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Self Assembly In Space Using Behaviour-Based Intelligent Components

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ABSTRACT

This report describes the results from a project performed within the Advanced Concepts Team of the European Space Agency investigating the assembly of structures in space using a *'swarm-intelligence'* approach. Initially a discussion is given which describes behavioural and swarm intelligence, the features which distinguish these approaches from classical artificial intelligence, and a brief summary of the work done to date in these fields, including work into increasing the formal understanding of such systems. Next, the sub-field of self-assembly is then introduced – through from biological and mathematical inspirations to actual physically implemented research into the developing field of reconfigurable (or 'morphogenic') robotics. The requirement for implementation of self-assembly and reconfigurability for space engineering purposes is then elaborated upon. The types of very large structures that are envisaged to require automated assembly in the future, as well as recent research into automated assembly in space, are discussed.

Having developed an appreciation of the field of self-assembly, the next section then describes the selection and development of a novel dynamical systems control methodology termed 'equilibrium-shaping' for rigid bodies in both free space and under the influence of a gravity-field. This is situated within a simple fusion action selection mechanism in order to provide an arbitrary number of elements with the ability to autonomously self-organise into an arbitrary configuration. The technique centres around the mathematical definition of three basis behaviours: *gather*, *avoid* and *dock*. These are summed to provide a dynamical system which through suitable selection of parameters, has as equilibrium points the desired formation of the agents. The kinematical field that results from the solution of this system can then be imposed on the agents using suitable control laws. The use of the Equilibium Shaping Technique has been investigated on test cases using four control laws: sliding-mode control, velocity-to-be-gained control, Lyupanov-based control and cross-product control. The technique is shown to be robust, and exhibits *emergent* behavioural artifacts typically of a swarm intelligent system.

In addition to this generalised scheme which allows acquisition of a formation for *N* spacecraft, variations are also described that will allow self assembly in more constrained situations. Three key architectures are described: the use of a Transition Rule Set is described which will allow construction of an arbitrary structure in space whilst adhering to any sequentiality constraints; the use of a master-slave architecture to allow the assembly of agents which do not possess their own actuators and; a sub-assembly architecture that allows for a greater degree of parallelism for large periodic structures.

As an aside, the developed approach is then contextualised within the conceptual design of an assembly scheme for the formation flying instance of the Integrated Symmetrical Concentrator (NASDA Reference system) [Mori et al., 2001; Oda & Mori, 2003] SPS concept. This assembly scheme makes use of the master-slave automated assembly scheme developed previously. The conceptual design of this system allows for a significant reduction in the total launch costs of the SPS system. This is achieved through injection of the array elements into MEO, where they then raise themselves by solar sailing to GEO. Here they are met by slave teams which serve as the thrust actuators for the assembly process. The slaves also gradually embed themselves into the array structure during construction in order to provide stationkeeping and geometry maintenance of the completed reflector. Ithe essential feasibility of this assembly scheme is assessed and shown to have the potential to reduce the required number of launches by a considerable amount, reducing the cost of the system substantially.

1 BEHAVIOURAL ROBOTICS IN APPLICATION TO SPACE EXPLORATION

1.1 INTRODUCTION TO THE SHIFT TO BEHAVIOURAL AI

In order to approach an introduction to the shift from 'classical' to 'behavioural' AI in mobile robotics, it is worth viewing some definitions of intelligence as given by several authororative sources:

- *'intelligence: the faculty of understanding; intellect [the faculty of knowing and reasoning]; quickness or superiority of understanding, sagacity [acuteness of mental discernment; soundness of judgement, shrewdness]; the action or fact of understanding something; knowledge, comprehension (of something). (Oxford Dictionary [Soanes & Stevenson, 2004]).*
- *'intelligence: the capacity to acquire and apply knowledge; the faculty of thought and reason. (The American Heritage® Dictionary[Hougton Muffin, 1980]).*
- *'intelligence: the ability to learn, understand and make judgments or have opinions that are based on reason. (Cambridge International Dictionary[Proctor, 2003]).*
- *'intelligence: the ability to learn or understand or to deal with new or trying situations; reason, also the skilled use of reason; the ability to apply knowledge to manipulate one's environment or to think abstractly as measured by objective criteria (as tests); mental acuteness, shrewdness; the act of understanding, comprehension. (Merriam-Webster Dictionary[Merrian Webster, 2003]).*

These definitions, which must be taken as representative of the common conception of intelligence, immediately reveal to the reader the complete dominance of symbolic, logical thought as the benchmark. As such, it is unsurprising that from inception, the dominant goals and tenets driving AI research throughout most of the field's history have been concerned with the reproduction of logical thought and higher-level reasoning, an idea encapsulated by the *Physical Symbol System Hypothesis*, which states:

> *"**A physical symbol system has the necessary and sufficient means for intelligent action.**"*

A physical symbol system "consists of a set of entities, called symbols, which are physical patterns that can occur as components of another type of entity called an expression (or symbol structure). A physical symbol system is a machine that produces through time an evolving collection of symbol structures. Such a system exists in a world of objects wider than just these symbolic expressions themselves." [Newell & Simon, 1976].

It is this conception of intelligence as being based on a symbolic substrate that has flavoured the direction of AI research for 30 years. The focus was on reproduction of human cognition (hence the use of *Cognitivism* as another name for the field) through emulation of the symbolic reasoning that occurs at a conscious level. Classical AI architectures typically involve functional decomposition, such that one module is responsible for sensing, another is perhaps responsible for extracting information from the sensor readings (i.e. converting sensor information into a symbolic form amenable to interrogation), another module is responsible for decision making based on this information and so forth. Little or no consideration is given to the physical substrate upon which cognitive intelligence rests (i.e. the neuronal substrate). Nor is much attention given to the relationship between the intelligent agent and the environment: the surroundings of the agent (if considered at all) are typically reproduced as an internal model, with good internal representation of the environment considered the key to success for a symbolic AI system. The agent would typically receive a restricted set of simple assertions fed to it by the designer; this model is then the subject of symbolic reasoning leading to an intelligent decision. [Brooks, 1990]. In this sense it is the designer of the AI system, not the AI itself, performing what is considered one of the key features of cognition – abstraction.

Classical AI has had notable success in areas such as theorem proving, playing chess, and operation within very narrow activity spaces (for example knowledge-based systems which address a very narrow field of expertise – such systems have been demonstrated to exhibit human-expert levels of performance.) In these areas, the activity space of the AI is typically very well defined; a game of chess for example can be completely and unambiguously specified in symbolic form, with completely discrete states of perfectly defined pieces, each with a repertoire of completely defined and discrete transformative relationships. The explosive increases in both computational power and affordability of computers during the time AI was developing as a field also inadverdently directed the research in questionable directions. Raw computing power led to search algorithms being extensively used which gave the illusion of intelligence but were in reality just brute-force approaches. In 1996, IBMs Big Blue supercomputer, programmed with unrestricted (i.e. no pruning or categorisation) search tree algorithms, narrowly lost to Garry Kasparov [Newborn, M., 1996], the acknowledged foremost chess player ever. In a rematch in 1997 Big Blue won.

Despite somewhat misleading successes such as this, classical AI systems based on logical inference have generally been unsuccessful in promoting the levels of decision-making, pattern recognition etc. that are displayed routinely throughout the animal kingdom. Of particular interest to AI researchers are navigation problems, whereby a robot is designed to perceive and subsequently navigate through an environment. This has been a notoriously difficult and frustrating problem for AI research for many years. Several tricks are used (unintentionally of course) to improve the performance of such a situated system using symbolic AI, such as simplification of the environment within which the agent operated. Shakey the robot at SRI is a good example [Nilsson, 1965], a navigating robot that operated in a very carefully constructed environment composed of large, coloured blocks and wedges, with uniform lighting and clearly defined boundaries between walls and the floor.

However, in a constantly changing and inevitably ambiguous ‘real world’ environment, planning techniques, internal models, task decomposition and other classical AI methodologies have been shown to be largely inadequate in providing a robust control architecture for autonomous systems. As a consequence of this failure of classical AI systems (relative to expectations) to emulate real-world intelligence, a fundamental rethink of the basic tenets of artificial intelligence began in the mid 1980s.

The nature of intelligence has been questioned from many different angles: inspiration for models of intelligence have come from widely differing fields such as ethology, biology and psychology, and an evolution of thought beyond the simple definitions given at the beginning of this chapter has proceeded for many years. It is now realised that intelligence is a tricky concept to pin down. The role of the environment of the agent is now accepted as being crucially important, as well as the physiology of the agent in question. For example, in humans the asset of an opposable thumb and therefore a highly developed ability to manipulate objects has resulted in the unparalleled human ability to manifest intelligence through action. Although this is a very obvious example, it does help to illustrate the importance of the coupling between an intelligent agent and the environment. For example, Moravec [Moravec, 1984] argues that mobility is crucial to intelligence, citing as evidence the observation that mobile organisms tend to evolve the mental characteristics that form the bedrock of human intelligence, whilst immobile ones do not. He gives as an example two different classes in the invertebrate phylum *mollusca*. Sessile members of this phylum are oysters (class *Pelecypoda* or *Bivalvia*, order *Filibranchia*, family *Ostreidae*), mobile members include the class *Cephalopoda* (squid, octopodes etc.). Despite common ancestry, a discussion of the comparable intelligence of these two groups is nonsensical: Octopodes are already known to have a level of intelligence and problem-solving ability broadly equal to that of a domestic cat, whilst osyters obviously have no discernible intelligence beyond that of a vegetable (nor if they did, the means to express that intelligence through mobility or manipulation of the environment). Moravec also uses as evidence the timescales over which forms of intelligence have evolved – we have developed our sensory and motor systems over almost a billion years; common sense reasoning has been around for a million years; deep logical thought has been culturally developed over the course of just a few thousand years. These observations suggest that once the ‘infrastructure’ for sensory-motor intelligence is in place, higher level thought and conscious reasoning should be a relatively easily achieved *emergent* property. This conclusion is reiterated by Brooks in [Brooks, 1990].

