Evolving a Collective Consciousness for a Swarm of Pico-Satellites

Final Report

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1 Introduction

1.1 Project motivation and objectives

Traditional space missions usually involve a single spacecraft endowed with a large set of functionalities. This spacecraft is typically complex, expensive, and in case of severe damage, the loss of the spacecraft is equivalent to the complete failure of the mission. Furthermore, many researchers in space applications believe that the inevitable physical limitations in space propulsion technology will make it impossible, in the future, to realize more complex missions in which a single and large spacecraft possesses the capabilities for performing all the needed tasks.

For this reasons, NASA and ESA are recently studying mission concepts in which coordinated swarms of satellites are involved. Prominent examples are NASA's ANTS [1] and ESA's APIES [2] missions. Both aim at exploring the asteroid belt. The danger of destructive impacts in a mission like this is very high, and the use of swarms of spacecraft is expected to increase fault tolerance. Moreover, being able to position themselves around an asteroid, the spacecraft composing the swarm can obtain measures in a way that is simply impossible for a single spacecraft. Besides this example of coordinated observation, the use of swarms of spacecraft has been proposed for other applications such as planet exploration and on-orbit self-assembly [3]. Among the many issues that this new way of conceiving space missions presents, one of the most challenging is the design of distributed control strategies for the spacecraft in the swarm. Collective robotics [4] and swarm intelligence [5] can play an important role in providing us with insight and new solutions [6].

The main goal of this project is to show that controllers for swarms of satellites can be developed using swarm intelligence principles and evolutionary robotics tools.

Drawing inspiration from the work of Izzo and Pettazzi [6], we develop individual mechanisms that result in a coordinated and effective collective response of the satellite swarm.

This project is intended as a "proof-of-concept" study: our results inform the aerospace community on the potentialities of the swarm intelligence and evolutionary robotics methodologies for the design of controllers for autonomous spacecraft.

1.2 Swarm intelligence and swarm robotics

Swarm intelligence is the discipline that studies phenomena whereby a system composed of many locally acting individuals displays a meaningful global behaviour. Such swarm systems make use of self-organising, decentralised control mechanisms. Swarm intelligence finds its theoretical roots in recent studies of animal societies, such as ants and bees. Natural swarm systems are highly scalable – they are sometimes made up of many millions of individuals. In addition, such systems tend to be flexible and robust. They respond well to rapidly changing environments, and continue to function even if many of the individual agents are incapacitated. Studies have shown that in many cases simple behavioural rules at the level of the individual are sufficient to explain complex group behaviour. Nor do these models require any global communication – they rely only on local sensing and communication. Researchers have therefore started to use similar behavioural models in artificially created swarms.

In swarm robotics the principles of swarm intelligence are directly applied to the design of hardware and/or control mechanisms of systems composed of swarms of robots tightly interacting and cooperating to reach their goals [7]. The potential advantages of the swarm intelligence approach are manifold:

- collective robustness – the failure of individual components does not significantly hinder the performance of the swarm;
- individual simplicity – agents act following simple rules. The local interactions among them make it possible for complexity to arise;
- scalability – the performance of the swarm is not dependent on the number of agents in the swarm.

The collective behaviour of a swarm of robots results from the local interactions among the members of the group. That is, the activity of a swarm is determined by the unfolding in space/time of individual actions taken in response to local contingencies. The latter are produced by the behaviour of the agents as well as by changes in the environmental conditions including those directly produced by the activities of the agents. As suggested in various works [1, 2, 8], the aerospace community is interested in scientific and technological advances in the design of swarms of autonomous robots because they may make possible the development of spacecraft with autonomous decision capabilities to carry out missions such as planetary exploration, on-orbit assembly, sensor web, formation fly, and so on.

