Crossroads
The ACM Student Magazine

Hungry Robots

by ***Tony Belpaeme*** and ***Andreas Birk***

Introduction

Artificial intelligence (AI) has been studied for more than fifty years and is an established specialty within computer science. A recent sub-specialty of AI is **artificial life**, also known as **alife**. Although alife research can be traced back to the 1960s, it has only found prominence in the last decade. Artificial life studies have two main goals: solving common problems inspired by biological phenomena and studying the basic properties of life with computer-based technology [10]. The first goal has been dubbed the "artificial life route to artificial intelligence" [20], emphasizing the relationship between a novel way of building and programming machines and the study of life through artifacts. While studying biological phenomena, some scientists in the field use animats as their research tool [25]. An animat is a robotic device whose physical appearance and inner workings are inspired by the animal world. (The word **animat** is a contraction of animal robot.)

In the mid-1980s, AI and robotics researchers began arguing against "classic" approaches that relied on symbolic representations and methods [5]. One researcher, Rodney Brooks, advocated new research questions and methods. Instead of building intelligent systems by solving abstract and highly formalized problems such as computer chess programs, he argued in favor of building intelligent robots that were inspired by nature. In doing so, he stressed the importance of reactive mechanisms and discouraged the use of models of the world: "the world is its own best model"[6]. These reactive mechanisms have a tight coupling between sensor values and motor activations and have no central control. Alife robots typically are controlled by short programs, without a central controller organizing the execution of the programs; each program is responsible for a specific behavior of the robot such as avoiding obstacles or seeking an energy source. These robots and the way they are programmed are therefore called **behavior-based**.

Interestingly, the study of animats returns robots to their roots. The term "robot" was introduced in 1921 by the Czech writer Karel Capek in his satirical drama *R.U.R. (Rossum's Universal Robots)*. There, robots were shown as artificial super humans. The science-fiction notion of a robot as a human-shaped device with seemingly unlimited strength and intelligence has over the years been replaced by the industrial notion of a robot as a dumb and bulky piece of machinery. Recently, the two disparate notions of a robot have begun to merge. The Sony Aibo dogs are a fine example of the convergence of super-device and drudge machine [**7**]. These mass-produced toy robots use considerable computing power, a camera, microphone, and touch-sensors to interface with the world.

In this article, we first introduce three basic properties of behavior-based robots. Then we describe a prototype alife experiment with an ecosystem of different types of robots competing for energy. We also explain why we found diverse collections of robots more interesting to study than single robots.

From Robots to Animats

Sometimes behavior-based AI is denoted as the bottom-up approach to AI. Behavior-based AI often focuses on systems that might be considered to be non-intelligent. Simple creatures, such as insects, and their behavior are investigated before more sophisticated animals. Although "simple," these creatures have inspired scientists to elegantly solve problems that are awkward or difficult to solve with classic computer science. The study of ant behavior, for example, has led to very efficient solutions for controlling digital network traffic.

This tendency to study simple organisms is also reflected in robotics activities. The robots used in artificial life are often rather uncomplicated and do not match the science-fiction vision of a robot that serves tea or solves world problems. Despite their simplicity, behavior-based robots or animats usually have three important properties:

- They are highly autonomous.
- They come equipped with complex sensor and motor-interfaces.
- They are integrated within an environment.

The word **autonomy** is derived from the Greek words auto (self) and nomos (law, rule). So, an autonomous system is a self-governed system. Loosely interpreted, autonomy can be seen as the independence of a device from direct and continuous human supervision and maintenance. Often, autonomy for robots is set at par with being mobile without an umbilical cord that connects the robot to a power supply and sometimes to an off-board computer. But this view is too simplistic: the robot should also have control autonomy, allowing it to decide and learn without much external aid.

Autonomous robots face two major problems. First, they have to adapt to novel situations. Second, they have to manage resources, such as energy. Both problems can be related to the so-called self-sufficiency of animats: they have to be able to sustain themselves over extended periods of time [18].

An animat is said to perform well when it manages to stay operational autonomously. Its performance is considered poor when it runs out of energy or breaks apart. This idea can be traced back to the field of cybernetics, which originated in the 1940s [24]. The cybernetician W. Ross Ashby formalized this idea as early as 1952 by introducing the notion of essential variables [1], the state variables that ensure successful operation as long as they are kept within the crucial boundaries or the viability zone of the agent's state space.