Consequently intelligence can be largely viewed as a situation-dependent quantity. Indeed, intelligence can only be meaningfully considered within some type of context. Furthermore, intelligence resides not just in the brain of the creature concerned, but can be viewed as being distributed throughout the whole organism, every aspect of which is contributing to an intelligent (for which read ‘effective’ or ‘appropriate’; words used inevitably in association with a value judgement – we can use genetic propogation as the ultimate measure here) action within the situation.

The coupling between environment, sensors and intelligence is now seen as crucial for generating effective behaviours in animals – and this is very obvious when we consider how animal senses are optimised for the particular environment within which they operate. This sensor-optimisation within the natural world his has led to the concept of *‘matched filters’* [Wehner, 1987], sensory organs that are spatially placed and highly tuned to a particular environmental feature. For example, desert ants possess eyes with horizontal photoreceptors, because the desert environment is dominated by the horizon. The visual system of many crabs is even more elaborate with photoreceptor spacing varying at right angles to the visual streak, a variation resulting in the stimulation of a constant number of receptors. This allows the crab to detect an object on the horizon of a constant absolute size irrespective of its distance – retinal images of objects larger than the crab appear above the eye horizontal, objects smaller appear below – this incredible sensor arrangement allows the crab to rapidly, and with a minimum of interneuron processing, respond to the visual stimulus of a potential predator – something bigger than itself - with a suitable motor response (i.e. scuttle away). The lesson here is that intelligence is built into every aspect of a particular agent.

1.1.1 Behavioural AI

As a consequence of this identification of ‘lower’ behaviours and functions (prey avoidance, pattern recognition, optimised sensors and morphology etc.) as being the basis of intelligent action in animals, during the 1980s some AI and robotics researchers began to challenge the assumptions and founding tenets of the AI community. This was a response to the marked failure of AI systems to achieve anything like the performance seen in the natural world regarding even seemingly simple behaviours. Leading this assault was Rodney Brooks who, in contrast to classical AI systems, which he termed SMPA (Sense-Model-Plan-Act) systems, suggested the *Physical Grounding Hypothesis* [Brooks, 1990; Brooks, R. A. (1991)], which states that internal models of the environment should be discarded. He advocated maintenance of a direct link between perception and action, without the intervening use of an inference engine and/or internal model of the environment. This lead to the four founding principles'' of what has since become *behavioural robotics*:

- *Situatedness* – Situatedness captures the notion where the agent has no internal state, effectively using the environment as it's memory. This is the design philosophy whereby the autonomous agent externalises as much information as possible, rather than trying to construct and maintain an internal model (which is typically complex, computationally expensive and subject to cumulative errors).
- *Embodiment* – the robots have physical form whereby the agent is physically grounded in the real world; this forces the designer to address all issues concerning the interaction of the internal control system with the real world. It also grounds the regress concerning the relation between the internal workings of the robot and the meaning they give to it's actions.
- *Intelligence* – ascribing intelligence to the agents is done by the observer, i.e. intelligence is in the eye of the beholder. The source of intelligence is not limited to just the computational engine, but also comes from the situation of the agent within the world, and the physical coupling between the agent and the world. A simple system which operates using a very simple internal mechanism can exhibit behaviour that appears very 'intelligent'. Conversely, a system operating under the control of a very complex internal mechanism can quite easily display behaviour that appears to the observer to be very stupid. The point here is that any assignation of intelligence to an agent must be bestowed by observing the intelligence of its' actions, *not* through consideration of the internal complexity.
- Emergence – intelligence of a system is an emergent property, and cannot be ascribed to one particular *homunculus* within the agent. Rather it is distributed throughout the agent and is the product of a combination of factors operating in parallel, a consequence of interactions between all the systems elements, sensors, actuators and so forth. Also, intelligent behaviour is a reflection of the environment as well as the inherent complexity of the agent. For example we could consider the example given by Simon [Simon, H. A. (1969)] of an ant walking across a featureless beach: the ant would be walking rather randomly in perhaps a roughly straight line – his behaviour would not appear very intelligent. However, if we were to place the same ant within the context of an ant mound, it would exhibit intelligent and varied actions in response to it's environment (hunting for food, foraging, managing a brood of eggs, cleaning the queen, constructing a nest etc).

Thus, behavioural intelligence is viewed not as some internal abstraction, but as the capacity of an agent to directly interact with their environment (indeed definable as such) through direct coupling between the agents sensors and their behaviours; leading to the situation where the agent becomes largely reactive, rather than using some form of internal abstraction to decide on a response to a particular stimulus.

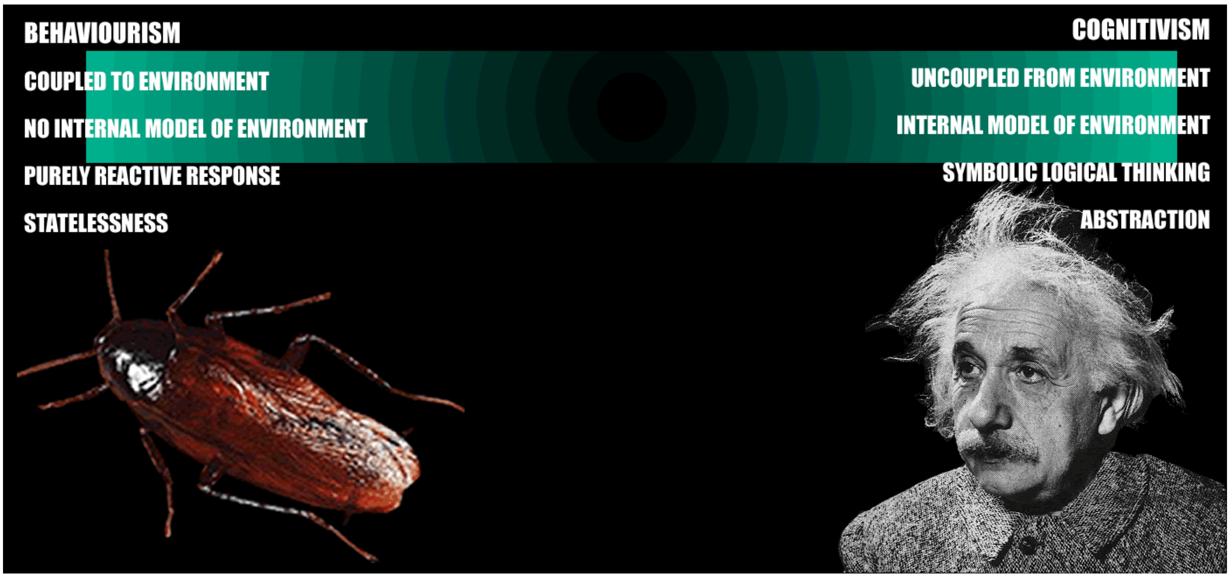

Figure 1.1 – Einstein versus the roach: two opposing views of intelligence

In terms of implementation, an engineering approach to behavioural intelligence and autonomy involves pre-programming the behaviours of the agent[1], typically by decomposing a particular problem into less-complex sub-problems. This leads to a modularisation of the internal control mechanism down to the level of individual basis behaviours. Basis behaviours can be viewed as fundamental building block behaviours that form the basis of more complex emergent behaviours. Thus a task-decomposition approach is taken rather than the function-decomposition of classical AI systems.

1.1.2 Architectures

How to coordinate, choose between and combine basis behaviours is a fundamental problem in behavioural robotics research. This is known as the ASP - *Action Selection Problem* [Pirjanian, 1999]. It concerns the agents selection of 'the most appropriate' or 'the most relevant' next action to take at a particular moment, when facing a particular situation. Due to various constraints (uncertainty, sensor noise, incomplete knowledge etc.) action selection is very unlikely to be completely rational or optimal – rather it is a satisficing or a 'good enough' solution – in this regard the ASP in behavioural robotics can be considered a parallel to bounded rationality [Russell, S., 1995] in classical AI. Two basic taxonomies of ASM exist – *Arbitration* and *Fusion*. A short and incomplete review of ASM mechanisms is given here[2] to provide the reader with a flavour of what can be considered the state of the art.

[1] other approaches to behavioural AI exist, centred around connectionist/ANN systems – see [Ziemke, 1998] for a good summary.
[2] for a more full discussion, see [Pirjanian, P. (1999). Behaviour Coordination Mechanisms – State of the Art].