1.3 Main achievements

We propose an algorithm that allows a swarm of small spacecraft, called *pico satellites*, to build an hexagonal lattice in orbit around a planet. The ability of constructing configurations like the one studied here is considered to be an important prerequisite for applications such as autonomous self-assembly of solar powered satellites [9], large antennas and large reflectors in space. As it is clarified in Section 3, the algorithm follows the principles of swarm intelligence: it is completely distributed and interactions among spacecraft are only local. Thanks to these characteristics, the algorithm is highly scalable. Other important features of the algorithm are the guarantee of convergence to the desired configuration for almost any initial condition and the absence of collisions when the initial relative speed of the spacecraft is not too high. The validity of our results has been tested in simulations of up to 500 spacecraft. We optimize the control parameters for a real orbital environment through a genetic algorithm, a well known optimization technique in evolutionary robotics. We study the precision of the formed lattice with a different number of satellites and with different initial conditions.

2 Problem Statement

To simulate the pico satellites and their environment, we set up a mathematical model in which the swarm is represented as a set of N identical point-masses.

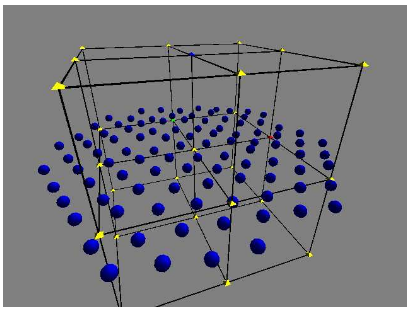


Figure 1: An example of hexagonal lattice with 100 satellites.

Orbit	ω (rad/s)	R (km)	T (s)
LEO	$1 \cdot 10^{-3}$	7,000	6,283
GEO	$7.3 \cdot 10^{-5}$	42,000	86,071
Amalthea	$1.5 \cdot 10^{-4}$	181,000	41,888
Metis	$2.5 \cdot 10^{-4}$	129,000	25,133
Io	$4.1 \cdot 10^{-5}$	421,600	153,248

Figure 2: Different types of orbital environments considered. ω is the angular speed of rotation around the planet, R is the distance from its center and T is the time needed to complete one orbit.

Initially, the satellites are randomly distributed in space under the gravitational influence of a near planet. Consider a predefined point $\vec{p}$ orbiting around the planet. Point $\vec{p}$ defines the origin of a reference frame that is moving with angular velocity ω with respect to the center of the planet. By saying "predefined", we mean that $\vec{p}$ and the orientation of the reference frame are decided by the designers of the mission. The control strategy we present in this document lets the satellites position themselves around the origin of the reference frame identified by $\vec{p}$. The target configuration is a regular hexagonal lattice located on the xy plane. The satellites keep a mutual target distance σ which is a control parameter fixed at design time (see Figure 1). From the mathematical point of view, the motion of a satellite in the reference frame defined by $\vec{p}$ can be modeled with the Hill's system of differential equations [10], sometimes also called Clohessey-Wiltshire equations:

$$\begin{cases} \ddot{q}_x - 2\omega\dot{q}_y - 3\omega^2 q_x = u_x, \\ \ddot{q}_y + 2\omega\dot{q}_x = u_y, \\ \ddot{q}_z + \omega^2 q_z = u_z, \end{cases}$$

where $\vec{q} = [q_x, q_y, q_z]$ is the position of the i-th satellite with respect to $\vec{p}$, and $\vec{u} = [u_x, u_y, u_z]$ is its control strategy, which dimensionally is an acceleration. The given form of the Hill's equation assumes that the orbit of $\vec{p}$ around the planet is circular. For all the experiments we used a fourth-order Runge-Kutta integrator [11].

In our simulations, the satellites have a mass $m = 100$ kg and a thrusting capability $T_{max} = 5 \cdot 10^{-2}$ N. The swarm has been tested in various orbital scenarios, reported in Table 2: geostationary orbits (GEO), low Earth orbits (LEO), and Jupiter orbits close to those of its satellites Amalthea, Metis and Io.

Besides the orbital environment and the limits of the satellites, other important requirements make the design of $\vec{u}$ even more challenging. Scalability is one of the main issues of this work: the control strategy must not depend (either explicitly or implicitly) on the number N of satellites forming the swarm. As explained in Section 3, we cope with this issue by letting the satellites interact only with its closest $M \ll N$ neighbors. Another issue is preventing the satellites from getting lost in space. The control strategy promotes gathering towards $\vec{p}$ by assuming that all the satellites in the swarm know their position

$\vec{q}$. This is not a stringent requirement in a space application because many well known techniques can be employed, spanning from the use of triangulation with fixed star positions to placing a special satellite in $\vec{p}$ that broadcasts its position in space. A final important constraint is avoiding collisions among satellites.