Classic robots are based on precise mechanics, which are necessary because the robots rely on exact models to describe and compute their kinematics. In contrast, behavior-based robots are more like natural devices. Their control schemes rely more on mechanisms and rules of thumb for their behavior. The Sony Aibo dog [7], for instance, consists of simple motors targeted for the toy market. Nevertheless it has very complex motor skills, as it is capable of walking on four legs, each of which has three degrees of freedom (DOFs). Each DOF corresponds to one free parameter in the physical device. A door hinge, for example, has one DOF. Hence the legged motion of the four-legged robot has to cope with a total of twelve DOFs, compared with the five to six DOFs of a typical industrial robot arm. Each DOF adds an extra possibility to the configuration of the system, and often more than one way exists to place a paw on the floor. Computing the most efficient way is a daunting task in robotics.

Behavior-based robots cannot rely on precise, complex models. Instead they are controlled with simple programs. Fortunately this means that their need for computational resources is small. Instead of intensive calculations of inverse kinematics, simple couplings between sensor-values and motor-activations are used. But how is it possible to save on the electro-mechanical and on the computational side? Where is the trade-off?

To some extent the trade-off is simply hidden in the kind of tasks classic and behavior-based robots are suited for. If very precise, repeated positioning is needed, classic robotics is ideal. On the other hand, for other tasks, behavior-based robots are often the more competitive option because they strongly benefit from developments in sensors, especially in computer vision and motors. More and more types of sensors are available at constantly dropping prices. Therefore they can be used as the basis for additional behaviors, increasing the robustness and usefulness of the robot. Camera-chips, for instance, which are primarily targeted at the entertainment and toy market, can be used for computationally inexpensive visual servocontrol compared with more common kinematic controls such as gyros or position sensors.

Last but not least, an animat is typically not seen as an isolated device but as part of an environment. This is discussed in some detail in the following section.

Living on your own?

Ecosystem-like settings are interesting from an alife perspective. Within ecosystems, the main goal of a robot is self-preservation (staying operational for an extended period of time [**16**,**20**]). Resources, especially energy, are limited in time and space. Consequently, robots must compete for them. Consequently, competition forms the basis of all robot interactions in the system. There is a substantial amount of alife research based on simulated ecosystems [**2**,**4**,**11**,**12**,**21**,**23**]; however, unlike the ideas presented above, perception and effector-control of the agent are decoupled from the real world.

The basic ecosystem located at the Flemish Free University of Brussels (VUB) [**19**,**14**] is a 5 m X 3 m space enclosed by walls (**Figure 1**). Initially it includes simple mobile robots, the *moles* (**Figure 2**). The name of this robot "species" as well as the following ones should not be taken too literally. Note that the names are used for convenience only and are not meant to imply direct relations to the natural counterparts. The name "mole" is derived from the limited vision capabilities of the robots, who can only perceive light intensities through a few simple photosensors. The photosensors, positioned at the front of the robot, are used to navigate and to find objects in the ecosystem.