1.1.3 Arbitration ASMs

Arbitration mechanisms include: priority-based; state-based; winner-takes-all. Arbitration mechanisms select one behaviour and give it total control, until the next behaviour is selected. In priority-based arbitration behaviours are ranked and behaviours with higher priorities can override 'lower' behaviours. State-based arbitration selects a behaviour that is associated with a given state of the agent (also termed FSA – Finite State Automation), and winner-takes-all arbitration allows behaviours to compete for control of the agent.

1.1.3.1 Priority-based

The most well known implementation of a priority-based architecture is the subsumption architecture, described by Brooks [Brooks, 1986]. In this architecture, the agent acquires levels of competence in a layered format; this also allows modularity and upgrading with more complex higher-level behaviours. Higher-level layers *subsume* lower levels when they wish to assume control – this is effected by supressing signals sent from the higher level behaviours to inhibit the lower level behaviours. More complex behavioural patterns are obtained using priorities and subsumption relations between the behaviours, such that certain behaviours can override others, or behaviours can operate in parallel, when two or more behaviours are signalled by a stimulus.

1.1.3.2 Winner-takes-all Arbitration

Winner-takes-all arbitration is based around a difference engine where a community of behaviours works to reduce the difference between present and desired state. This technique is called Means-Ends Analysis. Behaviours are activated by their activation energy reaching a specified level; activation energy is added and removed to the network of behaviours by external (goal, state, inhibition) and internal (predecessor, successor, inhibition) sources.

1.1.3.3 State-Based Arbitration

State-based arbitration architectures include Discrete Event Systems (DES), in which agents are modelled in terms of finite state automata (FSA) where states correspond to execution of actions/behaviours and events. A full description of the agent and its interaction with the environment is termed the plant. Implementation of the architecture involves the design of an additional controller FSA that interacts with the open loop behaviour of the plant to ensure the desired behaviour of the system as a whole. Other architectures include Temporal Sequencing (very similar to DES) and Bayesian Decision Analysis, where selection of an action is based around maximisation of the expected utility, using Bayesian probability.

1.1.4 Fusion ASMs

Command Fusion ASMs combine recommendations from several behaviours to form a consensus control action, aggregating one or more behaviours according to some rule; essentially the difference between different command fusion architectures resides in the function which is used to aggregate behaviours.

- Voting
- Superposition
- Fuzzy
- Multiple Objective
- Dynamical Systems.

1.1.4.1 Voting

Many voting architectures exist, all sharing the common feature that a polling mechanism is employed to select between 'competing behaviours'. An example of a voting command fusion architecture is the DAMN architecture [Rosenblatt, 1997]. DAMN consists of a group of distributed behaviors communicating with a centralized arbiter, either by sending votes in favor of actions that satisfy its objectives, or by indicating the utility of various possible world states. The arbiter is then responsible for combining the behaviors' votes and generating actions which reflects their objectives and priorities.

1.1.4.2 Fuzzy

Fuzzy architectures uses fuzzy inference and behaviour rules which are combined into a multivalued output. Behaviours that compete for control of the robot are then coordinated to resolve potential conflicts. Fuzzy behaviour coordination is performed by combining the fuzzy outputs of the behaviours using an appropriate operator; they are then defuzzed at the end to provide a clean final control action.

1.1.4.3 Superposition

The most straightforward type of behaviour superposition is a simple linear combination of behaviours, with behaviours being weighted and combined. The most popular is the potential field approach which has been extensively used, where agents move under the influence of a simulated potential field which treats goals as attractors and obstacles as repellers.

$$U_q = U_{att}(q) + U_{rep}(q) \qquad \textbf{Equation 1.1}$$

Movement towards the lowest energy configuration of the system. There can be problems with local minima (the usual formulation of potential fields does not preclude the occurrence of local minima other than the goal).

1.1.4.4 Multiple Objective Behaviour Coordination

Within this framework, a notion of optimality is explicitly defined, and then Multiple Objective Decision Theory is used to guide the behaviour of the agent. For each permissible alternative ($x \in X$) an objective function is calculated, reflecting that particular objectives desirability. With the link between objectives and their respective objective functions, multiple objective decision theory to simultaneously optimise a number of (possibly conflicting) objective functions. Formally, from the set of all possible alternative actions X, $\hat{x} \in X$ should be chosen such that:

$$\hat{x} = \arg\max_{x}\left[o_1(x), o_2(x), \ldots, o_n(x)\right] \text{, subject to } x \in X \qquad \textbf{Equation 1.2}$$

where *x* is an N-dimensional control vector. There are a number of methods available for solving problems of this type. Different objectives are often directly in conflict with each other, and hence solution methods that give pareto or satisficing solutions are often used.

The principles behind basis behaviours have important consequences for the architecture of the autonomous system. Although reactive intelligence is a central tenet of the behavioural approach to AI, behavioural architectures do not preclude systems with internal states, and proactive behavioural elements can be placed within a basis behaviour architecture to endow purposeful behaviour. Despite this ability for goals to be integrated within a basis behaviour architecture, a long list of hybrid systems have been investigated, whereby a reactive behavioural layer of control is placed below a classical AI ‘planner’ layer that formulates decisions and instigates goal-driven behaviours (for a discussion of integrating high-level planning with lower-level reactive behaviours, see [Payton et al., 1990]). This hybridisation of control typically involves a trade-off between goal-directed and reactive behaviours, which can be considered, in implementation terms, as orthogonal to each other.

1.1.4.5 Dynamical Systems

Many systems lack a solid theoretical foundation, but this one is an interesting exception. A nonlinear dynamics approach is adopted to capture both continuous and discrete integration of behaviours into a unified theoretical framework. A behaviour *b* emerges from the time evolution of the behavioural variables described by a differential equation:

$$\dot{\phi} = f(\phi) \qquad \textbf{Equation 1.3}$$

where ϕ corresponds to the behavioural variables such as velocity. Task constraints from the environment are used to describe the function, f.

$$\dot{\phi} = \sum_i f_i(\phi) + noise \qquad \textbf{Equation 1.4}$$

This can be extended for more than one variable, such that the (multiple) behaviour variables are held within the vector $\vec{x}$, such that:

$$\dot{\vec{x}} = \vec{f}_b(\vec{x}) \qquad \textbf{Equation 1.5}$$

f can be considered as a force that acts on the behavioural variables (according to the strictures of the environment). Multiple behaviours are aggregated by weighted summation of the individual contributions $\vec{f}_b$:

$$\dot{\vec{x}} = \sum_b |\omega_b| \vec{f}_b(\vec{x}) + noise \qquad \textbf{Equation 1.6}$$

The weights ω_b (between –1 and 1) define the strength of each behaviour and are based on the context within which the agent is operating. The noise term is small, and is present in order to enable the agent to escape from unstable fix-points. Coordination among behaviours is modelled by a competitive dynamic that controls the weights according to:

$$\tau_b \dot{\omega}_b = \alpha_b\left(\omega_b - \omega_b^3\right) - \sum_{b' \neq b} \gamma_{b'}, b\omega_{b'}^2, \omega_b + noise \qquad \textbf{Equation 1.7}$$

[Martens & Paranjape, 2001].

1.1.5 Analysis of Basis Behaviours

Basis behaviour driven systems are very successful (The SONY Aibo robotic dog being the most famous example of a behaviourally-driven robot [Arkin et al., 2001]). Whilst there are many proposed architectures to basis behaviour control as indicated in the previous section, there is a lack of theory. Proposed architectures are often arbitrary with little formal justification beyond an empirical observation that they produce the required behaviour (although this is of course the ultimate benchmark). For example, a linear superposition architecture cannot give theoretical guidance on weight selection for the behaviour aggregation; rather it is up to the designer of the system to use experience, rules of thumb and experimentation to find suitable values.

General criteria for basis behaviour selection at a qualitative level can be established, and include simplicity, locality, correctness, stability, repeatability, robustness and scalability [Parunak, 1997]. However, in addition to selecting a particular architecture, selecting and evaluating basis behaviours to use within that architecture is still largely a black art, since agent behaviour is defined by interactions with the environment and not all possible situations that the agent may encounter can be known beforehand, and therefore neither can agent response. The founding principle of emergence, where the intelligence of the agent arises out of interaction of basis behaviours with each other and the environment, is in this sense both a blessing and a curse. A blessing because it is a critical feature of what makes basis behaviour systems successful, a curse because the mysterious process of emergence is hard to formally analyse. Thus, a rather *ad hoc* approach is common, with much experimentation and trial and error typically involved in finding a suitable set of behaviours.

As a response to this lack of a formal underpinning to basis behaviour systems, there now exists a growing body of literature regarding the theoretical treatment of basis behaviours, attempting to apply a greater degree of formalism to their selection and combination. This is

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a crucial area of inquiry, since lack of care in behaviour selection can lead to a mutlitude of problems such as stagnation and cyclic behaviour. This attempt to analyse basis behaviour systems is still however at a very nascent stage. The following section introduces what has been found in the literature.