3 The Control Strategy

The control strategy $\vec{u}$ studied in this work follows the artificial potential approach [12]. This idea has been first introduced for robot path planning [13] and proved effective also in satellite control problems [14]. The original way of applying the method is to imagine that the satellite is immersed in a virtual potential field that is in fact the superposition of two fields: an attractive field, that pulls the satellite towards the goal position, and a repulsive field, which prevents the satellite from colliding with obstacles. The control strategy $\vec{u}$ acts therefore as a virtual force due to the virtual potential field. The final configuration corresponds to the status of minimum energy.

The features of the task we consider in this paper suggested a novel and completely different definition of the virtual potential field. In fact, the task of forming a flat hexagonal lattice in space can be decomposed in three distinct problems:

1. flattening the distribution of satellites on the xy plane;
2. creating the lattice on that plane while avoiding collisions;
3. preventing satellites from getting lost in space.

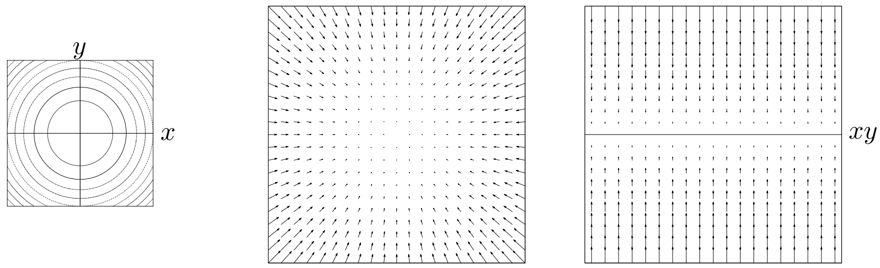
The control strategy $\vec{u}$ has been expressed as the superposition of three contributions:

$$\vec{u} = \vec{g} + \vec{l} + \vec{d}, \tag{1}$$

where

- $\vec{g}$ is a force that attracts each satellite towards the origin of the common reference frame (i.e. point $\vec{p}$) and flattens the distribution on the xy plane. Hence, $\vec{g}$ tackles problems 1 and 3;
- $\vec{l}$ is a force that creates local lattices with the neighboring satellites and avoids in-swarm collisions (problem 2)
- $\vec{d}$ is a damping factor analogous to viscosity, used to stabilize the behavior of the swarm and to ensure convergence.

The following discussion presents the details of each term. Simulations revealed that once the lattice has been formed, residual oscillations are present. These oscillations entail an undesirable loss of propellant, thus leading to the need for a stabilization mechanism to damp the oscillations. Such mechanism is explained in Section 3.4.



(a) The equipotential curves of g_{xy} on the xy plane.

(b) The force field due to g_{xy} on the xy plane. The center of the field is the origin.

(c) The force field due to g_z along the z axis. The middle line represents the xy plane.

Figure 3: The virtual force fields which build up the global field $\vec{g}$.

3.1 Global Attraction to the Origin

One of the requirements on the algorithm we have devised is to prevent satellites from getting lost in space. Moreover, the satellites are supposed to gather around point $\vec{p}$, defined at design time. If we assume that the satellites know their position with respect to this point, it is possible to define a very simple virtual potential field that attracts a satellite towards $\vec{p}$ with a force directly proportional to its distance from $\vec{p}$. Thanks to virtual viscosity (term $\vec{d}$ of Equation 1, see also Section 3.3), a satellite starting from any point in space converges, after some time, to the desired point.

In fact, the aim of this work is to create a planar structure on the xy plane of the global reference frame. The virtual potential above explained tends to create a sphere around the origin, where instead a circle on the xy plane would be needed. Furthermore, simulations showed that, when $\vec{g}$ and $\vec{l}$ act together, a virtual potential directly proportional to the square of the distance to the origin gives more stable results. For this reason, the actual global potential has been expressed as the superposition of two subfields:

1. the first attracts the satellites towards the origin and parallely to the xy plane;
2. the second subfield acts parallely to the z axis to flatten the distribution of satellites on the xy plane.

