

## Chapter One

# Collective Systems in Space and for Planetary Explorations

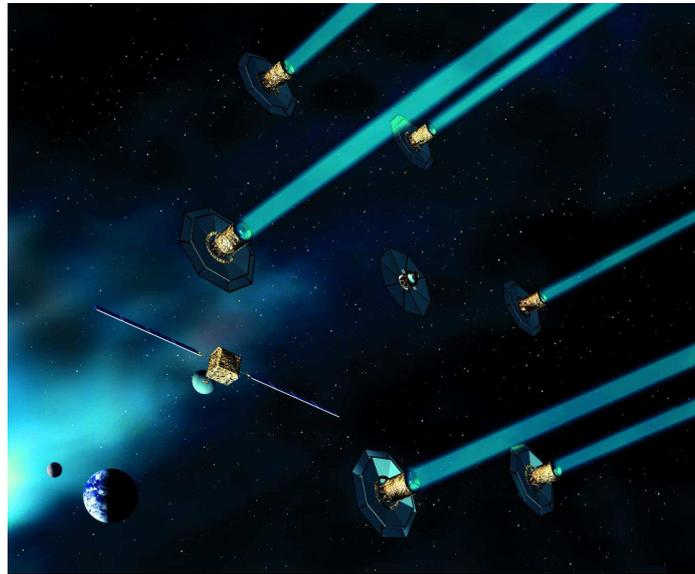
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### 1.1 Collective Systems in Space

In an issue of the *Wireless World* magazine, back in 1945, A. C. Clarke on a letter to the editor wrote “However, I would like to close by mentioning a possibility of the remote future-perhaps half a century ahead... Three repeater stations, twelve degrees apart in the correct orbit, could give television and microwave coverage to the entire planet.” These words envisioned, before the space era even started, the now overcrowded geostationary orbit, while also introducing one of the most lucrative commercial applications of the space business: telecommunications. It is worth noting in this context, how this early space mission concept made use of multiple satellites to achieve its goal. Twenty years later, the space era actually began with the successful launch of the Russian satellite *Sputnik I*. In the following years, many missions have been proposed, designed and realized that make use of multiple satellites, probes, planetary rovers, robots or, in general, of what can be called “space agents” to underline the connection to multi-agent-systems research. The European Space Agency (ESA) mission named *Cluster II*, currently orbiting around our planet, is made of four identical satellites that need to accurately fly in a tetrahedron formation during part of their orbit. This particular geometry allows for the determination of three-dimensional and time-varying phenomena related to the Earth’s magnetic field. Several satellite constellations, among which the currently active *GPS*, *Globastar* and *Iridium*, but also the planned *European Galileo* and *Swarm* constellation are formed of many identical spacecrafts (up to 50) that achieve a common overall objective thanks to complex orbital and communication strategies. The *Teledesic* innovative and ambitious project (involving contributions from *Bill Gates* and *Paul Allen*, but canceled in 2001) considered, at a certain point, to employ 840 active identical satellites orbiting around the Earth

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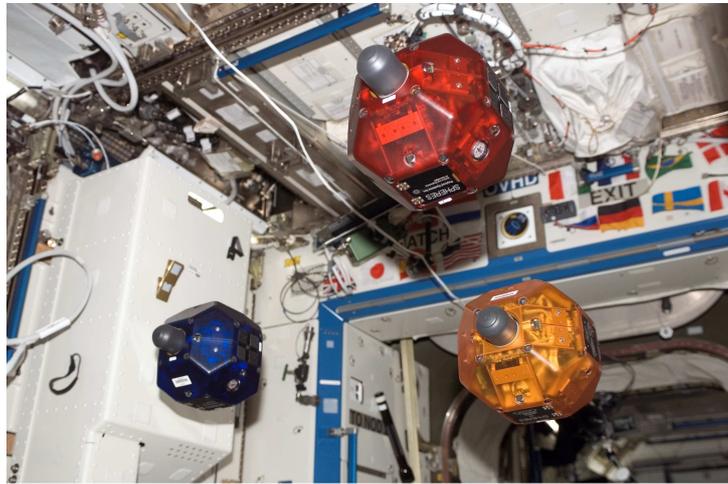
to provide a global Internet service. In the United States, the National Aeronautics and Space Administration (NASA) is working on a mission called Terrestrial Planet Finder (TPF), a mission consisting of five separate spacecrafts working together to function as one single huge telescope, likewise the considered ESA science mission named Darwin (see Figure 1.1.). The NASA rovers Spirit and Opportunity are currently performing a collective exploration of the martian planetary surface [Squyres (2005)] while allowing scientists to test sophisticated intelligent algorithms [Estlin *et al.* (2007)]. The ESA technology demonstrator Proba 3, currently in its design phase [Borde *et al.* (2004)], requires two heterogeneous satellites to acquire a quite complex and coordinated orbital movement with one satellite partially “shadowing” the second, allowing a solar coronagraphy experiment. A possible architecture of a human mission to Mars involves an in-orbit assembly of several heterogeneous components launched separately (this scenario was touched upon by the Concurrent Design Facility at ESA during the early architecture study of the Human Mission to Mars). These are only a few selected examples of space missions that need the coordination between two or more satellites to achieve their overall goal and that have been already developed beyond a purely conceptual design. This last criterion partitions the set of all the ever conceived space missions into quite distinct classes. It is no surprise that interesting missions belong also to the other class, the one often including concepts far fetched in the future, concepts that are typically attracting smaller investments as they currently fail to be economically viable or to have an appropriate technological readiness level. These include the homogeneous in-orbit assembly concept, where several identical spacecrafts assemble a large structure (e.g. a reflective mirror or a gigantic solar panel made of 861 elements placed in an hexagonal lattice [Izzo *et al.* (2005)]), the fractionated spacecraft [Mathieu and Weigel (2005)] where one whole spacecraft is substituted by independent heterogeneous modules carrying out specialized functions in coordination, the Japanese Petsat project [Nakasuka *et al.* (2006)] where the spacecraft is essentially made of LEGO type modules that can assemble in different types of shapes and reconfigure to carry out different tasks, the APIES mission [D’Arrigo and Santandrea (2003)] employing a swarm of spacecrafts to collectively explore the asteroid belt, the early NASA ANTS concept [Curtis *et al.* (2000)] and the many concepts on planetary exploration that involve multiple probes and rovers collectively performing tasks on planetary surfaces and atmospheres. It is worth to highlight the work done at the Massachusetts Institute of Technology in the framework of the project named *SPHERES* that considers, as objective, to develop and test sophisticated algorithms to achieve precise autonomous coordinated movement of three metal spheres placed in a zero-gravity environment. The three spheres are built (see Figure 1.2.) and, as of 2006, are functioning on board the International Space Station (ISS). A program to upgrade the hardware with cameras is ongoing and the *SPHERE-Zero-Robotics* initiative will soon provide students with access to a microgravity environment for experimentation and analysis. A number of papers [Mohan *et al.* (2009); Saenz-Otero *et al.* (2009); Nolet *et al.*] published recently report on the most significant advances obtained.



**Figure 1.1.** One of the early designs of the mission Darwin [Illustration by AOES Medialab]. The six-telescope infrared interferometer was proposed by European astrophysicists to study the atmospheres of exoplanets.

Many other examples exist and it may be useful to attempt a coarse categorization of mission concepts making use of the cooperation among multiple space agents useful to delineate those areas where current research trends seem to be focusing. A first division can be made between orbital, atmospheric and planetary collective systems. Orbital collective systems are quite unique because of the environment they move through, and they are typically asked to perform tasks such as self-assembling a large structure, flying in formation or providing a global and continuous monitoring of the planet, asteroid or spacecraft they fly around. The self-assembly task has, in space research, a particular appeal as it represents one possible solution to the problem of deploying large structures in orbit. As we do not have the technology to build a large structure on Earth and then launch it to space (launchers capabilities in terms of both mass and volume are often limited), we must consider to assemble it directly in-orbit. This was, for example, the case for the International Space Station (ISS), where assembly was done in-orbit employing many hours of astronaut Extra Vehicular Activity (EVA) and a substantial on-ground operational effort. In this perspective, any achievable autonomous collective behavior that could help such a process is desirable: from a simple 'remain grouped and avoid collisions' behavior to 'acquire a defined pre-assembly geometry' to the most difficult and complex 'self-assemble the entire final structure'. Atmospheric and planetary collective systems share similar tasks with their Earth counterparts (exploration, identification, patrolling), but they need to function in entirely different environments where gravity, temperature, power availability and atmospheric composition are different and uncertain.