[Iske & Ruckert, 2001] propose a methodology for behaviour design based around a tree structure that incorporates a method for estimating the resource requirements of component behaviours. [Martens & Paranjape, 2002] stress the importance of consideration of the environment when designing basis behaviours, and [Mali, A. D. (1998)] shows that goal-achieving behaviour can be incorporated into a behavioural system, allowing reactive and goal-fulfilling behaviours to be encapsulated within the same architecture. Using a specially developed notation, he investigates the constraints involved, and concludes that incorporating increasingly complex goals increases the requirement for coupling between behaviours, and attempting to eliminate this coupling will increase the number of required behavioural modules. He does however optimistically conclude that despite these constraints, there exists a rich space of possible behaviour-based architectures that allow highly directed behaviour to emerge. This paper examines the relationship between the behaviour space, goals and the environment, and explores modifying the behaviour structure and environment, rather than adding a planner or sequencer. It is shown that the environment has an important role to play in increasing the functional ability of the agent. A set-theoretic model of behaviour is developed based around the 2-tuple of sense and consequence:

$$\beta_i = < s_i, c_i >, \; 1 \le i \le |B| \qquad \textbf{Equation 1.8}$$

i.e. a direct mapping between a particular sensor reading and a resultant behaviour, expressed in conjunctive normal form. *B* is the total number of possible behaviours, also termed the *behaviour space*. s_i is composed of a number of literals which in turn correspond to a number (perhaps one) of sensor readings. A complex behaviour C is then modelled as consisting of a chain of basis behaviours, for example $C = \{\beta_1 : \beta_5 : ... : \beta_2\}$. All the possible temporal chains of behaviour are therefore not explicitly programmed into the agent at design time, but rather arise as responses to a particular environmental configuration. The action of an earlier behaviour in the chain impies an environmental change that implies a stimulus that initiates the next behaviour.

The development of this notational form is continued in [Mukerjee, 1998] and [Mali, 2003] in which a system of metrics for evaluating basis behaviour effectiveness is developed. Novel metrics are introduced (power, flexibility etc.) which are then used to investigate the properties of behaviour spaces. The work focuses on robot behaviours which use minimal communication and rely on environmental changes (i.e. the stigmergic approach) – as such it is extensible to multi-agent systems. The behaviour is extended to a 3-tuple: stimulus, action, and consequence:

$$\beta_i = < s_i, a_i, c_i > \qquad \textbf{Equation 1.9}$$

s_i and c_i are defined using first order predicates. For successful execution of a behaviour, all predicates in the stimulus (a stimulus can be one or more predicates) are true at start of execution, and that all predicates in the consequence are true at the end of the execution, and assume that the consequences of a behaviour are certain (i.e. an agent never fails in a task it decides to do). Behaviour chains defined as before, and tasks are defined as a transition of the world from one state to another, achieved through a temporal chain of behaviours, i.e:

Task = $< I, G >$ **Equation 1.10**

I is the conjunction of predicates true in the world state from which a state containing the conjunction of true predicates G needs to be achieved. The task space is the number of tasks that are potentially fulfillable (for two tasks to differ, they must possess either different initial states or different final states). Typically the set of predicates required for any set of behaviours is finite. Of this set, only a few will be affected by the behaviour chain; the rest constitute the universe *U*, formally expressed as:

$c_i \Rightarrow s_i + 1$, c_i contains U **Equation 1.11**

Defining *B* as a set of behaviour modules, a temporal chain of behaviours *C* is composable from B if,

$C \lhd B$ **Equation 1.12**

where $|C|$ denotes the length of *C* (the number of modules in the chain). This extends the previous analysis to include the treatment of concurrent behaviours (rather than temporally sequential), under the proviso that the concurrent behaviours do not interfere with each other (i.e. the consequences of both the behaviours will be true at the end of their execution). This can happen under three conditions:

- c_1 does not contain a predicate or negated predicate that is false in c_2
- c_1 does not make a predicate in s_2 false
- c_2 does not make a predicate in s_1 false

From this theoretical underpinning, several measures for behaviour evaluation are defined.

Power:

A behaviour $\beta =< s, a, c >$, is at least as powerful as $\beta' =< s', a', c' >$ iff $(s' \Rightarrow s) \wedge (c \Rightarrow c')$. And if $\neg(s \Rightarrow s')$ or $\neg(c' \Rightarrow c)$, then the behaviour β is more powerful than β'.

Greatest Potential Task Space:

The task space is notated by $\tau_G(B)$. B spans the task space τ if $\forall(t \in \tau)(\exists(C \lhd B)\, fulfills(C,t))$, where t is a task.

Usefulness:

This is a relative quantity, defined by ratio $\frac{|\tau_G(B)|}{|B|}$.

Flexibility:

A behaviour set is at least as flexible as behaviour set iff
$$\forall t \in (\tau_G(B) \cap \tau_G(B'))(\exists(C \lhd B)(fulfills(C,t) \wedge \forall(C' \lhd B')(fulfills(C',t) \Rightarrow |C| \le |C'|)))$$

Modularity:

A behaviour set is more modular if different modules in the set are more independent., i.e. there is minimal interference between them.

The use of these metrics is explored in order to give guidance in the design of behavioural sets. Methods for calculating the above metrics are discussed, and a number of guidelines are suggested.

1.2 INTRODUCTION TO GROUP AND SWARM INTELLIGENCE

"Go to the ant…; consider her ways, and be wise. Having no guide, overseer, or ruler, she prepares her bread in the summer, and gathers her food at harvest time". King Solomon - (The Bible, 1 Chronicles 27:25-31).

The conception of intelligence residing in a distributed form throughout an agent (i.e. in physiology, sensors etc.) developed previously can be extended to animals and agents that operate in groups. Taken as a collective whole, a society of animals is obviously using their interactions to increase the effectiveness of their behaviour – if this was not the case selective pressures would destroy the societal association very quickly. The reasons for societal interation within and across *special* groups (note that we do not consider non-societal interaction here such as *predation* – although there are also arguably benefits to both the predator and prey – or *commensul* interaction) but all contribute to increasing the genetic success of the individuals involved. Examples of such actions include the flocking of birds, or herding of gazelles, a strategy to minimise the individuals chance of being caught by a predator. Across species we can consider the farming of aphids by the Cornfield ant (*Lasius alienus*) for their 'honeydew' secretion, or the mutualism between Tick birds and the Black Rhino (*Diceros Bicornis*), an arrangement whereby the Tick bird obtains a food source whilst the Rhino is cleansed of parasites and uses the warning call of the bird to recognise danger.

Given these examples of the obvious benefits that society gives to groups of natural agents including of course humans, it would be reasonable to conclude that the same would hold true for a society of artificial agents – the use of multiple agents can be beneficial in addressing a particular problem. This can extend from tackling a problem which could be solved by one agent, such as foraging, but would be solved more quickly using multiple agents (provided they operate under a principle of minimum interference) to tasks which are only possible with more than one agent, for example pushing an object that is too heavy for one individual to move.

There are a huge range of approaches to artificial systems which are composed of more than one agent. At a coarse level, systems can be split into those involving agents with significant cognitive ability (a field collectly known as *Distributed Artificial Intelligence* - DAI), and those that rely on simple basis behaviours and little or no communication (which we can call *Swarm Intelligence*[3]). DAI has two strains: Distributed Problem Solving (DPS), operating under a benevolent agent assumption, where a group of cognitive agents collaborate together to achieve a goal; Multi Agent Systems (MAS), which are non-cooperative, and encompass such mechanisms as bartering and negotiation. Within this report, we do not consider DAI systems with agents that are derived from a classical AI paradigm, having significant cognitive ability, and hence the ability to partake in more human societal forms of interaction such as bartering etc. Rather the focus here is on behaviourally derived agents with a repertoire of basis behaviours – Swarm intelligence. However, it should be mentioned that there do exist architectures using behavioural agents that do contain a coordinative component, and some examples of these shall be given.

Before *Swarm intelligence* appeared as an alternative paradigm, group behaviour in robotic systems has traditionally been centralised around a 'command and control' structure, with global planning and decision-making. This was a reflection of the belief that in order to obtain global level intelligence, the intelligence must be engineered at a global level. However, there are serious problems with centralised multi-agent control. For example, exponential growth of the state space with the addition of agents ($|G| = S^a$, where G is the global state space, S is the state space of each agent, and a is the number of agents.) makes on-line global planning prohibitive and intractable for large numbers of agents [Parunak, 1997].

As early as the mid 1940s, Grey Walter, Wiener and Shannon studied turtle-like robots equipped with light and touch sensors and very simple behaviours. When placed together, these robots exhibited complex social behaviour in response to each other's movements [Cao et al., 1997]. Early examples like this suggested that complexity at a group level might be achievable with very simple individual agents, without the need for central control.

