Designing Robot Swarms and Bio-hybrid Systems for Adaptivity and Robustness

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Decentralized self-organizing large-scale systems, such as robot swarms (Hamann, 2018), can be designed to be adaptive, robust, and scalable. However, developing robot and system behaviors that are robust and adaptive to dynamic environments, dynamic system size, and faults is still challenging. We study a swarm showing robust scalability. The swarm needs to detect the change in its environment or in the system size, assess the quantity of the change, and appropriately adapt parameters of its control algorithm. In a second part, we discuss bio-hybrid systems of natural plants interacting with robotic nodes. In the studied example, robotic devices are used to steer the growth of natural plants by exploiting their adaptive behaviors. We use methods of machine learning to model natural plants and to guide their growth and motion with an autonomous system. In bio-hybrid systems, we can exploit natural adaptive behaviors to build, for example, systems that self-repair.

Adaptivity in Swarm Robotics

Swarm robotics is claimed to have the advantage of high robustness against failures (Brambilla et al., 2013). Their high degree of redundancy helps to overcome failures, such as breaking robots. Similarly, swarm robot behaviors are claimed to be scalable to different swarm sizes and sometimes also to different swarm densities (robots per area). High degrees of scalabilty can be achieved as swarms rely on local information and local communication only and has been shown in experiments (Rubenstein et al., 2014; Hamann, 2018). We also know that optimal swarm densities exist for many systems of swarm robotics (Hamann, 2013). However, if robots break at runtime, then the swarm density changes and the swarm possibly requires online scalability to remain efficient. We require the swarm to be robust against dynamic swarm sizes which can be called 'robust scalability.' If the swarm size changes, then each robot may require to change its behavior at runtime, for example, by adapting parameters of its control algorithm.

Wahby et al. (2019) present an aggregation experiment with $N = 10$ swarm robots. The robots' task is to aggregate at light spots and each robot needs to adapt to a dynamic environment (location and intensity of light spots changes). In an additional experiment, the robot swarm is halved and reduced to swarm size $N = 5$ during the experiment. For both adaptation to dynamic environments and adaptation to dynamic system size, the robots face an interesting and fundamental challenge. The adaptation can either be fast or accurate. A fast adaptation needs to be sensitive to any detected change that needs to be considered a precursor of changes requiring adaptations in the robot behavior. However, if we require a robust adaptation process, then robots need to avoid false positives (reacting to a change where there was no change). This is a tradeoff where improving in one capability results in worsening the other. Wahby et al. (2019) resolve that challenge by periodical measurements of environmental features (e.g., light) and other features (e.g., times between robot-robot encounters) indicating swarm density. These measurements are averaged over a limited time window and directly influence control parameters of the robot. Hence, the robots do not explicitly react to a detected change but forget old measurements that were recorded before the change. Besides measuring light intensities and remembering maximum/minimum light intensities, robots measure the time t_a between two encounters of a wall and the time t_r between two encounters of a robot. If we assume a regular floor plan (e.g., rectangular) without many obstacles (except for other robots), then the time between encountering walls indicates the side length and hence the area of the room. The time between encountering other robots is similar to a mean free path and indicates the robot density. The distribution of measured times between robot-robot encounters is similar to an exponential distribution and its mean, for example, drops significantly if the robot density is halved. Robots meeting robots on a light spot stay stopped for waiting time w. The time w is a parameter of the control algorithm that depends on these measured values. w is scaled proportionally to the measured time t_r. Measured time t_a was not used here as the area remained constant in this experiment. The results indicated that robots adapt successfully to a change of system size from $N = 10$ to $N = 5$ at runtime and outperform a swarm that was optimized offline for $N = 10$.

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Robustness in a Bio-hybrid System

Bio-hybrid systems combine living organisms with technology. Here, we combine natural plants with robot-like units. Key of the bio-hybrid approach is that we get 'life-like' features almost for free instead of trying to mimic behaviors of living organisms in a purely technological approach. An advantage is, for example, that a bridge built from living plants reinforces itself and grows stronger over time instead of decaying slowly but inevitably (Shankar, 2015). A challenge is that we need to understand how to interface the plants and how to exploit their natural adaptive behaviors. In the EU-funded project *flora robotica*, we have developed a bio-hybrid system of living organisms and robotic devices to steer and guide the growth and motion of natural plants (Hamann et al., 2015). We use the phototropism (growth towards light) and the thigmotropism (growth guided by touch, for example, in climbing plants) of plants. Bright blue LEDs are used to attract plants and scaffolds can be used to determine the growth options of climbing plants (Wahby et al., 2018a). Here, we shortly discuss two experiments: (A) high-precision control of growth and motion of a single plant using a single robotic device and (B) growth of a pattern by guiding a small group of plants using multiple robotic devices.

In experiment A, we use a simple setup with one plant (common bean), two lights (left/right), and a camera. We allow a user to define target points in 2-d space that the plant's tip should visit during the experiment (Wahby et al., 2018b). Our tool-chain to solve this engineering task is rather complex. We start from a dataset obtained by preliminary experiments where the two lights are switched on/off in a regular sequence. The plant is photographed every five minutes. Using computer vision, we extract data that represents the plant's reaction to given light conditions and a previous stem configuration (e.g., length, bend). With that data we train an LSTM network to obtain a holistic plant model that predicts the plant's reaction for a given configuration. We use the LSTM network and methods of evolutionary computation to evolve a controller that takes the plant's configuration, the light condition, and the user-defined target points as input and outputs the desired next configuration of the lights. In a last step, we use the light controllers that performed well in simulation to control a real plant and find that they succeed despite an expected reality gap (Jakobi et al., 1995).

In experiment B, we support the growth of a group of bean plants with a scaffold in the form of a diagrid. In the bifurcation points we place eight robotic devices that use proximity sensing to detect a close-by plant and that have red and blue bright LEDs (Wahby et al., 2018a). These robotic devices can also communicate between each other using WLAN. The task is to grow a user-defined pattern along the diagrid. The pattern is defined and programmed into the robots. After planting several bean plants, the autonomous system controls the remaining process. A first robot α in the user-defined pattern turns on its blue LEDs to attract the plants. Once α detects the first close-by plant, α communicates with the next robot β of the programmed pattern. α turns off its blue LED and β turns its blue LED on. This process repeats until the plant approaches the last robot in the sequence and the pattern has been grown. An experiment takes several weeks and was repeated successfully.

In future work, we plan to show a robust bio-hybrid system with the capability of self-repair. We want to scale up one more step (dozens of plants and 18 robotic devices) and to use a more complex scaffold. After having grown the plants for several weeks, we plan to punch a whole into the scaffold. The system is then expected to regrow that part while keeping other areas (e.g., windows) unobstructed.

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