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**Figure 1.2.** The MIT SSL SPHERES testbed on board the ISS [NASA].

### 1.2 Challenges

The examples presented in the previous section show how collective systems have always been in the research and development agenda of space research. Typically, the control methodology considered for these systems relies on complex ground operations which are i) extremely expensive due to the need of man-power and ii) impractical for some more ambitious missions due to the communication constraints imposed by the huge distances involved. While ground control for a collective mission to the Moon may be considered possible due to relatively small signal delays, the same might not be true for a mission to Mars or to Jupiter. An obvious solution to cut down on costs related to man-power and to enable ambitious space programs is to increase the autonomy level of these collective systems: a goal pursued by some of the reserach programs mentioned earlier. The challenges to face when designing autonomous multi-agent systems have been well outlined in previous chapters of this book; however, in case of space systems one needs to face additional ones specific to the space environment. First, the same yet unanswered question pertains for collective systems in space: how do we design the behavior rules at the level of the individual that give rise to a desired collective behavior (and in particular one that is useful in space)? In other words, how can we identify the local rules leading to the emergence of a certain global pattern? Second, while collective systems in robotic applications typically treat homogeneous in terms of morphology and/or control systems, realistic space applications often consider the concept of heterogeneity. Despite some rather few pioneering studies within the robotic community, designing the control system of collective heterogeneous systems still remains a difficult task and many fundamental questions underpinning heterogeneous control seek answers. Moreover, space applications are highly idiosyncratic; consider for example the involvement of humans in the loop (e.g., astronauts), which can be seen as a novel example of heterogeneity with obvious particularities. Complexity grows even more if we

consider orbital and non-orbital systems as one single system, characterized not only by different dynamics and physics, but also having different specifications and requirements. Besides, while a rover-collective exploring the surface of Mars shares, to a given extent, similar characteristics with swarms exploring an Earth robotic arena, things are intrinsically different when orbital systems are considered, as the dynamics become hardly comparable to anything Earth-based and pin-point positioning and navigation is often one prime concern. For example, applications such as docking, on-orbit self-assembly, interferometry, assemble mirror structures and formation flying require extreme precision (in the task execution), unlike most collective robotics systems and similar to industrial robotics applications. Such systems are much more sensitive to imprecise or rough approximations of the physics and dynamics, as there is no dissipative force acting to reduce the effects of simulation/reality discrepancies. Sensory noise on the other hand is less important for orbital applications as orbital systems have often access to rather precise information on their state. If the satellites belong to a constellation rather than to a close formation, their encounters will be quite rare and the inter-satellite communication network will be determined by the orbital mechanics of the single agents, complicating considerably the overall picture and any algorithm aimed to provide autonomy to the system. In all cases (orbital, planetary or atmospheric systems) space agents have limited (and not renewable) resources both in terms of energy and propulsion, introducing a challenge in the design of control systems able to make the wisest possible use of these scarce resources, while still being adaptive and robust (optimality and adaptivity typically drive the control design towards different directions). Great examples can be obtained looking at the case of the quite popular Cube-Sats. These are small satellites (typically built at Universities) provided with all subsystems and costing only a few thousand euros while weighting less than 10 Kg. For these satellites the launch costs (i.e. the cost to launch them into orbit) are often limited as they exploit launcher maiden flights or piggy-bag positions on main flights, making them perfect to develop and study advanced cooperation strategies for space missions. The challenge to make a useful mission out of the cooperation among these small satellites has been taken up by the international academia, but struggles to be met because of the limits on the performance that can be achieved using current technologies in these small space agents in terms of propulsion, energy, communication and payload mass.

One more key challenge faced when researching on collective systems for use in space missions is that of reliability. The enormous costs involved in putting even only one kilogram of mass into orbit or (even more) onto a planetary surface, often makes the risk of an agent loss unacceptable. If an algorithm has to be used to guide the agents autonomously during part of their mission, this needs to meet very strict requirements in terms of reliability and verifiability, an issue often preventing most advanced control architectures producing non-deterministic behaviors to be even considered by space engineers.

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### 1.3 Three selected projects from the Advanced Concepts Team

In order to shed light on some of the questions outlined above and to advance the research on space applications for collective systems, the Advanced Concepts Team (ACT) performs research together with European universities in three main areas: i) Behavior-based control for formation flying, ii) Evolution of Artificial Neural Networks (ANNs) for collective systems, and iii) Path planning strategies inspired by the collective behavior of root apices. We will give a brief account of the results and methodologies used in these three areas in the following sections.

#### 1.3.1 *Behavior-based methods for formation control*

We here consider a swarm  $\mathcal{S}$  formed by  $M$  individuals moving in a three dimensional space and having positions  $\mathbf{x}_i$  and velocities  $\mathbf{v}_i$ . At any particular time we define, most generically, the  $i$ -th individual kinematics as:

$$\dot{\mathbf{x}}_i = \sum_{j=1}^M \mathbf{g}_{ij}(\mathbf{x}_j - \mathbf{x}_i, \dot{\mathbf{x}}_j - \dot{\mathbf{x}}_i) + \mathbf{f}_i(\mathbf{x}_i) \quad (1.1)$$

In this form the swarm behavior will be determined solely by the functions  $\mathbf{g}_{ij}$  (describing the “social” behavior of the swarm individual) and  $\mathbf{f}_i$  (describing the cognitive behavior of the swarm individual). The problem of building the functions  $\mathbf{g}_{ij}$  and  $\mathbf{f}_i$  as to obtain a swarm motion having some predefined properties is (in this simplified case) a formalization of the emergent behavior synthesis problem at the heart of swarm intelligence research. One “heuristic” methodology to approach such a problem is inspired from behavior-based robotics and we will refer to it as behavior-based. In such a methodology the social and cognitive components are written simply as the sum of contributions, each one formally describing an abstract behavior such as ‘avoid collision’ or ‘forage’. Simple as it may seem, such an approach has been quite successful in collective robotics research in the last decade and proved to be suitable also to describe the behavior of biological swarms. Using one possible formalization of the social behaviors ‘avoid collision’, ‘stay grouped’ and ‘follow your neighbor’, Iain Couzin and his group built simulations that allowed to formulate interesting conclusions on biological fish schools [Couzin *et al.* (2005)]. In their work a fraction of the swarm individuals also have a cognitive component representing a preferred direction of motion. The main advantage of using Eq.(1.1) to describe a swarm, is in its simplicity. Under some general assumptions on the functions  $\mathbf{g}_{ij}$  and  $\mathbf{f}_i$  it is in fact possible to rigorously prove some important properties (stability and convergence) on the emerging swarm behavior [Gazi and Passino (2004a,b)].

The relevance of the swarm model described in Eq.(1.1) for space applications stems from its applicability to the design of distributed controls in formation flying or self-assembling concepts [Izzo and Pettazzi (2007)]. In these missions  $M$  satellites orbiting a primary planet or placed in a lagrangian equilibrium point are asked to either acquire and maintain a given geometry or to simply stay close to each other while spending a small amount of fuel. Here the difference with respect to an Earth swarm is essentially in the dynamics. The gravitational pull of nearby

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**Table 1.1.** Typical values for  $n$  in different orbital environments. This is the value of  $n$  to be used in the HCW equations.

Environment <sup>a</sup>	$n$ (rad/sec)	$R$ (km)	$T$ (days)
LEO	$1.078e^{-3}$	7000	$6.745e^{-2}$
GEO	$7.272e^{-5}$	42241	1
MEO	$2.411e^{-4}$	19000	0.3017
Mars	$9.581e^{-4}$	3600	$7.590e^{-2}$
Venus	$1.088e^{-3}$	6500	$6.686e^{-2}$
IO (Jupiter Moon)	$8.644e^{-4}$	2000	$8.412e^{-2}$

<sup>a</sup>LEO is Low Earth Orbit, GEO is Geostationary orbit, MEO is Medium Earth Orbit

**Table 1.2.** Typical values for  $n$ ,  $U_{xx}$ ,  $U_{yy}$  and  $U_{zz}$  for different Lagrangian Points. These values are to be used in the restricted three body problem equations.