Recalling that $\vec{q} = [q_x, q_y, q_z]^T$ is the position of a satellite with respect to $\vec{p}$, and defining the normalized vector $\hat{\vec{q}} = [\hat{q}_x, \hat{q}_y, \hat{q}_z]^T = \vec{q}/\|\vec{q}\|$, then

$$\vec{g} = \begin{bmatrix} -\eta_{xy}\|\vec{q}\|^2\hat{q}_x \\ -\eta_{xy}\|\vec{q}\|^2\hat{q}_y \\ -\eta_z q_z \end{bmatrix}, \qquad (2)$$

where η_{xy} is a design parameter that accounts for the attraction to the origin (i.e., $\vec{p}$) on the xy plane, and η_z plays the same role for the attraction to the xy play parallel to the z axis. The force fields on the xy plane and along the z axis are depicted in Figures 3b–3c.

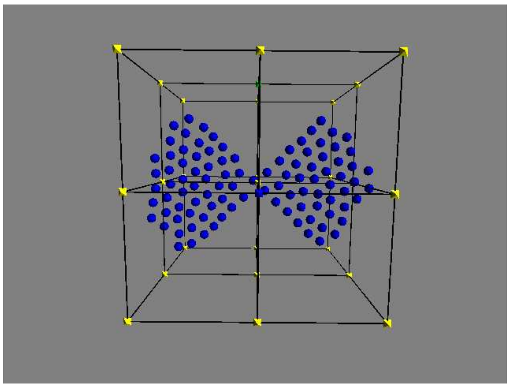
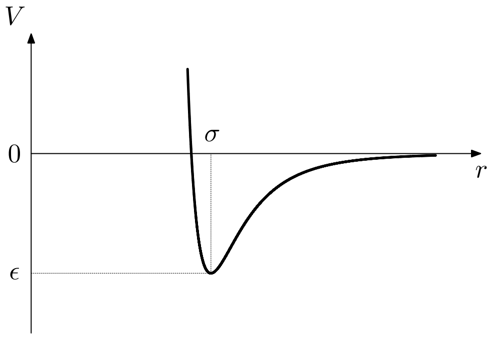
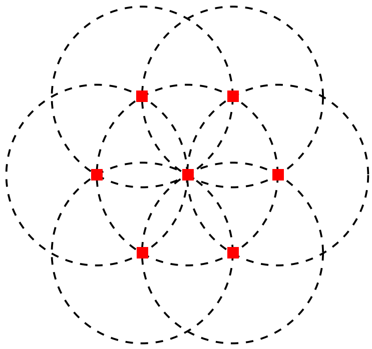


Figure 4: A butterfly shaped lattice obtained with a suitable $\vec{g}$ potential.



(a) The Lennard-Jones potential L that models the interaction between two satellites at mutual distance r. At the target distance σ the potential presents a minimum point whose value is ϵ. The deeper the minimum, the more stable is the mutual arrangement of the satellites at distance σ.



(b) The points of minimum energy of the Lennard-Jones potential define an hexagonal lattice.

Figure 5: The Lennard-Jones potential and its equilibrium state.

An important insight about this potential is the fact that sections cut parallel to the xy plane are circle shaped (see Figure 3a). Therefore, the global shape of the swarm is a circle. Using a potential with a different section contour, it is possible to change the global shape of the formation. This means that it is possible to control the shape of the formation by choosing the potential whose sections are of the desired shape. As an example, Figure 4 depicts a butterfly shape obtained with a different $\vec{g}$ potential.

3.2 Local Lattice Formation

The local potential field lets a satellite interact with its neighbors to create a lattice, while avoiding collisions. Inspiration for a virtual potential with these characteristics has been taken from a simple and very well known physical model of molecular interaction, the Lennard-Jones potential [15]:

$$V(r) = \epsilon\left[\left(\frac{\sigma}{r}\right)^{12} - 2\left(\frac{\sigma}{r}\right)^{6}\right], \tag{3}$$