The inspiration for Swarm intelligence has come primarily (and unsurprisingly given the name) from extracting metaphors from the observation of swarming insects such as ants and termites (for example such seminal work as that performed by Stuart [Stuart, 1969] on nest reparation by termites). Other examples of coordinated behaviour by insects includes Weaver Ants (*Oecophylla*) forming chains of their own bodies to manipulate leaves, the foraging and food gathering behaviour of Ant colonies in general, and nest construction by various social insects that can reach stunning levels of complexity. For example some species of Termites (*Macrotermes*) build highly complex nests, comprised of cone-shaped outer walls that often have conspicuous ribs containing ventilation ducts running from the base of the mound to the tip. Brood chambers are situated within the central 'hive' area, consisting of thin platforms supported by pillars, a base plate with spiral cooling vents, a royal

[3] For a very good introduction to intelligent interaction between behaviour-based agents, refer to [Mataric, 1994]

chamber housing the queen – a protective bunker punctuated by minute holes through which individual termites can pass. Also fungus gardens, and peripheral galleries which connect the mound to foraging sites. This level of architectural complexity, which to our minds appears to be the result of directed, intelligent thought, is the product of a large society of very simple animals working at a local level.

This emergent intelligence can be easily ascribed to ant colonies and other eusocial creatures, where individuals can be said to exist for the benefit of the group as a whole [Fong et al., 2003]. However, emergent intelligence obviously operates within what can be termed individualistic (society for the benefit of individual) human society, for example in the case of a liberal economic society where collective efficiency (in sorting and distribution of goods for example) arises from the actions and interactions of purely selfish agents. Furthermore, there are many other instances within nature where self-organising behaviour is observable, for example in the hormonal control of cells during *morphallaxis* [Shen et al., 2000]. Metaphors have been extracted from many different sources of inspiration.

Swarm intelligence can be definable as the exhibition of collective intelligence and Self Organisation (SO) by groups of simple agents [Bonabeau et al., 1997], and as such draws from a rich heritage in areas such as Cellular Automata (CA) and Artificial Life (AL). The Swarm intelligence approach argues that there exists an alternative approach to problem solving that operates at a community level. That is, a large part of the intelligence required to solve a problem can exist within the *modes of interaction* between a society of individuals, in addition to the individuals themselves.

Another concept central to swarm intelligence is the concept of *stigmergy*, whereby two agents interact indirectly when one of them modifies the environment and the other responds to the new environment at a later time. In other words, agents have an effect on their environment through their simple behaviour that acts as a behaviour-determining signal to other nearby agents. It is this mode of indirect 'communication' through changing the environment that allows swarm systems to coordinate their actions.

Stigmergy allows a dynamic collective response to environmental changes by unchanging small agents (a huge advantage for engineers trying to create robust systems - response to perturbations is possible without reprogramming individual agents). Stigmergy can be continuous – reacting to a quantity of an environmental feature, or discrete – with a direct mapping between the presence in the immediate environment of the agent and the execution of a particular behaviour. Swarm behaviour is characterised by:

- **No centralised control**
- **No internal model of the environment**
- **Environmental perception**
- **Ability to change environment**

Because of the absence of internal models, the application of swarm intelligence is closely related to basis behaviours and the paradigms introduced largely by Brooks [1990, 1991] of *situatedness*, *statelessness* and *emergence*. Behaviour in social insects is thought to be a stored programme that is prompted by specific sensory stimuli, i.e. the coupling between sensors and stimuli is direct, with no mediation by an internal model of the world. Very simple basis behaviours (often based around *allelomimesis* – 'do what thy neighbour is doing') of identical individuals, when combined into a group, can exhibit a very high degree of group-level complexity and problem solving ability.

The cooperative behaviour between agents is not restricted to indirect communication through environmental change; direct communication can and does also take place (e.g. the waggle dance of the honeybee). However, the central concept of stigmergy is that, particularly in homogenous groups, a significant amount of information about individuals goals can be inferred from observable (i.e. external) state and behaviour, with no communications required. In addition, homogeneity within the group means no requirement for designations (again encompassing statelessness), further simplifying the interactions between group members. Whilst classically swarm intelligence is concerned with statelessness, homogenous collections of agents, it does not preclude the use of systems of individuals with internal states, and/or systems composed of heterogeneous agents.

A simple example of a swarm intelligence system composed of simple behaviour-based agents can be found in the path planning of ants engaged in foraging for food. The behaviour exhibited by ants during foraging can be essentially encapsulated by the following simple behavioural primitives:

(1) avoid obstacles
(2) wander randomly (with a weighting towards pheromone trails)
(3) if holding food, drop a pheromone trail
(4) if find food (if not carrying) and pick it up
(5) if find nest, drop food

Figure 1.2 – ants engaged in foraging behaviour: a path has been set up, avoiding obstacles and leading to and from a food source and the nest.

This simple behavioural set, when exhibited by each ant in the community results in the effective identification of food sources, path formation and dynamic response to a changing environment (in the form of obstacles and depletion of food sources). Noting behaviour (2) above which contains a stochastic component. Some degree of randomness in behaviour is often a crucial element within swarm intelligent systems [Kube & Zhang, 1992], since it enables the discovery of new solutions. This randomness, coupled with the local sensing and action of individual behaviours of agents, means that solutions found using swarm intelligence cannot be considered optimal (for example, when constructing a nest, bees have been observed to tear down their neighbours work in order to obtain resources for their constructive efforts – this cannot be considered optimal problem solving behaviour). Rather, swarm intelligence centres around the establishment of pragmatic solutions that work effectively, and which are more importantly extremely robust in the face of dynamically changing environments.

1.2.1 Swarm and Group Architectures

Swarm and Group architectures for multi-robot systems are as varied as the fields from which they draw inspiration. In this review[4] we give some general discussion about design principles for group architectures, and then describe as an example one of the better known architectures – the Digital Hormone Model. Swarm intelligence has a close relationship with basis behaviours, in that the individual agents are typically equipped with a repertoire of basis behaviours, with a representative ASM chosen from amongst the examples given earlier. However, we do not preclude systems where some communication and centralised computation occur, but rather include some examples of this type of system along with purely stigmergic systems where no explicit communication occurs.

In constructing a Swarm intelligence system, the primitives required are only those related to the salient features of the metaphor being copied. A reasonable and common path as already seen is to study social insects and try to reproduce their group behaviour – a purely biomimetic approach. However, an engineer with a problem to solve obviously does not have to be concerned with biological plausibility, and construction of a system that solves the problem is the highest priority.

General engineering principles include keeping agents small [Parunak, 1997]: With many small agents, the collective dynamic (which is where the emergent intelligence 'resides') dominates. Also, many small agents gives possibly larger behaviour space (recall $|G| = S^a$) the number of agents is a multiplicative factor in implementation effort, but exponential in system overall state space. This smallness extends to having a small (or zero) internal state, and local sensing and action only. When a phenomenon is SO, the following features are usually present:

- SpatioTemporal Structures arising from an initially homogenous state.

[4] The reader is directed towards [*Cooperative Mobile Robotics: Antecedents and Directions*. Autonomous Robots, Vol. 4, 1.-23 (1997). Uny Cao, Y., Fukunaga, A. S., Kahng, A. B] for an excellent general review of cooperative robotics, which gives a thorough introduction into the field.

- The possible coexistence of several stable states (multistability)
- Bifurcation as some parameters are varied. Bifurcation is not an artifact of changing explicitly the behaviours of the agents but rather a ‘phase-change’ consequence of the environment cues.

SO is arbitrary, unless a template is present, e.g. a pheremone gradient. Pheremone gradients are used in nest construction by many insect species such as Leptothorax albipennis and Macrotermes subhyalinus.

1.2.2 Digital Hormone Model

In the Digital Hormone Model (DHM) model [Salemi et al., 2001], [Shen et al., 2000] [Shen et al., 2002a] [Shen et al., 2002b] robots are viewed as biological cells that communicate and collaborate via hormones, and execute local actions via receptors. This model therefore has large parallels with pheremone-driven models. The model takes as inspiration complex cell formations that are common in nature, mediated by hormonal signals. The primary motivation comes from *Morphallaxis*, the process whereby an organism can regenerate a part or the whole from a fragment by self-reorganisation of existing cells (non epimorphic), observable especially in invertebrates such as certain lobsters. The classic example of this process is found in the hydra, which when split into two, the two halves can each reorganise their cellular configuration (for example the head could reconstitute into a new foot) and result in two smaller but complete versions of the original creature. The DHM centres around Turings Reaction-Diffusion equation [Turing, A. M. (1952). The chemical basis of morphogenesis. Philosophy Transactions of the Royal Society of London B, Vol.237, pp.37-72]. In this model a set of differential equations model pattern formation in a ring of discrete cells or continuous tissues which communicate hormonally (he termed the information carriers ‘morphogens’). Under the assumption that there are $r = (1,\ldots N)$ cells in the ring, and two morphogens among these cells, and letting the concentration of X and Y in cell r be X_r and Y_r. The cell to cell diffusion rate of X and Y will be u and v, and the increasing rate of X and Y caused by chemical reactions be $f(X,Y)$ and $g(X,Y)$, the dynamics of the ring are described by:

$$\frac{dX_r}{dt} = f(X_r, Y_r) + u(X_{r+1} - 2X_r + X_{r-1}) \qquad \textbf{Equation 1.13}$$

$$\frac{dY_r}{dt} = g(X_r, Y_r) + v(Y_{r+1} - 2Y_r + Y_{r-1}) \qquad \textbf{Equation 1.14}$$

For the robotic implementation of this framework (i.e. moving away from a grid-based to a continuous-space implementation) three components are required: a dynamic, self reconfigurable network of agents that have connectors for physical or communication links; a set of probabilistic receptor functions that allow individual robots to select actions based on local topology, state, sensors and received hormones; and a set of equations for hormone diffusions and reactions. Hormones propogate through the system, transmitted from bot to bot. All robots have the same decision-making protocol, but they react to hormones according to their local topology and state information. So a single hormone may cause different robots in the network to perform different actions depending on their position and hormonal environment.