Environment <sup>a</sup>	$n$ (rad/sec)	$U_{xx}$	$U_{yy}$	$U_{zz}$	$U_{xy}$
Sun-Earth $L_1$	$1.991e^{-7}$	9.1278	-3.0639	-4.0639	0
Sun-Earth $L_2$	$1.991e^{-7}$	8.8889	-2.9444	-3.9444	0
Sun-Jupiter $L_1$	$1.678e^{-8}$	9.8922	-3.4461	-4.4461	0
Earth-Moon cislunar point $L_1$	$2.662e^{-6}$	11.2958	-4.1479	-5.1479	0
Earth-Moon translunar point $L_2$	$2.662e^{-6}$	7.3810	-2.1905	-3.1905	0
Earth-Moon trans-Earth point $L_3$	$2.662e^{-6}$	3.02139	-0.0107	-1.0107	0
Earth-Moon equilateral points ( $L_4, L_5$ )	$2.662e^{-6}$	0.75	2.25	-1	-1.2675

<sup>a</sup> The  $L_i$  are named according to the classic convention to denote Lagrangian points

planets acts differently on each swarm element (positioned in  $\mathbf{x}_i = [x_i, y_i, z_i]$  in the local horizontal local vertical (LHLV) frame of a reference orbit) and has a non negligible effect on the relative satellite motion. As a first step, one can take the Hill-Clohessy-Wiltshire (HCW) equations (for a brief introduction see [Izzo (2005)]) to describe the relative motion of a swarm orbiting a primary body having gravitational parameter  $\mu$  at a distance  $R$ :

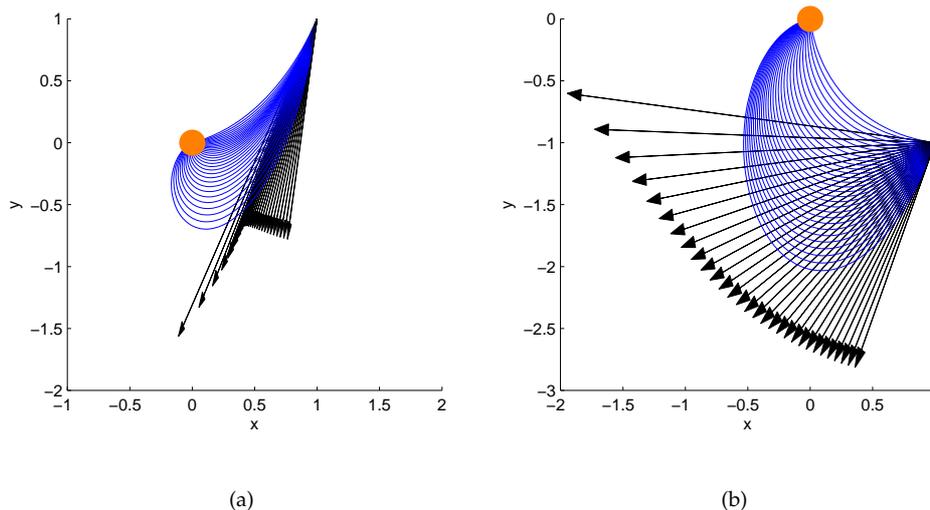
$$\begin{aligned} \ddot{x}_i - 2n\dot{y}_i - 3n^2x_i &= u_{x_i}/m_i \\ \ddot{y}_i + 2n\dot{x}_i &= u_{y_i}/m_i \\ \ddot{z}_i + n^2z_i &= u_{z_i}/m_i \end{aligned} \quad (1.2)$$

where  $n = \sqrt{\mu/R^3}$ . Table 1.1 shows typical values for  $n$  for some orbital environments of interest, together with the considered  $R$  and the resulting orbital period  $T$ . Similarly, one can consider the equations of the circular restricted three body problem (for a brief introduction see [Wie (1998)]) linearized around the equilibrium points (lagrangian points) to describe a swarm moving nearby a lagrangian point of a binary system having gravitational parameter  $\mu_1$  and  $\mu_2$  and an inter-body distance  $D$ :

$$\begin{aligned} \ddot{x}_i - 2n\dot{y}_i - n^2U_{xx}x_i - n^2U_{xy}y_i &= u_{x_i}/m_i \\ \ddot{y}_i + 2n\dot{x}_i - n^2U_{xy}x_i - n^2U_{yy}y_i &= u_{y_i}/m_i \\ \ddot{z}_i - n^2U_{zz}z_i &= u_{z_i}/m_i \end{aligned} \quad (1.3)$$

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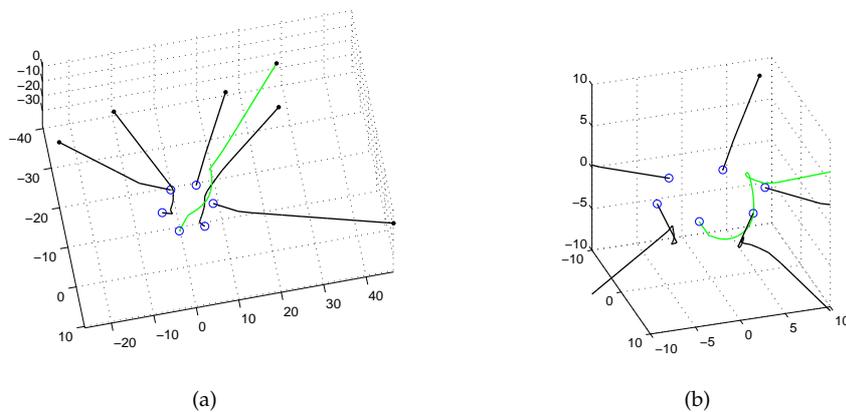
where  $n = \sqrt{(\mu_1 + \mu_2)/D^3}$ . Table 1.2 shows typical values of  $n$ ,  $U_{xx}$ ,  $U_{xy}$  and  $U_{xz}$  for some environments of interest. We notice the presence of Coriolis, centrifugal and tidal gravity forces characteristic of these models. The above equations assume implicitly that each individual has a constant mass – in space this is only an approximation as each individual spends mass in order to create its control action  $\mathbf{u}_i$  ( $|\mathbf{u}_i|$  for an ion engine is of the order of milli Newtons) according to the equation  $\dot{m}_i = -1/(I_{sp}g_0)|\mathbf{u}_i|$ , where  $I_{sp}$  is the spacecraft propulsion specific impulse and  $g_0 = 9.8m/s^2$ . For this reason the use of thrust-free ‘behaviors’ is very important. We define, in general, thrust-free phototaxis trajectories as those trajectories that lead, without any control, from an initial condition  $\mathbf{x}_0$  to a final point (light)  $\mathbf{x}_f$ . In an Earth-based frictionless arena these are straight lines joining the initial to the final point (without losing generality we consider the origin as the final point  $\mathbf{x}_f = \mathbf{0}$ ). In this case the associated velocities also lie on the same line and the time to reach the origin along such a solution is given by the simple formula  $t = |\mathbf{x}_0|/|\mathbf{v}_0|$ . For an orbital swarm described by the HCW equations we get, instead, the results visualized in Figure 1.3. The thrust-free phototaxis trajectories are no longer straight lines and the resulting trajectories tend to cover the entire space. The simple phototaxis task cannot, for an orbital agent, be solved efficiently by just pointing toward the light! This has important consequences in the framework of a behavior-based approach where straight lines are often explicitly used to define the basic behaviors. The simple instinct to “go straight to the light” is no longer adequate if fuel efficiency has to be accounted for, and needs thus to be substituted by a more complex phototactic behavior that accounts for the relative orbital motion dynamics [Izzo and Pettazzi (2007)].



**Figure 1.3.** Thrust-free phototaxis trajectories for HCW equations. Black arrows indicate the initial velocity needed. (a) Initial position  $\mathbf{x} = [1, 1]$ ; (b) Initial position  $\mathbf{x} = [1, -1]$ . Note how tidal gravity and the Coriolis acceleration act to bend what would otherwise be straight lines.

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Let us focus our discussion on the formation control task. We define such a task as that of acquiring and keeping  $M$  final positions  $\xi_i$  without pre-allocating the final position of a particular individual – the swarm needs to develop a complex strategy, agreeing on one of the  $M!$  different final configurations while also planning its path toward it. Recent results suggest that a general solution in the case of  $M$  agents is difficult (if not impossible) at least for a behavior-based approach. Partial solutions require either to use final configurations having a precise number of symmetries [Izzo and Pettazzi (2007); Pinciroli *et al.* (2008)] or to preallocate some individual to preferential locations in the formation [Gazi and Passino (2004b)].