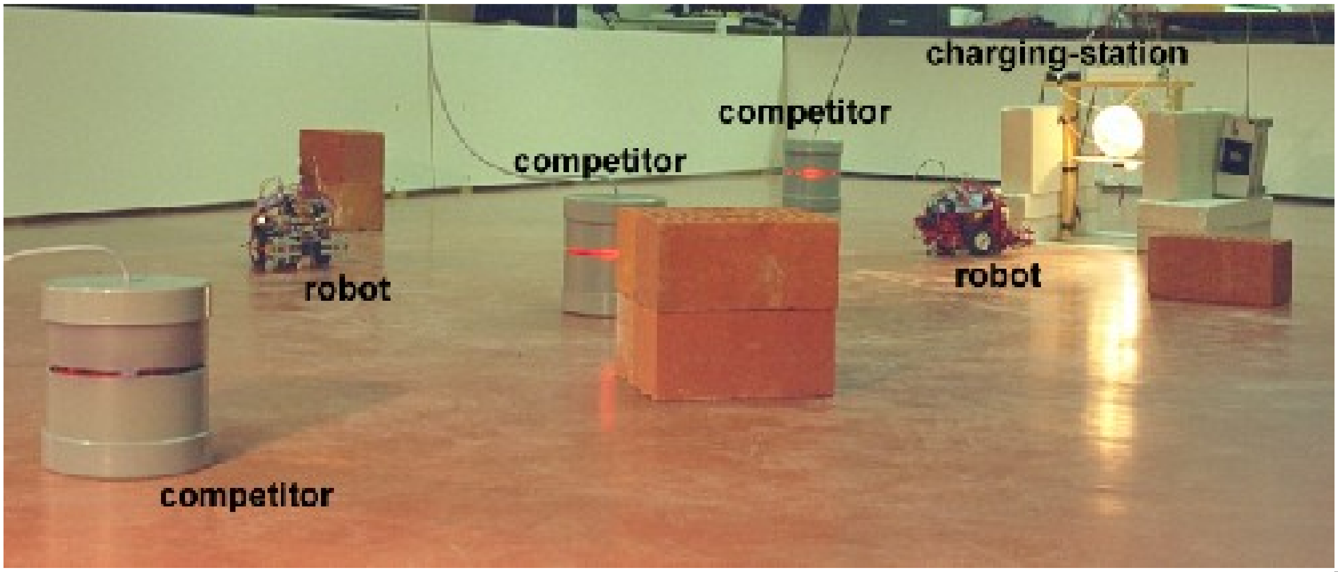

Figure 1: A part of the basic ecosystem with charging station, two robot moles, three competitors, and several bricks as obstacles.

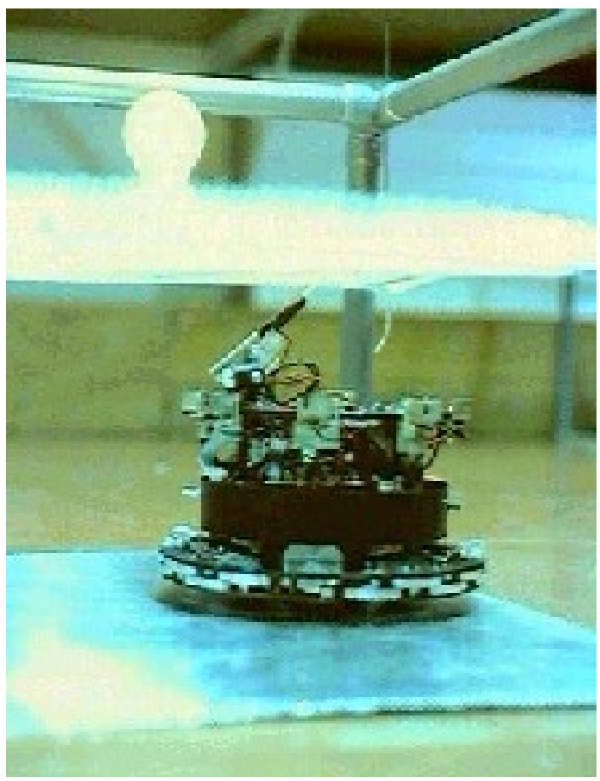

Figure 2: A so-called mole, a simple autonomous robot that is capable of staying operational in the ecosystem over extended periods in time. Illustrated here is one of its basic behaviors: photo taxis (movement in response to light stimulus) to the charging station to recharge its batteries.

The arena also contains a charging station, where the robots can autonomously recharge their batteries. The robots drive into the charging stations and make contact with conductive plates that connect them to the energy source. This electrical energy is *food* for robots. The robots constantly monitor their energy level and in this way know when they are hungry. The robots' whole world revolves around earning and competing for the electrical food. There is a limited amount of food in the ecosystem. Also, the ecosystem contains competitors: small boxes that house lamps emitting a modulated light. These lamps are connected to the same global energy-source as the charging station; they therefore feed on the same source as the robots. The robots must knock out the competitors (**Figure 3**). If a robot knocks a competitor several times, the lamps inside the competitor dim, and the robot has an additional amount of energy at its disposal from the charging station. After a while, the competitor recovers and the lamps inside return to their default intensity. The competitors establish a kind of work task for the robots that is paid in electric energy.

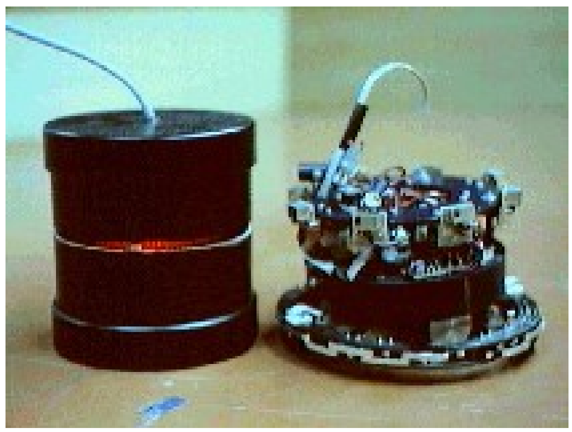

Figure 3: Moles exhibit photo taxis to competitors, which results in "fighting" behavior.