1.2.3 Analysis of Swarm and Group Architectures

As with basis behaviour architectures, there is with swarm and group intelligence a distinct lack of theory to allow formal analysis or design of swarm/group architectures. In this regard, group robotic systems are even more difficult to analyse than single behaviour based agents. Again as with the analysis of basis behaviours this lack of theoretical basis is currently being addressed from a number of directions. The following section gives a brief review of the current state of the art in analysis of multi-agent systems. In [Lerman & Galstyan, 2001] Lerman and Galstyan describe an approach to analysis composed of a system of coupled differential equations describing the macroscopic dynamics of an agent-based system. They propose this after recognising that the main difficulty in designing a swarm system is in estimating the effect of changing an agents behaviours will have at a global level, and note the lack of tools available for formal analysis. They discuss the 'traditional' approach to swarm system design (extracting a selection of behaviours, perhaps from a biological metaphor and then fine tuning through extensive simulation) but argue that this approach is time-consuming. The model described represents systems of agents that obey the Markov property – i.e. the agents future state depends only on the current state, with no hysteresis. Many behaviour-based systems satisfy this property, as they are purely reactive, with minimal or no internal state (and hence no 'memory'). The modelling approach is at a macroscopic level, viewing the swarm as a stochastic system. It is argued that a swarm has many complex influences, such as sensor noise, environmental uncertainty etc., and that therefore a probabilistic description is suitable.

The analysis of the MAS in this framework centres around the definition of behaviours into *states*. States can be composed of behaviour aggregates in order to coarse grain and hence simplify the analysis. A behaviour aggregate state could for example be *'go to base'* but would in reality be composed of an aggregate of behaviours such as $move\_towards\_base \wedge avoid\_obstacles$. Each agent in a MAS is in exactly one of a finite number of states during a short time interval dt. For a system of L states:

$$k = 1,2,\ldots,L \qquad \textbf{Equation 1.15}$$

The distribution of the agents amongst the L states can be formally expressed as:

$$n = \sum_{k=1}^{L} n_k \hat{q}_k \qquad \textbf{Equation 1.16}$$

where n_k is the number of agents in state k. A probability distribution $P(\vec{n},t)$ expresses the probability that the system is in configuration $\vec{n}$ at time t. Obviously this sums to unity over all the states. Using the Markov property of the system to state that the configuration of the system at time $t+\Delta t$ depends only on the configuration of the system at time t. This allows the marginal probability density of the system to be rewritten in terms of the conditional probabilities:

$$P(\vec{n},t+\Delta t)=\sum_{\vec{n}} P(\vec{n},t+\Delta t|\vec{n},t)P(\vec{n},t) \qquad \textbf{Equation 1.17}$$

now because:

$$\sum_{\vec{n}} P(\vec{n},t+\Delta t|\vec{n},t)=1 \qquad \textbf{Equation 1.18}$$

It is possible to rewrite the change in probability density as:

$$P(\vec{n},t+\Delta t)=\sum_{\vec{n}} P(\vec{n},t+\Delta t|\vec{n},t)P(\vec{n},t) \qquad \textbf{Equation 1.19}$$

Leading to the master equation which defines the transition rates between states:

$$W(\vec{n}|\vec{n}^{'};t)=\lim_{\Delta t\to 0}\frac{P(\vec{n},t+\Delta t|\vec{n},t)}{\Delta t} \qquad \textbf{Equation 1.20}$$

The configuration of the system is changed by transitions to and from states, and the master equation fully describes the evolution of the stochastic system. Defining all the possible transitions between states allows formal analysis of a MAS. The authors illustrate the approach through application to simple models investigating collective behaviour artifacts such as coalition formation and collaboration. FSA diagrams are used to define the agent states and then deduce the mathematical forms of the transition rates between states.

In [Gerkey & Mataric, 2003] Gerkey and Mataric Introduce a formal framework for task allocation in (Multi Robot Task Allocation) MRTA, based on combinatorial optimization. The method is concerned with intentional and communicative cooperation, not emergent (stigmergic) cooperation. The approach treats MRTA as an optimisation problem. Consequently, it requires what every optimisation technique requires, an objective function. In the case of this approach, the OF is encapsulated in the concept of utility, a scalar (and arbitrary) performance estimate. Utility is a concept that exists in a wide range of settings – economics (classical economics being based on rational agents that maximise their utility), game theory and operations research. It is assumed that each agent within the system is capable of estimating its fitness for every task it can perform. This estimate is composed of two factors: the expected quality of the task execution and the expected resource cost – a subtraction of these two values (that are expressable as scalars) yields a scalar utility measure and hence a measure to optimality. This utility calculation will of course in practise be inexact given sensor noise, uncertainty etc., but these low-level fidelity issues are assumed exogenous (i.e. unavoidable) and hence the measure of optimality obtained is valid.

Given a subset system (E,F), composed of a finite set of objects E and a nonempty set of subsets F of E that satisfy the property that if $X \in F$ and $Y \subseteq X$ then $Y \in F$. The total utility of the system is then maximised. The authors apply the method to a number of MRTA problems.

1.3 Applications of Behavioural and Swarm Systems to Space

The requirement for autonomy in future space exploration has been identified by several researchers ([Bresina et al., 1998], [Huntsberger et al., 2000] and [Huntsberger et al., 2001]). As precursor exploration in preparation for manned Moon and Mars missions becomes a reality, both fully autonomous and partially autonomous systems are likely to play key roles in many areas, such as scouting, exploration and site preparation. The nature of future manned missions will require that the combination of each astronaut with technology is as productive as possible; astronauts will be elevated to high-level decision makers, and largely autonomous equipment will be required to carry out high-level commands, taking responsibility for every micro-decision encapsulated within those commands. Autonomous and tough systems with minimal requirements for maintenance and supervision will fulfil this role. Within this context, there exists a substantial and growing body of work concerned with the application of basis behaviours, both in single and multiple agent context, to the exploration of environments beyond the earth using autonomous agents. Although autonomous control of spacecraft is considered in papers such as [Gipsman et al. 1999] and [Elfving et al., 2003], the main arena of activity addressed by research into behaviour–based autonomous systems is planetary surface robotics.

Behaviour-based systems are particular suited to planetary surface tasks due to the low computation and power supply constraints that such systems will face. The energy costs of computation are a fundamental problem for future small planetary rovers [Gat et al., 1994]. Behaviour based systems are particularly suited to solving this problem as they typically impose a very low computational load, because behavioural control algorithms are typically computationally quite simple. This fact has been recognised and work has been conducted in developing behavioural rovers for planetary exploration. Examples include the development of a multi-agent robotic team with application to space exploration [Earon et al., 2001], and the discussion of cooperative robot teams applied to the site preparation task [Parker et al., 1994].

The potential of behaviour-based autonomous systems to space activities has therefore been established; however, a large amount of work remains to be done. In particular, defining effective types and combinations of behaviour. Natural systems are likely to provide inspiration, and the extent to which behaviours are adopted from natural systems is a fundamental question.

1.4 SUMMARY

This section has described the shift from cognitive to behavioural robotics that has occurred over the last twenty years. Some behavioural robotic architectures have been described, as well as recent efforts to develop tools to analyse them. The field of swarm intelligence, closely related to behavioural robotics, is then introduced, and the general features of swarm intelligent systems are described. As with behavioural robotics, some of the nascent efforts to analyse swarm intelligent systems are then presented. Finally, the desirability of applying behavioural and swarm intelligence to space applications is then outlined.

2 SELF ORGANISATION AND SELF ASSEMBLY

2.1 INTRODUCTION

Self organisation is the result of a set of dynamical mechanisms whereby structures appear at a global level due to the interactions amongst lower-level components. Self assembly can be considered a sub-domain of self organisation, where lower-level components actually form structures out of themselves rather than inert elements of the envrionment. One definition of self assembly is 'the spontaneous self-ordering of substructures into superstructures driven by the selective affinity of the substructures' [Reif et al., 2004]. Both self organisation and self assembly are ubiqitous throughout nature. Taking a tour through the natural world from the smallest to largest scales, we can observe the self-organisation of subatomic particles into stable atomic configurations, crystal formation, nanoscale self organisation of peptides and polymer chains, organisation of polymers into larger functional structures, for example protein folding by the liposome, DNA replication [Winfree, 1998] and virus shell assembly [Berger & Shor, 1994]. At a cellular level, processes such as morphogenesis and mineral deposition lead to a multitude of hiearchical structures such as muscle, bone, cutin, bark etc, whilst *morphallaxis* [Hotz, 2003] allows the structural reordering of cells without proliferation. At the level of whole individual organisms, we can see the construction of incredibly complex nests by eusocial insects such as Termites (Macrotermes) [Luscher, 1961] and Tropical Wasps (Epipona) [Jeanne, 1975]. Some species of social insects can also self-assemble into structures composed of their own bodies – for example in the chain formation of *Oecophylla longinoda* [Holldobler & Wilson, 1978]. Observing these instances of self-organisation and self assembly we can marvel at the robustness of the processes and the complexity of the structures that are produced. Completely unsentient artifacts such as biological cells achieve advanced global structure without any centralised control or sequentiality, and their orchestrated actions are superbly tolerant in the face of pertubations such as random cell death or malfunction [Kondacs, 2003]
Self Assembly (SA) is intimately related to Swarm intelligence, with perhaps the principal difference in the *timespan* over which the self-organised artifact persists. The group behaviour of an ant swarm involved in foraging leads to the assembly of structures in the form of trails to and from food sources, although these are of course fairly transient, degenerating when food sources are exhausted. Self assembled artifacts are usually more persistent. In either case, in a system that exhibits SO, the following features are usually present [Bonabeau, E., Dorigo, M., Theraulaz, G. (1999)]:

- SpatioTemporal structures arising from an initially homogenous state
- The possible coexistence of several stable states (multistability)
- Bifurcation as some parameters are varied. Bifurcation is not an artifact of changing explicitly the behaviours of the lower-level elements of the system but rather a 'phase-change' consequence of environmental cues.