**Figure 1.4.** Hexagonal formation acquisition using the Equilibrium Shaping approach [Izzo and Pettazzi (2007)] and starting from random initial conditions. **(a)** Overall Trajectories; **(b)** Detail of the final phases. Colours are used to help differentiating between trajectories.

Let us take, as an example, the case of an orbital swarm requested to form an hexagonal formation such as could be the case in the early plans of the European Space Agency's mission Darwin (see Figure 1.1.). The six agents would operate in the  $L_2$  Sun-Earth lagrangian point and their dynamics could be approximated, for the purposes of the control system design, by Eq.(1.3) with the values reported in Table 1.2. The agents, at the beginning of the maneuver, are given the location  $\xi_j$  of the hexagon vertices. We start by planning each agent's path according to Eq.(1.1) specializing the social and cognitive component as follows:

$$\dot{\mathbf{x}}_i = \sum_{j=1, i \neq j}^6 b e^{-d_{ij}/k_A} (\mathbf{x}_i - \mathbf{x}_j) + \sum_{j=1}^6 \left( c + d e^{-l_{ij}/k_D} \right) (\xi_j - \mathbf{x}_i) \quad (1.4)$$

where  $d_{ij} = |\mathbf{x}_i - \mathbf{x}_j|$  and  $l_{ij} = |\xi_j - \mathbf{x}_i|$ . Note that, to keep the discussion and formula as simple as possible, we do not introduce a complex phototactic behavior and each agent will thus aim in straight lines to his goal. This will produce non thrust-free trajectories and the agents will then spend fuel to actually track the produced paths. We assume a final hexagon with side length of 6m and, following the Equilibrium Shaping approach [Izzo and Pettazzi (2007)] we impose to the dynamical system described by Eq.(1.4) to have equilibrium points at all the possible 720 final configurations of the six spacecrafts in the hexagon vertices. Thanks

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to the hexagon symmetry this reduces to one simple relation between the coefficients  $b, c, d$ , once we fix the action radius  $k_A$  of the social component (the avoid behavior) and the cognitive action radius  $k_D$  of the cognitive component. We select  $k_A = k_D = 6\text{m}$ ,  $b = 1.222\text{ s}^{-1}$ ,  $d = 0.444\text{ s}^{-1}$  and, using the equilibrium shaping formula,  $c = 3.214e^{-5}\text{ s}^{-1}$ . According to their initial conditions, the agents will then plan their path to end up in the requested hexagon formation. In Figure 1.3. we show one example of the planned trajectories for a random selection of the initial conditions. The trajectories, at this point, are only “planned” in terms of velocities. In order for each agent to choose his control action  $\mathbf{u}_i$  so that, accounting for the real dynamic of Eq.(1.3), the swarm will have the designed behavior, we may simply use the feedback:

$$\mathbf{u}_i = k(\dot{\mathbf{x}}_i - \mathbf{v}_i) + \ddot{\mathbf{x}}_i - \mathbf{a}_{in}$$

where  $\mathbf{v}_i$  is the real (i.e., not the planned) spacecraft velocity,  $\dot{\mathbf{x}}_i, \ddot{\mathbf{x}}_i$  are evaluated from Eq.(1.4) and  $\mathbf{a}_{in}$  are the various accelerations due to centrifugal, Coriolis and tidal gravity forces, as described by Eq. (1.3).

**Concluding remarks** Behavior-based methods as the equilibrium shaping technique reviewed above are, in some useful special cases, able to provide controllers for a homogeneous set of space agents that need to acquire a final predefined formation. Space specific needs such as the reduction of propellant mass used and the peculiar dynamical environment may be taken into account by designing ad hoc behaviors on a case by case basis. The extension of this type of technique to include the attitude dynamic of satellites would be particularly useful and prove the possibility of having a rather simple decentralized control system for orbital formations. Similar techniques could also be useful for planetary multi-rover systems and in particular for their path-planning control layer.

### 1.3.2 *Evolutionary robotics based controllers*

The behavior-based control introduced above (equilibrium shaping) is a “bottom-up” approach to the design of swarm controllers. The local interaction rules among agents are engineered directly as to obtain a predefined collective behavior (in this case, formation control). The Evolutionary Robotics (ER) methodology [Nolfi and Floreano (2000)] allows for an implementation of a “top-down” approach. ER is constantly gaining momentum in the collective robotics community as it aims at a completely automated design of controllers. The main tool of ER is artificial neural networks (ANNs) reinforcement learning via evolutionary optimisation techniques. The global collective behaviour is not decomposed into local individual ones; instead, the system is evaluated as a whole, without reference to how individuals perform, and reinforcement learning is performed by the individuals on their performance in a collective task. Also, ER does not need assumptions about behavioural mechanisms agents should use, as those are shaped by artificial evolution [Nolfi and Floreano (2000); Ampatzis *et al.* (2009)]. Thus, this technique complements (and contrasts) approaches based on the engineering of the local rules at the level of the individual.

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A characteristic of this approach is that the designer does not need to understand much of the physics of the world the agents (robots, rovers, satellites etc.) will live in, except being able to code it in a computer simulator. Artificial evolution produces solutions that are tailored to the environment, solutions which take into account the results of the interaction between agents and environment. For example, evolved solutions to the formation control task would look very different if the environment simulates friction and gravity, absence of friction and gravity, lunar gravitational pull etc., or if the motion model is kinematic or dynamic. Still, the experimenter theoretically needs only launch a new set of evolutionary runs after simply modifying the underlying physics. This comes in sharp contrast to bottom-up approaches, such as behaviour-based approaches as the one employed in the experiment of the previous section. In that case, the behavioural blocks have to be redesigned taking into account the new modified physical environment.

However, applying ER to space problems takes as a prerequisite the confrontation with several new constraints specific to space. First, research on evolving heterogeneous systems is still in its infancy and as mentioned previously, heterogeneity occupies a rather central conceptual role in research on space problems. Secondly, ANNs have proved to be very successful in steering mainly wheeled and legged (but also some flying robots), in simulated and real earth-like environments [Ampatzis *et al.* (2009); Nolfi and Floreano (2000); Trianni *et al.* (2006); Ruini and Cangelosi (2009); Lipson *et al.* (2006)]. However, assuming that the same holds for environments like open space where gravity is quite different and friction is absent would seem unrealistic, and experiments are needed to assess the plausibility of using (evolved) ANNs for the control of spacecrafts operating in space. The results achieved by Bernd Dachwald and his collaborators on applying evolved neurocontrollers to guide low-thrust spacecrafts in the interplanetary medium [Dachwald (2004); Carnelli *et al.* (2009)] constitute a first important step in this direction. Moreover, the sensory input space agents receive differs substantially from their non-space counterparts. Instead of relative information, provided for example through perception of a light source via distributed sensors, or obstacles via infra-red sensors positioned on a robot's body circumference, space agents typically may assume access to absolute and full state information with much smaller noise levels, e.g., making use of Global Positioning Information. Assessing the potential of ANNs to produce behaviour in the case of such input is a necessary step still to be performed. Finally, the objectives of tasks typically assumed for spacecrafts in interplanetary missions are radically different than those set by researchers involved with collective robotics applications. Some typical objectives in the case of spacecrafts are fuel or time minimization, and in general, optimality with respect to certain criteria. Contrary to that, typical research in evolutionary robotics adopts a more "Artificial Life" point of view where optimality is not taken into account and researchers are rather interested in the rough realisation of certain goals.

**Experiments** In this section we describe experiments in which ER is applied to space-related problems to address the issues outlined above. In particular, we present the results of three different experiments. All the experiments refer to the

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formation control task described in section 1.3.1 where  $M = 2$ ,  $\xi_1 = [-0.5, 0]$ ,  $\xi_2 = [0.5, 0]$ . The agents need themselves to negotiate their position in the final configuration. What changes among the different experiments is the environment. In particular, the three experiments performed are:

- **kinematic** This is an environment that is often considered for robotic simulations of path planning. The two agents can be seen as two robots, or rovers, that move in an arena with friction, and their motion is governed by a kinematic model. The maximum speed of the robots is fixed to a given value. Formally, each agent dynamic can be written as:

$$\dot{\mathbf{x}}_i = \mathbf{u}_i$$

where  $|\mathbf{u}_i| < V_{max}$ .

