified representation of the CAS helps in understanding its different aspects. Holland (2006) distinguished CAS by the extensive use of computer simulations as a research tool. Agent-based simulation is one of the techniques that serve as platforms for initiating the nonlinear characteristics of real-world complex systems presented in Niazi and Hussain (2012). Most of the works on MAF use agent-based simulations to represent a foraging system from different views and help at understanding the dynamic of the system when varying its parameters.

In this paper, we provided a vision on the foraging problem from different views and presented some tools that could help in understanding the foraging problem and introducing related works which could be a starting point for beginners as well as advanced researchers.

At first, we presented two classical definitions of the foraging problem. Then we gave our own definition to the problem from our vision and set out an abstract model based on a FSM representation. After that, we overviewed existing foraging and robotic systems taxonomies. We concluded that these taxonomies focus on particular aspects of systems and do not produce a complete and fair comparison of existing foraging works. Thus, we proposed a new taxonomy that overcome the latter issues. We presented this new taxonomy as a hierarchical graph including principal axes and descriptive features to each of them. We summarized the related foraging works and we verified the effectiveness of the proposed taxonomy through a comparison of existing works. We discussed the real implementation of MAF systems and we presented a comparison between simulated and real experimented related works. Finally, we presented some challenges and open issues that can help at enhancing the foraging systems and at conducting them to more realistic ones.

Authors' contributions

Each of the authors made the contributions in below: OZ (1) made contributions to conception and design, (2) drafting the manuscript, (3) acquisition analysis and interpretation of data, (4) made corrections; NJ (1) helps in acquisition of data, (3) revising the paper critically; HS (1) revising the paper for eventual faults, (2) contribution to the conceptualization of the comparison framework; GF (1) have been involved in drafting the manuscript, (2) revising it critically for important intellectual content or eventual typos, (3) supervised the whole work, (4) have given final approval of the version to be published. All authors read and approved the final manuscript.

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