SO is an initially random phenomenon unless some form of template is present. For example in brood sorting experiments of the ant (*Lasius niger*) [Chrétien, (1996)], an initially homogenous spread of corpses in a homogenous environment (a petri dish) were observed to be sorted by workers into randomly positioned piles. However, the presence of heterogeneities in the environment will guide the self-organisation in particular directions to a greater or lesser degree. This can manifest itself as a robust ability to deal with environmental heterogeneities (both static and dynamic) – a form of fault tolerance. However, 'purposefully' (we use this word carefully) heterogeneous environments are also widely used in natural self-organising systems to guide the assembly towards the desired final structure – a form of template use. For example, in the polymerisation of viral shells, the self assembly of the shell is sometimes aided by 'scaffolding' proteins, which form a precursor shell, but are removed before the shell matures [Berger & Shor, 1994] The environment of cells is also richly populated with hormonal cues and structural heterogeneities which guide the process of self assembly, for example stem cells can transform into many different specialised cell types according to cues from their hormonal and physical environment. Many eusocial insects use pheremone templates to guide nest construction. e.g. a pheremone gradient is present in nest construction by most wingless hive insects, such as *Leptothorax albipennis* [Franks & Deneubourg, 1997] and *Macrotermes subhyalinus* [Bruinsma, 1979].

2.2 Artificial Self Assembling Systems

There are many examples of self assembly in the natural world that can provide inspiration in the design of engineered self-assembling and metamorphic systems. At present, these mechanisms from the natural world that could be useful in engineering self assembly are investigated from a theoretical and idealised perspective within such fields as Cellular Automata and Artificial Life. Systems are also considered from a computational/computer science perspective (e.g. [Prencipe, 2000], [Adleman et al., 2001] [Rothemund & Winfree, 2000] and have been subjected to work on techiques using planning. For a planning approach, given a random starting configuration, it is computationally intractable to find the optimal solution (see [Chirikjian et al., 1996] for a discussion) for self assembly of even a modest number of identical elements. However, restricted planning methods to self-assembly have been explored, such as suboptimal optimisation based on local searches of an arbitrary (suboptimal) macrosequence that gives the configuration change [Chiang & Chirikjian, 2001] Other suggestions include using intermediate 'junction' configurations that are easy to enter and exit [Rus & Vona, 1999].

More theoretical AL and CA approaches focus on pattern generation, usually in dicretised 2-dimensional grids with locally acting elements. Typically, a set of local action rules is formulated and applied, and the resulting patterns are then observed. In [Kondacs, 2003; Nagpal et al., 2002; Nagpal, 2002] a formal language is presented for the assembly of arbitrary two-dimensional shapes by identical, decentralised agents, taking cellular morphogenesis and developmental biology as inspiration, more specifically using behavioural primitives inspired by Odell's epilethial cell model [Odell et al., 1981]. At present there is no formal understanding of the number of state values required to build an arbitrary structure.

Another example of a cellular morphogenesis/morphollaxis inspired approach is the Digital Hormone Model (DHM) introduced eariler [Salemi et al., 2001; Shen et al., 2000; Shen et al., 2004; Shen et al., 2002; Shen et al., 2000] In this model the elements are viewed as biological cells that communicate and collaborate via hormones, and execute local actions via receptors. The model takes as inspiration complex cell formations that are common in nature, mediated by hormonal signals. The primary motivation comes from *Morphallaxis*, the process whereby an organism can regenerate a part or the whole from a fragment by self-reorganisation of existing cells (non *epimorphic*), observable especially in invertebrates such as certain lobsters. The classic example of this process is found in the hydra, which when split into two, the two halves can each reorganise their cellular configuration (for example the head could reconstitute into a new foot) and result in two smaller but complete versions of the original creature.

The DHM centres around Turings Reaction-Diffusion equation [Turing, 1952] In this model a set of differential equations model pattern formation in a ring of discrete cells or continuous tissues which communicate hormonally (he termed the information carriers 'morphogens'). Under the assumption that there are $r = (1,...N)$ cells in the ring, and two morphogens among these cells, and letting the concentration of X and Y in cell r be X_r and Y_r. The cell to cell diffusion rate of X and Y will be u and v, and the increasing rate of X and Y caused by chemical reactions be $f(X,Y)$ and $g(X,Y)$, the dynamics of the ring are described by:

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Hormones propogate through the system, transmitted from agent to agent. All robots have the same decision-making protocol, but they react to hormones according to their local topology and state information. So a single hormone may cause different robots in the network to perform different actions depending on their position and hormonal environment

Examples of techniques that are not inspired by biological metaphors include those that use physical laws such as potential fields as inspiration. One such approach is described in [Gordon, 1999], which investigates using algorithms based on physical laws (e.g. gravity) to enable swarm formation. The technique described, based on a modified form of Newton's law of gravitation. Using this simple approach is particularly useful to the formation of a hexagonal array of elements due to simple radial relation between agents. A square lattice is also created using agents with 2 spin settings, with the modified force law which spaces the elements renormalised for agents with the same spin. Both cases were found to lead to reasonable structures but with global flaws. However, application of a sorting algorithm allowed the production of flawless lattices (including globally reproduced shapes, e.g. a perfect hexagonal lattice).

Non-biological techniques for self assembly of a large class of structures also include the Transition Rule Set [Jones & Mataric, 2003], a method to organise interactions of agents in self assembly by specifying interactions and state declarations required for interaction between the elements in order to build the structure. This will be introduced in more detail later.

2.2.1 Physically Implemented Architectures

Work from these approaches is complemented by the implementation of self assembly in real engineered systems – the field of *metamorphic robotics* [Pamecha et al., 1996]. These are systems of modular, usually homogenous, robotic elements that are able to self-configure and reconfigure themselves into different functional structures. In this regard, a morphallaxis (where elemental reorganisation proceeds without proliferation of elements) rather than a morphogenesis (where both elemental proliferation and organisation proceed) metaphor is more suitable. The following section gives a brief review of some of the work.

There are several proposed, simulated and hardware-implemented concepts for morphogenic robotic systems. These include TETROBOT which uses novel spherical joints to enable a truss structured robot. In [Bojinov et al., 2002], a metamorphic control architecture for *Proteo* robots is described using the fact that simple contact allows modules to sense neighbours without processing. Simple, local rules (termed primitives) are used based around growth (the mechanism by which structures are created), seeding (the status of a module that initiates growth – relate this to heterogenties in the environment) and scents (global communication between agents, relate to DHM).

2.3 SELF ASSEMBLY FOR SPACE APPLICATIONS

We can view the interest in self-assembly for space applications from a consideration of the engineering constraints that face a typical space mission. For engineering purposes, a self assembling system can be defined as one where order and structure arise without human intervention. Self assembly can also be characterised as the formation of large structures out of smaller components. These two descriptions of self assembly immediately reveal why engineering the ability to self-assemble into future space structures would be very desirable.

There are upper mass and volume limits associated with the delivery of structural elements to space. For example, the ISS has been delivered to orbit over the course of many launches for the simple and obvious reason that it could not be contained within the fairing of one launch. This is coupled with the fact that there will be many construction situations in the future where a human presence is not possible or practical. From a cost perspective, the assembly of large structures by astronauts even in LEO would be prohibitively expensive [Shen et al., 2003]. Remote supervision and control of assembly could be possible from the ground for LEO and near Earth instances, but obviously further afield would also be impractical due to typically long communication delays – these reasons lead to the conclusion that construction in space of large structures will by necessity require automation. Note that the word automation in this regard is used rather loosely, and does not preclude the use of systems that deploy themselves due to intelligent but ‘dumb’ design, i.e. structures that automatically unfold to a stable configuration without explicit use of intelligence beyond that which is built into the mechanical design of the structure. The following section briefly reviews some of the approaches to ‘unsupervised’ deployment and construction of large structures in space that have already been suggested.