- **kinematic.drift** This environment is identical to the environment described above, with the important difference that the environment presents unpredictable random drifts. This means that at different parts of the environment, there will be a drift of a given magnitude and direction, randomly chosen at the beginning of every trial, applied to the robot or rover. Formally, each agent dynamic can be written as:

$$\dot{\mathbf{x}}_i = \mathbf{d}(\mathbf{x}_i) + \mathbf{u}_i$$

where  $\mathbf{d}$  is a stochastic parameter representing the terrain drift and  $|\mathbf{u}_i| < V_{max}$ . In particular, the terrain drift vector differs in 9 rectangular areas of the arena, in each of which it is of a random direction and of a random magnitude, bounded between 0 and 30% of the maximum velocity of the agents. The size of the nine areas is randomly set by two stochastic variables, *drift\_x* and *drift\_y*. In Figures 1.6. and 1.7. we show an instantiation of the terrain drift. The nine areas can be distinguished by the four dash-dotted lines determined by *drift\_x* and *drift\_y* and the drifts in each area by the black arrows.

- **dynamic.tidal** In this environment the agents can be considered small satellites that move in the orbital environment described by Eq.(1.2) where  $|\mathbf{u}_i| < T_{max}$ .

For the sake of clarity, it should be mentioned that in all the experiments evolution is performed offline. This means that the ANN's parameters are evolved (optimised) offline and then the respective neuro-controllers are cloned to the agents.

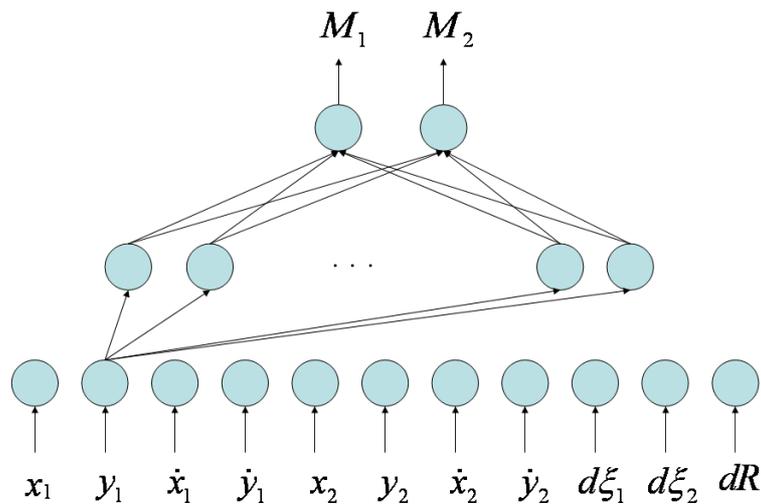
**Sensors** The two agents receive as input the full state information, both of themselves and the other agent, plus distance information to the two lights and to the other agent. In particular, the inputs of each agent are: its x and y position, its velocity on the x axis and y axis ( $\dot{x}$  and  $\dot{y}$ , respectively), these same four values for the other agent, its distance to the two lights ( $d\xi_1$  and  $d\xi_2$ , respectively) and its distance to the other agent (dR).

**Actuators** The actuators that the agents have at their disposal  $\mathbf{u}_i$  change interpretation with respect to the experiment. In the case of the first two experiments

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(*kinematic* and *kinematic\_drift*), they can be seen as the motors of a robot; they set the speed of the agent on the x and y axis ( $\dot{x}$  and  $\dot{y}$ ). In the case of the third experiment (*dynamic\_tidal*), they correspond to the thrusters on board the spacecraft, thus they implement a velocity update, not a position update.

**Controller** The controllers used to evolve the desired behaviour are in all cases Multi-Layer Perceptrons (MLPs) with 30 hidden neurons. In Figure 1.5., we show the feed-forward structure of the neural networks, the inputs they receive and the outputs they produce. The task we consider demands the implementation of a basic role allocation between the two agents while satisfying time minimization. In case the information provided to the agents is relative and the perception of the environmental changes is not directly available as an input, a neural network able to produce non-reactive behaviour (e.g., a Continuous Time Recurrent Neural Network [Beer and Gallagher (1992)]) would have been selected. However, in our case the choice of the MLP which is a reactive controller is an adequate choice because the agents have access to the full state of each other.



**Figure 1.5.** The multi-layer perceptron architecture controlling both agents in each environment. We also show the sensory input to the network and the actuators. The input arrangement in the Figure corresponds to the case of the first agent. In the case of the second agent, the first four inputs would be swapped with the next four.

**Fitness function** The fitness function rewards evolved neuro-controllers driving the two agents in the close vicinity of the two lights, while also rewarding time minimization and punishing collisions. In particular, the following formula implements the above high level description:

$$\begin{aligned}
F &= C \times (\alpha \times \beta \times \gamma \times \delta + T) \\
C &= \frac{1}{1+n_c} \\
\alpha &= \frac{1}{1+|dR-d\xi|} \\
\beta &= \frac{1}{1+|\theta R-\theta\xi|} \\
\gamma &= \frac{1}{1+|\frac{\xi_1.x+\xi_2.x}{2}-\frac{x_1.x+x_2.x}{2}|} \\
\delta &= \frac{1}{1+|\frac{\xi_1.y+\xi_2.y}{2}-\frac{x_1.y+x_2.y}{2}|} \\
T &= \frac{T_0-t}{T_0}
\end{aligned} \tag{1.5}$$

where  $n_c$  is the number of collisions between the agents at the end of the trial,  $\xi_1.x, \xi_2.x, x_1.x, x_2.x, \xi_1.y, \xi_2.y, x_1.y, x_2.y$  are the x,y coordinates of the two lights and two agents,  $T_0$  is the maximum trial duration set to 50 seconds of simulated time,  $t$  is the time elapsed from the beginning of the trial and  $dR$  and  $d\xi$  are the distance between the two agents and lights, respectively. The different components of the fitness function implement a collision-free deployment of the two agents from their initial position to one of the two possible lights at the end of the trial, while minimizing time. If the agent stays in close vicinity of the final target formation for more than 20 timesteps, the trial is terminated and the fitness attributed to a genotype is equal to  $F = 1 + T$ . During evolution, the fitness assigned to a genotype is the average of 30 different trials with random agent initialisation.

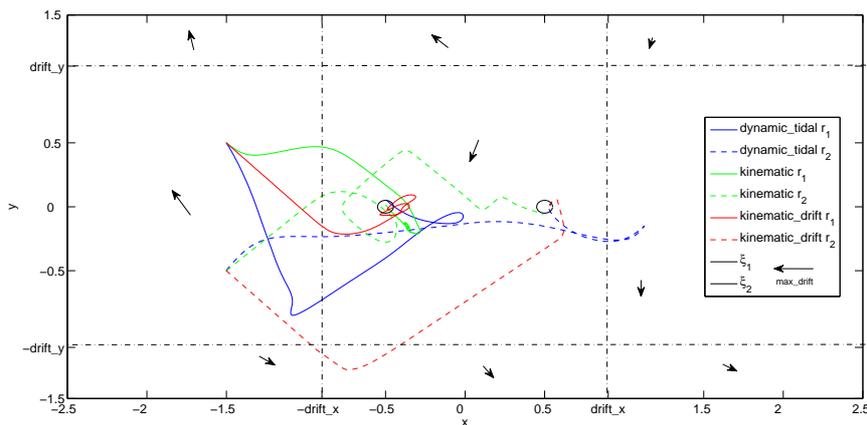
For the sake of clarity, it should be mentioned that the fitness calculation is done off-board; the optimisation of the ANN is performed offline and the agents do not calculate and eventually receive the fitness value as an input to influence behaviour.

**Evolutionary Algorithm** The evolutionary algorithm employed to optimise the weights of the neural network described previously is a genetic algorithm with roulette wheel selection, mutation rate of 0.3, operating on a population of 100 individuals. 5 individuals are retained unchanged from each generation.

