Swarm robotics

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Swarm robotics is the study of how to design groups of robots that operate without relying on any external infrastructure or on any form of centralized control. In a robot swarm, the collective behavior of the robots results from local interactions between the robots and between the robots and the environment in which they act. The design of robot swarms is guided by swarm intelligence principles. These principles promote the realization of systems that are fault tolerant, scalable and flexible. Swarm robotics appears to be a promising approach when different activities must be performed concurrently, when high redundancy and the lack of a single point of failure are desired, and when it is technically infeasible to set up the infrastructure required to control the robots in a centralized way. Examples of tasks that could be profitably tackled using swarm robotics are demining, search and rescue, planetary or underwater exploration, and surveillance.

Origins

Swarm robotics has its origins in swarm intelligence and, in fact, could be defined as "embodied swarm intelligence". Initially, the main focus of swarm robotics research was to study and validate biological research (Beni, 2005). Early collaboration between roboticists and biologists helped bootstrap swarm robotics research, which has since become a research field in its own right. In recent years, the focus of swarm robotics has been shifting: from a bio-inspired field of robotics, swarm robotics is increasingly becoming an engineering field whose focus is on the development of tools and methods to solve real problems (Brambilla et al., 2013).

Characteristics of swarm robotics

A robot swarm is a self-organizing multi-robot system characterized by high redundancy. Robots' sensing and communication capabilities are local and robots do not have access to global information. The collective behavior of the robot swarm emerges from the interactions of each individual robot with its peers and with the environment. Typically, a robot swarm is composed of homogeneous robots, although some examples of heterogeneous robot swarms do exist (Dorigo et al., 2013).

Desirable properties of swarm robotics systems

The aforementioned characteristics of swarm robotics are deemed to promote the realization of systems that are fault tolerant, scalable and flexible.

Swarm robotics promotes the development of systems that are able to cope well with the failure of one or more of their constituent robots: the loss of individual robots does not imply the failure of the whole swarm. Fault tolerance is enabled by the high redundancy of the swarm: the swarm does not rely on any centralized control entity, leaders, or any individual robot playing a predefined role.

Swarm robotics also enables the development of systems that are able to cope well with changes in their group size: ideally, the introduction or removal of individuals does not cause a drastic change in the performance of the swarm. Scalability is enabled by local sensing and communication: provided that the introduction and removal of robots does not dramatically modify the density of the swarm, each individual robot will keep interacting with approximately the

same number of peers, those that are in its sensing and communication range.

Finally, swarm robotics promotes the development of systems that are able to deal with a broad spectrum of environments and operating conditions. Flexibility is enabled by the distributed and self-organized nature of a robot swarm: in a swarm, robots dynamically allocate themselves to different tasks to match the requirements of the specific environment and operating conditions; moreover, robots operate on the basis of local sensing and communication and do not rely on pre-existing infrastructure or on any form of global information.

Potential applications of swarm robotics

The properties of swarm robotics systems make them appealing in several potential application domains.

The use of robots for tackling dangerous tasks is clearly appealing as it eliminates or reduces risks for humans. The dangerous nature of these tasks implies a high risk of losing robots. Therefore, a fault-tolerant approach is required, making dangerous tasks an ideal application domain for robot swarms. Example of dangerous tasks that could be tackled using robot swarms are demining, search and rescue, and cleaning up toxic spills.

Potential applications for robot swarms are those in which it is difficult or even impossible to estimate in advance the resources needed to accomplish the task. For instance, allocating resources to manage an oil leak can be very hard because it is often difficult to estimate the oil output and to foresee its temporal evolution. In these cases, a solution is needed that is scalable and flexible. A robot swarm could be an appealing solution: robots can be added or removed in time to provide the appropriate amount of resources and meet the requirements of the specific task. Example of tasks that might require an *a priori* unknown amount of resources are search and rescue, tracking, and cleaning.

Another potential application domain for swarm robotics are tasks that have to be accomplished in large or unstructured environments, in which there is no available infrastructure that can be used to control the robots—e.g., no available communication network or global localization system. Robot swarms could be employed for such applications because they are able to act autonomously without the need of any infrastructure or any form of external coordination. Examples of tasks in unstructured and large environments are underwater or extraterrestrial planetary exploration, surveillance, demining, and search and rescue.