Figure 5a depicts $V(r)$, r being the distance between two molecules. The force $\vec{F}(r)$ between two molecules is given by

$$\vec{F}(r) = -\nabla V(r) = -\frac{d}{dr}V(r)\hat{\vec{r}}, \tag{4}$$

where $\hat{\vec{r}}$ is a normalized vector directed as the line going from the center of the first molecule to the center of the second. The force the molecules experience is null when their distance coincides with the target distance σ; the force is increasingly repulsive as $r < \sigma$ becomes smaller and smaller; the force is attractive when $r > \sigma$. As Figure 5a shows, the attraction is very strong when r is not much larger than σ, but after a certain distance this force fades to zero. This means that two molecules, or in our case two satellites, interact strongly only when their mutual distance is within a certain value, thus explaining the reason why we called this potential *local*. The stable arrangement of two molecules interacting with each other is such that they respect the mutual target distance σ. Increasing the number of molecules, the stable arrangement is a perfect hexagon as Figure 5b proves with a geometrical construction.

The reason why the Lennard-Jones potential is so interesting for the lattice formation problem is not only its behavior. In fact, the design parameters of the potential are few and very intuitive to set: σ is the mutual distance among the satellites in the lattice, while ϵ is the depth of the potential well, which accounts for the attractiveness and stability of the minima located at distance σ. Another important feature of this potential is that the lattice is formed on the basis of positional information only: no communication is needed.

According to Equations 3 and 4, the magnitude of the virtual force of interaction $\vec{l_i}$ between a satellite and its i-th neighbor is given by

$$l_i = -\frac{d}{dr}V(r) = \frac{12\epsilon}{r}\left[\left(\frac{\sigma}{r}\right)^{12} - \left(\frac{\sigma}{r}\right)^{6}\right].$$

Since the global potential $\vec{g}$ attracts the satellites to the xy plane, it is enough that the direction of $\vec{l_i}$ is parallel to this plane, so $\vec{l_i} = [l_i\hat{q}_x \quad l_i\hat{q}_y \quad 0]^T$. Eventually, $\vec{l}$ is defined as the average of the virtual forces due to the M closest neighbors:

$$\vec{l} = \frac{1}{M}\sum_{i=1}^{M}\vec{l_i}.$$

Without averaging, the magnitude of $\vec{l}$ would be strongly dependent on M. Since $\vec{l}$ and $\vec{g}$ are summed, this in turn would make the choice of η_{xy} and η_z dependent on M: averaging removes this unnecessary dependence.

Similarly to what has been discussed about the link between the sections of the global potential and the shape of the formation, it is possible to control the local lattice changing the Lennard-Jones potential with a different potential. Hence, the proposed method of defining the artificial potential is general, and its effectiveness goes beyond the shape we show in this paper. For example, it is possible to substitute the Lennard-Jones potential with another molecular model already studied in crystallography, thus obtaining another lattice. In other terms, the work presented here suggests a link between crystallography and lattice formation in robotics.

3.3 Ensuring Convergence

From a physical point of view, $\vec{g}$ and $\vec{l}$ define conservative fields. This means that convergence to a stable state is impossible, without a dissipative term. The role of $\vec{d}$ in Equation 1 is exactly to dissipate the artificial energy of the swarm as it moves through the artificial field.

To this aim, a simple physical reasoning suggests to imagine the satellites immersed in a viscous medium, such as for example air or some liquid. Therefore, the mathematical expression of $\vec{d}$ is analogous to viscosity: $\vec{d} = -\xi\dot{\vec{q}}$, where ξ is a design parameter, usually smaller than 0.2.

3.4 Formation Stabilization After Convergence

Once the swarm converges to its final configuration, the gravitational influence of the planet tends to disrupt the formation, therefore the satellites need to use their thrusters to maintain their relative positions. Simulations show that the satellites actually oscillate around their equilibrium points, thus wasting propellant.

A solution to this problem can be found again with physical considerations. In fact, by increasing the damping factor ξ, oscillations decrease as well. The value D for which oscillations disappear depends on the orbit at which $\vec{p}$ is located.