**Successful navigation and pattern acquisition strategies** We performed 10 optimisation runs, each terminated after 1000 generations, for each of the three experiments outlined above and selected the individual from each run which resulted with the highest fitness during evolution. These individuals were post-evaluated in 1000 trials with random starting conditions and the one with the highest average fitness was selected and further analysed, for each experiment. The selected controller was able to complete the task successfully within the allowed time 99.6% of the times in the *dynamic\_tidal* experiment, 91.3% of the times in the *kinematic\_drift* experiment and 93.8% in the *kinematic* experiment. In the following we show the different strategies produced for each of the three environments, with the same starting conditions. We select two different initial conditions: i) The agents are initialised at the same distance from the two lights. This means that they have to engage in some sort of negotiation that allocates the one in the proximity of the one light and the other in the vicinity of the other light. Notice though that their perceptions at the beginning of the trial are not symmetrical. ii) The agents are initialised with different distances to the two lights. In this case, if of course time

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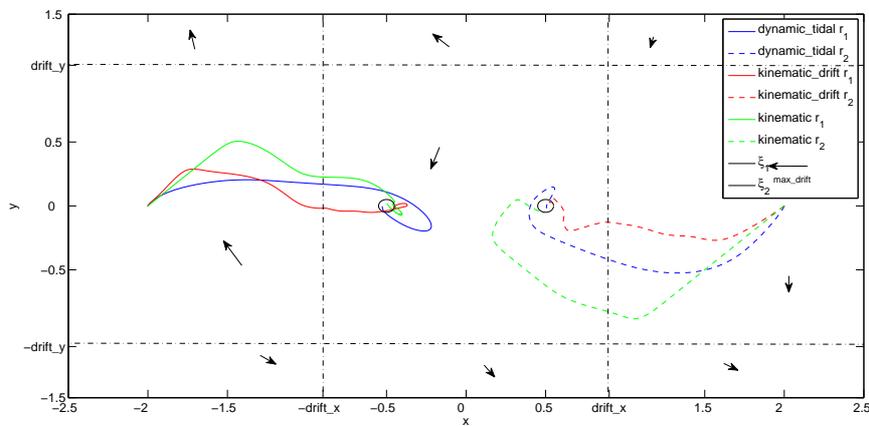
minimization is taken into account, it is evident that they should navigate each to the light closer to their initial position. Again we stress that their perceptions at the beginning of the trial are not symmetrical because their information is absolute and not relative. For the first case we plot the trajectories in Figure 1.6.. We notice that no matter the physical environment, the agent initialised at  $y=0.5$  always converges to the light at  $x=-0.5$  ( $\xi_1$ ), see solid lines with different colours, while the other agent always ends up to the other light ( $\xi_2$ ), see dashed lines with different colours. Also, it is clear that all trajectories differ substantially in their nature, and this is a consequence of the physical environment and of course of the stochasticity of the evolutionary algorithm. For the second case we plot the trajectories in Figure 1.7.. This time both agents converge to their closer light. It is noteworthy that in the case of the *kinematic* environment, the trajectory is not a straight line as one would expect but a highly curved line to the target. Even if this may seem surprising at first sight, it can be explained by the fact that these controllers have been evolved to achieve pattern acquisition in minimal time, for a random sample of different initial conditions. Thus, the focus was on the robustness of these strategies with respect to the initial conditions and not on their optimality with respect to a given initial condition.



**Figure 1.6.** Both agents are initialised at exactly the same initial distance to the two lights: the neural networks have to figure out who goes where in minimal time.

**Concluding remarks** In this section we have used evolved neuro-controllers to solve the formation control task for two agents subject to three different dynamics including the classical relative satellite motion equations; two agents controlled by the same feed-forward network (multi-layer perceptron) that receives the absolute full state information are able to autonomously select their final position in a final formation. We have tackled two different classes of problems: i) design of a controller for a group of two agents that may be seen as robots or rovers acting on a planetary surface, moving in a fixed, and in an unpredictable environment with traction (*kinematic* and *kinematic\_drift*), and ii) design of a controller for a group of two agents that may be seen as small satellites acting in an orbital environment

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**Figure 1.7.** The two agents are initialised each close to one light; in this case the minimal time solution is obvious.

(*dynamic\_tidal*). Our study shows that evolved neuro-controllers are able to cope with some of the particularities involved in space-like environments, demonstrating in practice the theoretical advantages of using an automatic design technique (Evolutionary Robotics) to design the control structure. One element to be stressed here is that while the environment changes (i.e. friction, no friction, drift, no drift etc.), the design technique stays the same. This is a big advantage of this technique as it stays blind with respect to the particularities of the task and the environment, and simply yields at the end of the optimisation process the best found controller for the task, given the environment. Clearly, our results are of a preliminary and a proof-of-concept nature; for example, the controllers produced during the *dynamic\_tidal* experiment refer to a simplified environment and thus would not be usable in a real formation-flying mission. However, it should be stressed that if the environment is modeled in detail and the evolutionary machinery is correctly set, evolution can in principle produce appropriate controllers. Concerning the rover-like environments, obviously the evolved controllers cannot be downloaded to any realistic physical rover, because they were optimised in a simulated environment modeling an abstract two-wheeled small robot. A real rover would receive significantly more complex and more numerous sensory inputs and would be governed by much more complex motion principles, however none of these elements is modeled here. Instead, the focus of the two experiments presented is on the coordination strategies between two rovers receiving absolute positioning information and on their ability to handle and compensate for unpredictability in the environment in the form of random drifts. We thus showed that artificial evolution can design neuro-controllers able to produce collective and adaptive behaviour in either “standard” (e.g., orbital) space environments, or in environments characterised by elements present in space missions, such as unpredictability. Therefore, even if these experiments are of a purely proof-of-concept nature, they reveal a high potential and many benefits of the ER methodology, which in turn suggest that this design technique should be further researched in connection to more complex space missions.

### 1.3.3 A deployment problem solved by plant roots

In order to confront ourselves with the third and admittedly most visionary topic, we turn our attention away from orbital scenarios toward planetary, exploratory applications. We have so far presented two complementary approaches for the design of autonomous collective systems for space applications. One approach exploits a deep engineering knowledge of the problem to construct the global behavior, while the other relies on principles of stochastic optimization to obtain local rules which self-organize into a global structure. Both approaches share conceptually the biological inspiration, flocking behavior in the first case and evolution by natural selection in the second. Arguably, the complexity, flexibility and adaptation demonstrated by natural collective systems is unmatched by any man-made system. In consequence, our third line of research ventures into the analysis of biological models beyond the obvious analogies. Most hitherto analyzed swarm models have rather similar sensing and reaction capabilities [Couzin *et al.* (2005)] and it might well be that the almost uniformly applicable swarm rules do not suffice for less apparent biological swarms. A generalized definition considers swarms as large groups of simple autonomous agents interacting locally and hence may in principle include less developed organisms such as bacteria, see e.g., [Atkinson and Williams (2009)]. From here, it is only a small step to consider a plant or parts of a plant, like the root system, as a swarm of autonomously acting units. Decisions of directional growth are taken in the apexes, the tips of a root (or shoot). Indeed, in earlier times philosophers like Erasmus Darwin, the grandfather of Charles Darwin, referred to plants as swarms [Darwin (1800)] cited in [White (1979)], describing the almost autonomous behavior of single root apexes and shoot apexes forming the plant as a whole. However, a root swarm is situated in a fundamentally different setting than fish, birds or insects. The sensory capabilities as well as the computational powers are tremendously reduced and on top of that the medium's properties put additional constraints. Therefore, a simple rule like 'align with your neighbor' which may be in place in fish schools, appears rather difficult to follow for an apex in the absence of elaborated sensors and being situated in the sensing-inhibiting soil. Finding nutrients is a major task of a root and important for the success of a plant, exploiting scientifically interesting sites is the major task of any exploratory mission. Every mission tries to answer more than just one scientific question, but the sites relevant to find answers might be different. Our study thus challenges the general applicability of the hitherto known rule-sets for swarm modeling and focuses on delivering strategies for diffuse sensing capabilities and coping with unreliable and heterogeneous substrates. Ongoing work includes translating the knowledge derived by the simulation of the collective behavior of root apexes into an algorithm for controlling robot (or rover) swarms exploring unknown terrains.