Some environments might change rapidly over time. For instance, in a post earthquake situation, buildings might collapse—thereby changing the layout of the environment and creating new hazards. In these cases, it is necessary to adopt solutions that are flexible and can react quickly to events. Swarm robotics could be used to develop flexible systems that can rapidly adapt to new operating conditions. Example of tasks in environments that change over time are patrolling, disaster recovery, and search and rescue.

Scientific implications of swarm robotics

Beside being relevant to engineering applications, swarm robotics is also a valuable scientific tool. Indeed, several models of natural swarm intelligence systems have been refined and validated using robot swarms. For example, Garnier et al. (2005) validated the model of a collective decision-making behavior in cockroaches using robot swarms.

Swarm robotics has also been used to investigate, via controlled experiments, the conditions under which some complex social behaviors might result out of an evolutionary process. For example, robot swarms have been used to study the evolution of communication (Mitri et al., 2009) and collective decision making (Halloy et al., 2007).

Current research

In this section, we follow the taxonomy presented in Brambilla et al. (2013).

Design

The design of a robot swarm is a difficult endeavor: requirements are usually expressed at the collective level, but the designer needs to define hardware and behavior at the level of individual robots. The resulting robots should interact in such a way that the global behaviour of the swarm meets the desired requirements. Approaches to the design problem in swarm robotics can be divided into two categories: manual design and automatic design.

In manual design, the designer follows a trial-and-error process in which the behaviors of the individual robot are developed, tested and improved until the desired collective behavior is obtained. The software architecture that is most commonly adopted in swarm robotics is the *probabilistic finite state machine*. Probabilistic finite state machines have been used to obtain several collective behaviors, including aggregation (Soysal and Sahin, 2005), chain formation (Nouyan et al., 2009), and task allocation (Liu and Winfield, 2010). Another common approach is based on *virtual physics*. In this approach, robots and environment interact through virtual forces. This approach is particularly suited for spatially organizing collective behaviors, such as pattern formation (Spears et al. 2004) and collective motion (Ferrante et al., 2012). Currently, the main limit of manual design is that it is completely reliant on the ingenuity and expertise of the human designer: designing a robot swarm is more of an art than a science. A systematic and general way to design robot swarms is still missing, even though a few preliminary proposals have been made (Hamann and Worn, 2008; Berman et al., 2011; Brambilla et al., 2012).

In swarm robotics, automatic design has been mostly performed using the evolutionary robotics approach (Nolfi and Floreano, 2004). Typically, individual robots are controlled by a neural network whose parameters are obtained via artificial evolution (Trianni and Nolfi, 2011). Evolutionary robotics has been used to develop several collective behaviors including collective transport (Groß and Dorigo, 2008) and development of communication networks (Huaert et al., 2008). One of the main limits of evolutionary robotics is that defining an effective evolutionary setting is often difficult and labor intensive.

Analysis

The analysis of a robot swarm usually relies on models. A model of a robot swarm can be realized at two levels: the microscopic level, that is modeling the behaviors of the individual robots; or the macroscopic level, that is modeling the collective behavior of the swarm.

Modeling the microscopic level involves forming a detailed representation of each individual robot in the swarm. Unfortunately, microscopic modeling is problematic due to the large number of robots involved. Often, microscopic modeling relies on computer-based simulations (Kramer and Scheutz, 2007; Pinciroli et al., 2012).

Macroscopic models avoid the complexity and scalability issues of having to model each individual robot by considering only the collective behavior of the swarm. One of the most common macroscopic modeling approaches is the use of *rate* or *differential equations* (Martinoli et al., 2004; Lerman et al., 2005). Rate equations describe the time evolution of the ratio of robots in a particular state, that is, of robots that are performing a specific action or are in a specific area of the environment. Rate equations have been used to model many collective behaviors, including object clustering (Martinoli et al., 1999) and adaptive foraging (Liu and Winfield, 2010). Another common approach is the use of *Markov chains*, which allow researchers to formally verify properties of a robot swarm (Dixon et al., 2012; Konur et al., 2012; Massink et al., 2013). Control theory has also been used to analyze whether a robot swarm eventually converges to a desired macroscopic state (Liu and Passino, 2004; Hsieh et al., 2008).