Research on robotic ecosystems usually deals with homogeneous agents [**8**,**13**,**17**,**22**], which is also the case for the ecosystem described above. A heterogeneous set-up, in contrast, is more interesting for several reasons. First, heterogeneity substantially adds to the complexity of the environment, which is of key interest to alife-oriented research [**9**,**25**]. Second, artificial ecosystems with just one species are hardly biologically relevant [**15**]. The extended ecosystem features a new inhabitant in the form of the so-called *head*, which consists of a camera on a pan-tilt-unit and substantial vision capabilities (**Figure 4**). However, as it is fixed to its position, the head cannot access the charging station, and it is forced to cooperate with the mobile moles. The head can track mobile robots, and it can perceive pitfalls that partially discharge the batteries of the mobile robots and diminish their chance of survival. When a mobile robot approaches a pitfall, which it cannot distinguish from the charging station, the head can warn the mobile robot. The mobile robot in exchange can share the benefit of the saved energy with the head.

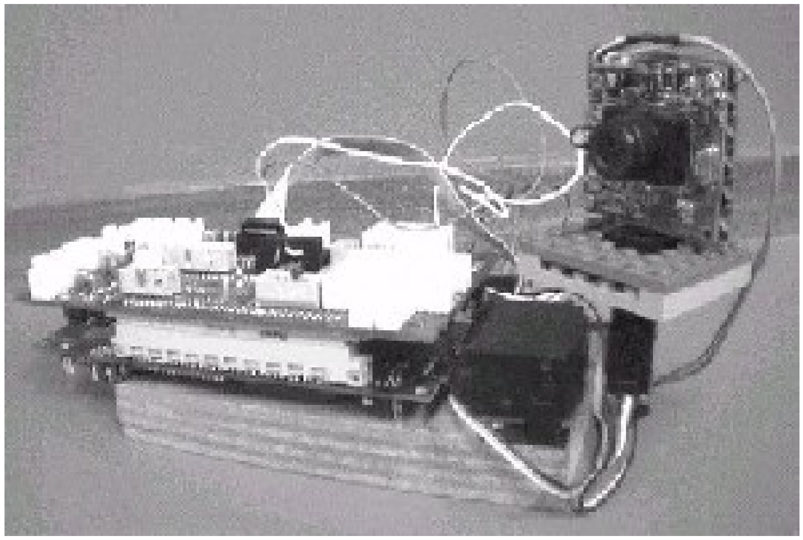

Figure 4: The head, an immobile robot with strong vision capabilities. It is forced to cooperate to receive food in the form of electricity.

This scenario can be used to study the origins of cooperation and trust between *agents* [3]. The agents probe each other for trustworthiness. This trustworthiness can not be directly observed, so the agents have to use trial and error to find trustworthy agents. When a reliable partner has been found, cooperative behavior between the two agents results. On the other hand when an agent proves untrustworthy, for example, by defecting in a prisoner's dilemma interaction, other agents in further interactions will shun it. The agents learn which agents are to be trusted by receiving a pay-off for their actions. It is remarkable that these relationships develop just through interactions with other agents and without the need for strict protocols. When a stable equilibrium is reached in the agents' relations to each other, they manage to survive in the ecosystem for a much longer time than they would on their own. Simulations have shown that this approach scales up, but the time it takes before the ecosystem reaches a stable state increases exponentially with the number of agents. Robotic agents could conceivably take too much time to explore their relation to others and run down their batteries before they achieve any success.

Recent developments have also shown that communication between robots is very important; robots need to be able to share information and intentions. And they have to negotiate their relationship with each other: "I will show you a food source! Let me warn you of danger! What will you give me if I do this?" Recently scientists have started to study how robots can construct a primitive language to communicate exactly these kinds of concepts. Imagine the power that lies in robots teaching new behaviors or the topography of an unknown environment to each other in a teacher-apprentice relationship.

Conclusion

Animat research provides an elegant and tangible way to study natural phenomena such as self-preservation and cooperation. It also allows for hands-on experiments with systems in real and noisy environments, and gives researchers insights unattainable by computer simulation. In most animat research, the emphasis has been on homogeneous robot experiments, where all robots joining in an experiment have the same physical and cognitive capabilities. Heterogeneous robots, robots that have different physical structures and competencies, provide a more realistic way of studying natural ecosystems and allow one to study more complex interactions such as symbiosis, cooperation, and competition between different species. Future animat research may lie in the heterogeneity of the robots and in robot communication.

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Biography

Tony Belpaeme (**tony@arti.vub.ac.be**) is a full time researcher at the **Artificial Intelligence Laboratory** of the **Flemish Free University of Brussels (VUB)** where he studies active robot vision, concept formation and linguistic influences on concept formation. He is a research assistant of the Fund for Scientific Research - Flanders (Belgium) (FWO).

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