#### 1.3.3.1 The biological model

**The root in the soil** The physiological union of the tips of the roots of a plant (apexes) serves the greater task of supporting and nurturing the plant (among oth-

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ers). In fact, all directional growth decisions and a majority of environmental sensing are made in the apex. Growth patterns of roots are basically influenced by gravity, genetics, soil conditions, and distribution of nutrients (H<sub>2</sub>O, CO<sub>2</sub>, minerals, etc.). Since there is no anatomic evidence for a central sensing and decision unit and considering the rather low computational capacity of a plant cell (compared to neuronal systems of animals, for example), it appears meaningful to consider the apex as a simple autonomous unit taking decisions on own account [Baluška *et al.* (2004)]. There is some evidence of communication between apices [Davies and Zhang (1991); Ali *et al.* (1999)], but a higher, centralized brain has never been observed in plants. Yet, when looking at the root as a collective, growth patterns are not chaotic, but seem to follow a higher order, and emerge as a result of the individual decision-making of the apices. Considering a plant as a swarm of individuals is not a new concept, as it was firstly described in 1800 by Erasmus Darwin [Darwin (1800)]. At that time, plant-philosophers discussed the individual 'minds' of plant apices (mostly those of the sprout) and their power to turn into an entire plant when cut off and put into soil as joining a greater organism and functioning similar to a swarm of individual animals. In later discussions this swarm concept was dismissed as a philosophical concept but still the absence of a central master mind and the distribution of decision loci led to the formulation of metapopulation to characterize plants [White (1979)]. Analyzing and subsequently simulating root growth has been in the focus of previous research (root analyses, e.g.: [Berntson (1994); Coutts (1983); Doussan *et al.* (1998); Ozier-Lafontaine *et al.* (1999); Lynch (1995); Pregitzer *et al.* (2002)]; growth and branching simulations e.g.: [Pagès *et al.* (1989); Lynch *et al.* (1997); Hermann (2005)]. The major justification for these analyses derives from agricultural/physiological questions on root efficiency, soil exploitation, nutrient uptake per volume root, etc. The main means used are fractal methods, i.e., describing root architecture as a fractal. This work nicely models root architectures, also able to incorporate lack of nutrients, CO<sub>2</sub>, water etc. However, this technique involves recursive formulation and hierarchical levels and although the simulations of roots match quite well the observed growth patterns in real plants, it does not reflect the decision processes actually going on during root growth. Trying to infer basic operational principles from plants, and in this case root swarms, to design efficient exploration algorithms has the advantage that the exploration strategy's blueprint is imprinted on the root and thus directly observable. Contrary to other biological systems for which thousands of experimental trials have to be observed in order to deduce patterns in the exploration strategies, in the case of roots these strategies are available and at our disposal right from the start. Even if the social-insect metaphor is straightforward for implementation on engineering the design of efficient exploration algorithms, it suffers from an inherent disadvantage: the exploration of an unknown terrain (or volume) takes place before the discovery of food sites, etc., the motivation of a single wandering ant (e.g. looking for a food site, a new nest site, learning runs, etc.) is unclear and hence is very difficult to systematically observe.

Our qualitative considerations justify considering root-apexes of a plant as a swarm with behavior emerging from local behaviors. But what is actually the

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ecology of a root? Where does it live, what does it sense and which purpose needs the root as a whole to fulfill? In the following we outline the ecology of roots, identifying parallels with collective robotic tasks.

**Apex-soil interaction** Modeling fish or bird swarms only mildly requires considerations of the properties the animals move in and in running insects, the properties are - apart from trivia - almost negligible. We know that gravity is a downward driving force for birds but is almost perfectly balanced for fish and irrelevant for ants. Roots however, use gravity as a primary navigational cue as they emerge from the air-soil interface and head into the soil. The soil, however, is a much more complex medium than those mentioned before and hence requires full attention. Soils are not homogeneous, displaying increased compactness with increased depth, but also contain patches or layers of different mechanical properties. Different soils and soil-states additionally exhibit different capacity for nutrients and water. Without an appropriate representation of the soil, it will be impossible to model and understand root growth. Understanding the mechanical properties of root growth, i.e. knowing the strength and direction of forces exerted by the root in face of local soil anisotropies are key to understanding their behavior. A rather recent approach to the modeling of soil biophysics was undertaken by Pierret and co-workers [Pierret *et al.* (2007)]. Finally, each root system must maintain a static equilibrium balancing the weight of the plant and additional dynamic loads the plant is exposed to. The entire interaction between soil and single apex appears to fit the interactions between a rover and the environment it is trying to cope with. The area may have a certain topology which makes access to certain places easier than to others. The fine structure of the substrate may allow easy locomotion in one place but inhibit it in another one - despite similar topology. Similar, but situated at the extreme, are obstacles which are not accessible to the rover at all, as outlined in the point below.

**Negotiating obstacles** Obstacles are an extreme of compact soil patches. In the worst case, rocks display a region of in-accessibility to the apex which needs to be circumvented to continue growth and soil exploitation. Coping with obstacles is hence critical for the overall performance. The effect has been known for over a hundred years but the mechanisms were only briefly described. Falik and co-workers [Falik *et al.* (2005)] demonstrated that roots of *Pisum sativum* detect and avoid obstacles by a mechanisms of self inhibition. Allelopathic exudates accumulate in the vicinity of obstacles (as their diffusion is obstructed) and growth toward the obstacle is in consequence inhibited. Pierret and co-workers [Pierret *et al.* (2007)] have implemented a similar mechanism in their simulation mentioned above.

**Exploiting nutrient patches** The root's strategy to find and exploit nutrients in a balanced way is crucial to its overall performance. Accessing the nutrients distributed within the soil is actually one of the major tasks a root has. Indeed, nutrients do not behave homogeneously and make foraging a challenge. Basic nutrients are Nitrogen and Phosphate, but also the availability of Water and Oxygen play a role. Some of these are volatile and get distributed and subsequently washed out

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by water, others are rather equally distributed and do not follow water dynamics. Other nutrients appear in patches or layers and need to be precisely located [Lopez-Bucio *et al.* (2003)]. In summary, each component requires its own foraging strategy. Patches with increased nutrient concentration trigger roots to proliferate compared to roots of the same plant outside that zone [Hodge (2006, 2004)]. A similar behavior is observed with toxic or poisonous substances. Although they chemically belong to the group of nutrients, toxic substances trigger similar avoidance behaviors as solid obstacles do, as is the case with, e.g., Aluminum [Miyasaka and Hawes (2001)].

**Self/non-self recognition** A root system of a plant needs to coordinate the growth of the individual apices - when and where to proliferate, how to balance growth between apices, which apex to 'send' into a certain direction. All these decisions require that a root is capable of recognizing the presence of other roots around it. These roots may be of the same plant or of foreign plants, these plants again may be of a close kin or a potential aggressor. Self recognition of roots is mediated internally, i.e., via the direct connection of the roots upstream. As soon as this connection is lost, the recognition as self fails [Biedrzycki *et al.* (2010)]. Recognition of foreign roots happens through exudates, messenger molecules, in the soil. Young seedlings of *Arabidopsis thaliana* were confronted with exudates from (i) siblings, (ii) strangers, and (iii) own exudates. Roots encountering the stranger's exudates showed increased formation of lateral roots in comparison to those encountering sibling's exudates [Biedrzycki *et al.* (2010)]. However, there is no uniform reaction among plants to a non-self encounter. Depending on the self-species and the non-self-species the reaction can vary between approach and avoidance. The root exudates mediating the recognition process are actively secreted and can be deactivated by inhibitor substances. The reaction of roots when interacting with self, kin or strangers is seen as a strategy to increase individual fitness by maximizing resource exploitation in a competitive environment despite the fact that reactions differ between species [Callaway and Mahall (2007); Lynch (1995)]. Do robots of a collective mission seek each other to support each other, or shall they exhibit avoidance behavior and literally not disturb their colleagues and re-screen a previously analyzed area? These questions can only be answered by the type of mission that is intended and similar is the plants' behavioral repertoire. We will need to analyze reasons for different behaviors of apices in sight of their kin.

**Root-shoot interaction** Root and shoot equally form the entity of the plant, standing in direct and constant bi-directional interaction. Downstream, the major signaling happens in form of the availability of photosynthetic products, high energetic carbon-hydrates which are used for growth or stored. The upstream signaling is more complex and also of higher relevance for our modeling approach. Root signals in the form of signaling molecules move to the shoot within the transpiration stream ([Bacon *et al.* (2002)], but also slow-traveling electric signaling in plants is discussed. Although the transpiration stream moves rather fast, it can take days to transmit a signal from the root of a tall tree to the tips of the shoot.