A hybrid way of modeling robot swarms is based on *Fokker-Plank* and *Langevin* equations (Hamann and Worn, 2008; Berman et al., 2009; Prorok et al., 2011). Using these equations, one can model both the behavior of the individual robot, in the form of a deterministic component of the model; and the collective behavior of the swarm, in the form of a stochastic component of the model.

Collective behaviors

A large part of the research effort in swarm robotics is directed towards the study of collective behaviors. Collective behaviors can be categorized into five main groups: spatially organizing behaviors, navigation behaviors, decision-

making behaviors, human interaction behaviors, and other behaviors.

Spatially-organizing behaviors focus on how to organize and distribute robots and objects in space. Examples of such behaviors are aggregation (Soysal and Şahin, 2005), pattern formation (Spears et al. 2004), chain formation (Nouyan et al. 2009), self-assembly (O'Grady et al., 2010), and object clustering/assembling (Werfel et al., 2011).

Navigation behaviors focus on how to coordinate the movement of a robot swarm. Examples of such behaviors are collective exploration (Ducatelle et al., 2014), collective motion (Turgut et al., 2008), and collective transport (Baldassarre et al., 2006).

Collective decision-making behaviors focus on how robots influence each other in making decisions. In particular, collective decision-making can be used to achieve consensus on a single alternative (Garnier et al., 2005; Campo et al. 2011) or allocation to different alternatives (Pini et al., 2011).

Human-swarm interaction behaviors focus on how a human operator can control a swarm and receive feedback information from it. For example, robots can distributedly recognize the gestures of a human operator (Giusti et al., 2012) or form groups based on visual and vocal inputs (Pourmehr et al., 2013).

Other behaviors that do not fall in the previously mentioned categories are collective fault detection (Christensen et al. 2009) and group size regulation (Pinciroli et al, 2013).

Open issues

Despite its potential to promote robustness, scalability and flexibility, swarm robotics has yet to be adopted for solving real-world problems. Various limiting factors are preventing the real-world uptake of swarm robotics systems. Further research is needed on robotic hardware to overcome hardware shortcomings that limit the functionality of current robotic systems, while further research on behavioural control is needed to discover effective ways to let a human operator interact with a robot swarm. More effort is required to provide compelling case-studies—in particular to demonstrate swarm robotics in outdoor applications (e.g., waste removal), but also to develop business cases and business models that show how and where swarm robotics can be more effective than other approaches. Finally, an engineering methodology is still lacking for swarm robotics systems, which would include the definition of standard metrics, performance assessment testbeds and formal analysis techniques to verify and guarantee the properties of swarm robotics systems.

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External links

- Swarm Intelligence (http://www.springer.com/11721) : The main journal in the field.
- *ANTS - International Conference on Swarm Intelligence* (http://iridia.ulb.ac.be/~ants) : This series of conferences, held for the first time in 1998, is the oldest in the swarm intelligence field.
- *IEEE Swarm Intelligence Symposium* (http://www.computelligence.org/sis/2006/past.php) : Another series of conferences dedicated to swarm intelligence, started in 2003.
- Swarm-bots (http://www.swarm-bots.org/) : research project 2001-2005
- ARGoS (http://iridia.ulb.ac.be/argos/) : A multi-robot, multi-engine simulator for heterogeneous swarm robotics
- Swarms (http://www.swarms.org/) : research project 2003-2007
- i-Swarm project (http://www.i-swarm.org/) : research project 2005-2008
- Swarmanoid (http://www.swarmanoid.org/) : research project 2006-2010
- Symbrion (http://symbrion.org/tiki-index.php) : research project 2008-2013
- E-SWARM (http://www.e-swarm.org/) : research project 2010-2015
- Kilobots (http://www.eecs.harvard.edu/ssr/projects/progSA/kilobot.html) : a low-cost robot for swarm robotics

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