Stabilization around the equilibrium point is therefore obtained increasing the virtual viscosity ξ according to the following rule:

$$\dot{\xi} = \begin{cases} Ke^{-\xi/2} & \text{if } \xi < D, \\ 0 & \text{otherwise.} \end{cases}$$

Another separate problem is when to trigger the stabilization. In the current status of our work, we have devised a simple time-based criteria. Each satellite individually measures the time elapsed since the beginning of the shape formation process. After a certain time threshold T, which is a further design parameter, stabilization is triggered. A more elegant method would be to trigger the stabilization with a distributed consensus algorithm, such as those in [16].

4 Results

In this section we report the results of the experiments we run to study the features of the algorithm. Initially, we set parameters by hand and we discovered that even with suboptimal parameters the system works reasonably well. Convergence, scalability and independence of initial conditions are always at an acceptable level. Our tests also showed that usually good parameters for an orbital environment are not equally good for another [17, 18]. In the second phase, we optimized the parameters to minimize positioning errors in the lattice. With these parameters, we tested the behavior of the swarm for different

Parameter	Value
Number of generations	1000
Population size	50
Mutation probability	0.2
Crossover probability	0.9
Elitism	*the best survives*

Figure 6: Parameters of the genetic algorithm employed for setting the control parameters.

Parameter	Value
η_{xy}	$1.6295 \cdot 10^8$
η_z	$5.96201 \cdot 10^8$
ϵ	$4.5332 \cdot 10^4$
ξ	0.165984

Figure 7: Values of the control parameters obtained via the genetic algorithm.

numbers of satellites to study scalability. Finally, we tested the dependence of the algorithm on initial conditions (placement of satellites and their initial speed).

4.1 Optimizing the Control Parameters

We optimized the control parameters with a classical genetic algorithm [19]. Figure 6 summarizes the parameter values used for the genetic algorithm. The control parameters to optimize, see Figure 7 are few: for the global potential field we optimized η_{xy} and η_z, while for the local potential field we optimized ϵ. The viscosity factor, ξ, has been optimized too.

Evolutions were performed with 10 satellites in a GEO environment. Each satellite was interacting with the 6 closest neighbors keeping a mutual distance $\sigma = 300$ m. The trials lasted 1000 time steps, each time step being 12.5 s long. The placement of a satellite has been evaluated as follows:

$$\chi_i = \frac{1}{N_i} \sum_{j \in \mathcal{N}_i} \frac{|\sigma - r_{ij}|}{\sigma}$$

where $\mathcal{N}_i$ is the set containing the closest neighbors of satellite i, N_i is the number of neighbors in $\mathcal{N}_i$, r_{ij} is the relative distance between the satellites i and j at the final lattice acquisition time.

The genetic algorithm minimizes the worst satellite placement, defined as $\chi = \max_i \chi_i$.

The best control parameters that we obtained are reported in Figure 7. They yield a score $\chi = 0.012842$, which corresponds to a positioning error of 3.85 m ($\sigma = 300$ m).

4.2 Scalability

Figure 8 reports the behavior of the placement error for different numbers of satellites. The placement error is calculated as

$$\bar{\chi} = \frac{1}{N} \sum_{i=1}^{N} \chi_i$$

As the graph shows, although the parameters were obtained through trials involving only 10 satellites, $\bar{\chi}$ keeps practically constant around the value 0.02 (that corresponds to 6 m), with a minimum of 0.007 (2.1 m) and a maximum of

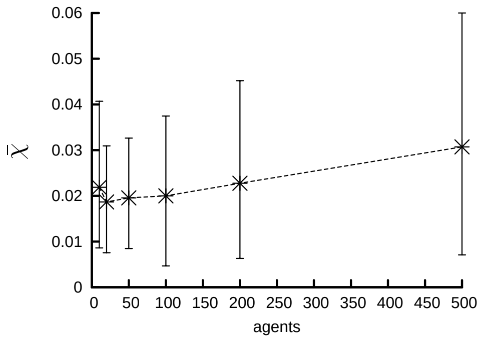


Figure 8: Average placement error for different numbers of satellites: 10, 20, 50, 100, 200 and 500.

Distribution	$\bar{\chi}$
Centered Cubic	0.0215913
Centered Spheric	0.0199159
Decentered Cubic	0.0207984
Decentered Spheric	0.0191019

Figure 9: Placement error $\bar{\chi}$ obtained with different initial spatial distributions.