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The strength of any stream-related signal depends on the concentration of the signaling substance within the liquid but apparently, daily variation of transpiration rate can be compensated for [Freundl *et al.* (1998)] and the signal kept constant. Common signal molecules are abscisic acid (ABA) and ethylene (e.g. [Dodd and Davies (2006)]). For example, ethylene concentration rises in presence of root stress and possibly regulates plant growth in drying soil [Spollen *et al.* (2000); Hussain *et al.* (1999)]. The analogy may be found in the interaction of a swarm of robots with its mother-base (nest), which is actually waiting for the products, i.e. the data collected. Here this might be realized in a form of relay station to earth, which also supplies the rovers with energy for a new excursion.

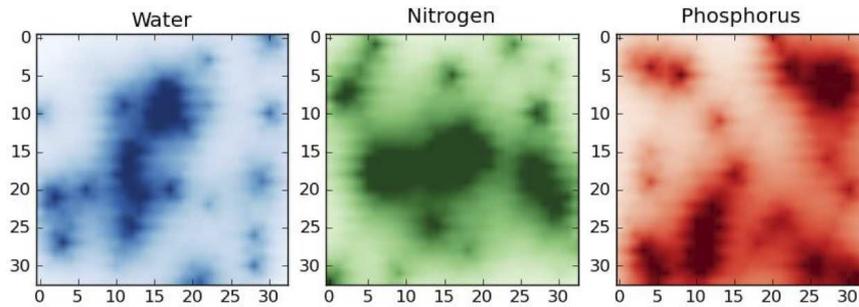
1.3.3.2 *The technological transfer*

The previous section outlined a few of the most important behaviours that can be isolated characterizing root growth. If this description is to be of any use for a technical application, a sensible approach to formulate root behaviours in a technical way is to be found. It is clearly a simulations-approach that best allows to extract and modify root growth rules to technical needs. Here two major aspects had to be considered: (i) the soil properties including diffusion processes of water and nutrients within the soil and (ii) diffusion processes going on in the apex dealing with water and nutrients. Both aspects serve as a stigmergic communication channel.

**Soil simulator** Soil is a highly heterogenous substrate with variations in physical properties, water-content and nutrient concentration. We came to the conclusion that a lattice formed by hexagonal fields best allows to reproduce a soil-like environment. Simultaneous updates are controlled through cellular automata. We came to the conclusion that a lattice formed by hexagonal fields best allows to reproduce a soil-like environment. Simultaneous updates are controlled through cellular automata. So far, the soil is initialised up by choosing the lattice of hexagons. Then three model parameters are initialised: water content, nitrogen, and phosphorus which are generally seen to be the most important soil contents for root growth. After a random choice of location the mentioned diffusion mechanism is applied to generate a smooth distribution of the compounds resulting in a soil patch similar to the one displayed in Figure 1.8.. This environment is then presented to the root simulator. The environment will be exploited by the root resulting in a depletion of nutrients at the relevant position but diffusion of nutrients (or water) to a depleted area is not applied at the present stage.

**Root simulator and controller** The root is simulated as a collection of autonomous agents. Each root apex (tip) is an agent which tries to locate and grow into patches of high nutrient concentration moving from soil cell to soil cell. Obviously in this multiparametric soil as seen in Figure 1.8. the agent will not be able to maximise all three parameters. However it is sufficient that the whole root maximises exploitation of all three nutrients and hence a communication pathway was introduced. This communication pathway is formed by diffusion processes taking place inside the root. Given enough updates, even an apex in an area without a certain nutrient will receive this nutrient through the internal diffusion and hence

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**Figure 1.8.** Model of initialised soil. ((cite luis report))

receive a representation of its internal concentration. The challenge is now to create a root controller, i.e. a set of growth rules, which maximises the soil exploitation in any given soil patch. Here we investigate two fundamentally different approaches. The first one involved the evolution of a rule set which is semantically understandable to, e.g., a plant biologist. The second one involved the usage of artificial neural networks (ANNs). In summary, the first approach promises to deliver “readable” results allowing for comparison with and conclusions on the biological model and hence would serve for further scientific investigations as well as for confirmation of the findings. Using ANNs on the other hand always posts difficulties in concluding on the controller and the rule-set in place. However, ANNs are known to function very robustly and lead to quick and useful results.

### 1.3.3.3 *A representative space application*

Coordinating multiple agents is a challenging task but on the other side allows for mission scenarios hitherto not thought of. Hence, there is no blue-print space mission available that will directly profit from the introduction of a complex swarm as observed in plant roots. However, there are many scenarios which such a root-inspired swarm might enable. The root-inspired swarm will be controlled at the individual level (rover, micro-probe or robot in general) by the same algorithm (rule-base or ANN) modeling the swarming behavior of the biological root (at the level of the individual apex). One example is a deployment task on a planetary surface. Here a large net of many individual agents might be deployed from a central location to quickly cover a large area but nevertheless concentrate on locations with increased scientific interest as defined by multiple criterias. Such a concept would apply to a net of small geological probes as well as to monitoring the landscape composition or topography of a planet acquiring local data which then can be concatenated to form a large scale map with adaptive resolution, i.e. more data from interesting spots and less data from comparably homogenous spots.

### 1.3.3.4 *Concluding remarks*

Swarms are often considered to be formed by groups of animals (birds, fish, insects, etc.). In a somewhat provocative statement we claim that one motivation of

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swarm modeling lies in the simplicity of the observational approach: Swarms of birds, fish, or ants can be spotted effortlessly; morphs and dynamics open themselves to any contemplating mind. However, at a more abstract level, we can see other groups of autonomously deciding but jointly acting agents as a swarm, as long as the system is characterized by a lack of central coordination, limited and rather simple communication protocols and simplicity of the individual agents. In contrast to the easily observable animal-swarms, roots are mostly hidden underground and come across most of us after the plant's life has ended. Additionally, their dynamics take place outside the average human attention span and by that may have received an undeserved lack of attention when talking about distributed control strategies and navigation of multi-parametric spaces. Here we undertake the first steps to characterize basic root behaviors in confrontation with their most prominent environmental stimuli.

In the previous paragraphs we have introduced only a minor overview of the complexity and multitude of root apex behaviors and the reader will have noticed the big challenge the distributed apexes are confronted with. The root system successfully navigates within a multi-parametric space which additionally includes dynamic interactions between the parameters mentioned. Root growth is even more intriguing when we take into account that the minute brains located in the apexes are situated in a medium which does not allow precise sensing or easy maneuvering. We built a simulator that accounts for the most important processes. Together with researchers from the University of Lisbon and the New University of Lisbon we address this challenge in several steps. Currently our work is focused on a root-soil simulator which tries to reflect the dynamic interactions between root, soil and soil components. In future work, the digital root-swarm model will be optimised as a multi-agent system with several goals and tasks. In our case, these tasks will be the simultaneous exploitation of the resources present in the soil where the root lives and grows. Using a top-down approach we will obtain control structures for individual apexes, that when cloned on all apexes can reproduce biologically plausible global root patterns. Finally, we will directly employ these control structures optimised in the context of the real biological system to implement the exploratory behaviour of a swarm of robots, simple rovers or micro-probes, exploring an unknown planetary surface for scientifically interesting data. The difference with other works in the swarm intelligence and swarm robotics literature is that the communication topology the root structure imposes to the multi-agent system is fixed and directly models the biological system. The above mentioned analogies between roots and robots will guide our work but not necessarily limit the applications to the most obvious ones.

**Acknowledgments** We thank Rita Ribeiro and Luis Simoes from the New University of Lisbon and Cristina Cruz and Luis Correia from the University of Lisbon for the fruitful discussions during this project.

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In this chapter we have given a few examples of space missions that require multiple agents to achieve their goals. We have argued how these systems are already extensively used in space but lack the autonomy levels that could be reached by advancing further space research in the field of collective robotics. We described in more details three practical examples, having different levels of maturity, of projects aiming at providing a higher level of autonomy to space systems made of multiple agents. Clearly, the results we have presented are of a rather proof-of-concept nature; for example, the orbital environments in which both the behaviour-based and evolved neuro-controllers are designed to operate are greatly simplified and thus these controllers would hardly be usable in a real formation-flying mission. Many more parameters would have to be considered, and the environment dynamics would have to be modeled with a higher precision, if we wish to design controllers that could eventually cope with the particularities of a realistic scenario.

The practical examples presented in this chapter are only giving a glimpse into the type of collective robotics applications that are being studied and considered in space research. Much more has still to be done and it is probably not in the next few years that multiple agent systems will be put in space and decide autonomously, as a collective, on how to achieve a given mission goal. It is, nevertheless, the inevitable future of complex space systems.

## List of Contributors

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