0.035 (10.5 m). Only with 500 satellites the maximum error is slightly larger: 0.088 (26.4 m). Scalability is a very important feature. Since the effectiveness of the control parameters (and therefore also the placement error) is influenced by the orbital environment, it is possible to optimize the parameters with a minimal number of satellites thus finding quickly a convenient setup.

4.3 Initial Conditions

From a mathematical point of view, convergence to the final structure can be easily proven by the presence of the global attractor located at the origin of the artificial global field and by the known results about the Lennard-Jones potential.

Figure 9 shows the results of a set of experiments run to test if $\bar{\chi}$ is affected by the initial spatial distribution of the swarm. In the *centered cubic* distribution, the satellites are placed uniformly in a cube with side of 6 km and centered around the origin. The *centered spheric* distribution is a hollow sphere centered around the origin with radius 3 km and 300 m thick. The *decentered* distributions are identical, the only difference being that they are centered in point [3 3 3] (coordinates in km). For all the experiments, the same experimental conditions described in Section 4.1 have been used. Swarms of 100 satellites were used. The results show that $\bar{\chi}$, as expected, has values similar to those found for the scalability tests.

5 Conclusions

Autonomous multi-robot systems have recently attracted the interest of roboticists since, when compared to single-robot systems, they provide increased robustness by taking advantage of parallelism and redundancy. Moreover, multi-robot systems provide the heterogeneity of structures and functions required to undertake different activities in hazardous and partially or totally unknown environmental conditions. Because of these properties, they may represent a suitable platform to carry out various activities in space. In particular, multi-agent systems whose control structures are designed by using the principles of swarm intelligence seems to be among the most promising technologies for the design of autonomous vehicles to undertake missions in the space [6].

The objectives foreseen in the project proposal have been met:

- *The control system of each single agent shall be defined first. It will map the sensed environment into actuation commands and it will typically depend upon a number of parameters.*
  The proposed system consists in a control strategy followed by each agent that maps the sensed position relative to the global meeting point and to the closest neighbours into a thrusting action. The system is based on the artificial potential field approach. A novel way of defining the potential is proposed, that allows the designer to split the problem of forming the lattice into two more intuitive subproblems: an artificial field attracts globally the satellites towards a meeting point and controls the shape of the formation; another artificial field takes care of defining the interactions among the satellites to form local lattices. In this work, the Lennard-Jones potential has been used as local field. The control parameters to be set by the designer are few and very intuitive.

- *[The control parameters] shall then be optimised globally in order to minimise some objective function rewarding the achievement of the considered collective behaviour. One possibility is to think about the combination of neural controllers and evolutionary strategies, but this study is opened also to different suggestions.*
  Results showed that an acceptable performance can be obtained even by setting the control parameters by hand. Using a genetic algorithm, a very well known technique in evolutionary robotics, we have optimized the control parameters to minimize the placement error.

- *Various optimisation techniques shall be considered as well as different control system parameterisations.*
  We have focused on the simplest parametrization possible for our system. Being the potentials physics-based, we set some of their values to the physically realistic number to diminish the complexity of the system and to make optimization faster. The good results easily obtained with the genetic algorithm made it unnecessary to try other optimization techniques.

- *Various behaviours shall be chosen during the research and will include 'remain grouped with little fuel consumption', 'establish a formation', 'maintain a formation'.*
  We implemented two basic behaviours: 'establish a formation' and 'maintain a formation' (here referred to as 'stabilization').

- *Swarm elements and the optimised controls will be defined and simulated on a number of case studies defined during the research. The satellites will be modelled as three or six degrees of freedom bodies and the sensed quantities will be the relative positions and velocities or the absolute ones.*
  We simulated the satellites as three degrees of freedom bodies. The sensed quantities are the relative positions of a satellite with respect to its N closest neighbours and the absolute position and speed of each satellite with respect to a predefined point in space that is the position of the center of the formation to be created.

An interesting feature of the proposed system is that the positioning error is independent of the number of satellites and of the initial spatial distribution of the swarm.

The way here proposed to define the artificial potential field suggests a possible link between lattice formation in robotics and known results in crystallography. Further works could study other potentials that are known in the literature, extending the approach here presented.

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