Large Deployable Reflectors (LDR) represent the most often addressed class of deployable space structure. Extant and partly flight proven concepts for LDR include the EGS mesh reflector, the Harris cable-rod deflector, and the ‘Thuraya’ AstroMesh reflector [Bsaier et al., 2000]. Under the *gossamer spacecraft initiative* NASA has identified several new mission concepts, including very large aperture telescopes, large deployable and inflatable antennas, solar sails and large solar power collection and transmission systems. In order to realise concepts such as these, ultra-lightweight deployable structures are being investigated under various initiatives [Darooka & Jensen, 2001].

One example of this array of concepts is described in the ULTIMA studies [Zeiders, 1999], which have shown that a very attractive configuration for a very large space telescope is the three-mirror Gregorian design, shown in Figure 2.1. This uses a segmented primary mirror whose abberations are corrected by a secondary mirror, and whose deflections are corrected by the matched segmented tertiary mirror where the primary can be imaged.

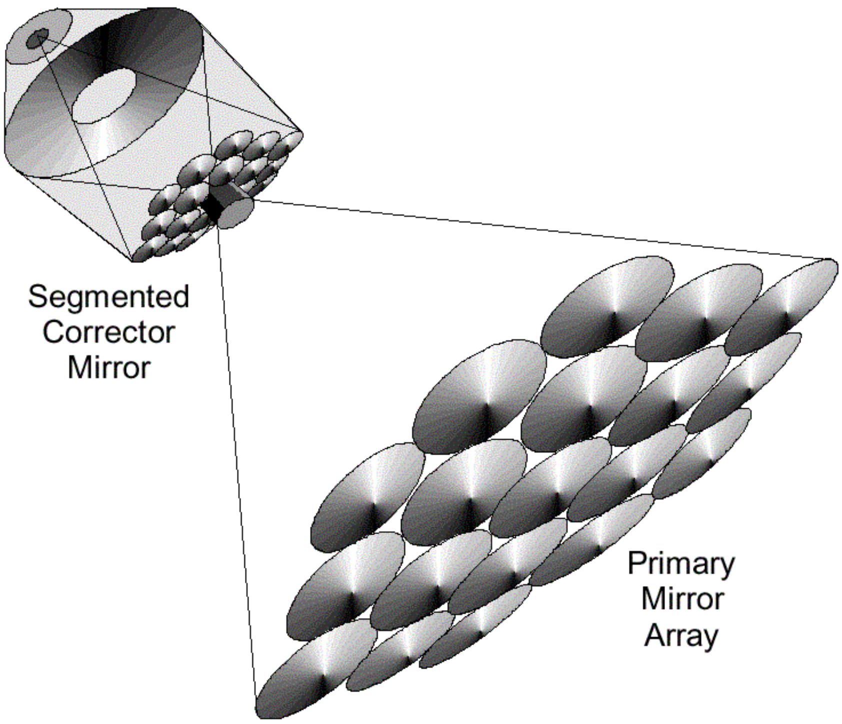

Figure 2.1 - The ULTIMA telescope configuration (adapted from [Zeiders, G. W. (1999)]

An important (perhaps indeed principal) subgroup of the structures that require in-situ assembly of a number of separate components in space are a number of SPS concepts such as those described in [Carrington, 2002]. The concepts can be divided into three primary classes, all of which are conceived of as being both extremely massive and composed of literally thousands of components: Sun-Tower configurations (composed of an array of solar panels arranged on a backbone structure alligned with the gravity gradient, which collect and conduct power down to a monolithic microwave transmitter at the base) with a lower reference concept mass of 22,300 MT; abacus-reflector configurations (the array and transmitter are built as one fixed unit, and a lightweight microwave reflector is rotated in front of the transmitter in order to direct the microwave beam towards the earth) with a lowest reference mass configuration of 27,000 MT; integrated symmetrical concentrator configurations (incoming sunlight is collected in two large clamshells located on the ends of a mast, reflected on photovoltaic arrays located midway along the mast) with a lower reference mass of 18,000 MT (see Figure 2.2).

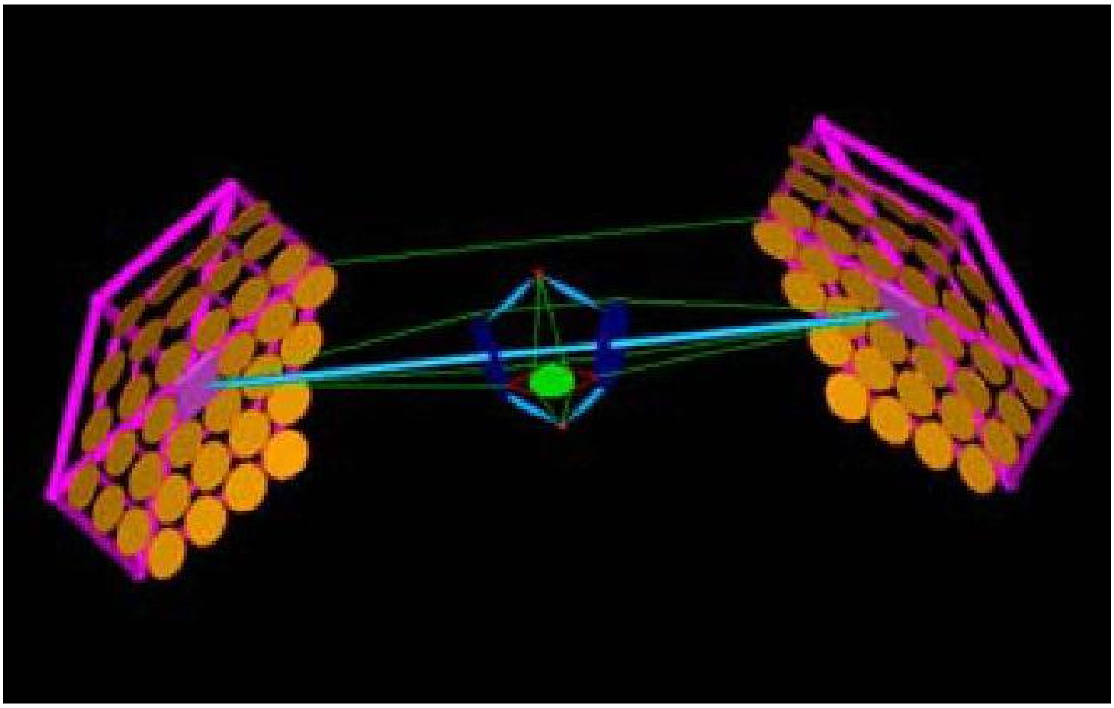

Figure 2.2 - ISC SPS array concept

There also exist other concepts based around large arrays for solar power generation include SPS-based concepts for exploration (such as Boeing's SEP Mars Transfer concept [Boeing, 2001].

Deployment of large structures in space has been studied, particularly by the Japanese during the 1980s. A number of concepts were suggested, including beam deployment concepts [Natori & Miura, 1986, folding tetrahedral elements [Natori et al., 1986], a number of membrane and folding deployment concepts [Miura 1986b] including those inspired by the unfolding of leaves and flowerheads [Miura, 1980], [Guest & Pellegrino, 1996], [Kato et al., 1988]], [Matanuga et al., 1990] More modern concepts include those based on integrity under compression – 'tensegrity' concepts. Tensegrity-based frame concepts are very interesting from a space application perspective due to both their high strength and compact packing. An example of this type of concept applied to space can be found in deployable tensegrity masts [Tibert & Pellegrino, 2003]]. Another tensegrity-derived concept is a family of large deployable space reflectors consisting of bi-stable radial ribs combined with additional annular ribs or tensioned membranes to form the backside structure of the reflector [Baier et al., 2000] An interesting deployment concept for arrays composed of hexagonal components include that suggested in [Zeiders, 1999] which consists of a hinge/clamp toggle mechanism to stack elements in a vertical configuration for packing; they would then be unfolded following the path shown in Figure 2.3, with enough lateral freedom in the toggle to allow lateral movement to align the elements before locking them into place.

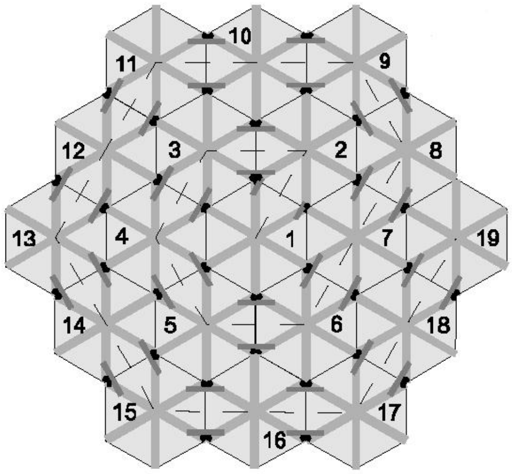

Figure 2.3 – Sequential deployment mechanism for a 19 element hexagonal array [Zeiders, G. W. (1999)]

Also worth mentioning (although not neccesarily a self-assembly concept) is the concept described in [Komerath & Wanis, 2004]]; this paper follows up on the idea of using potential fields for automatic construction of massive objects of desired shape in Space. Specifically, the work considers how electromagnetic waves could be utilized in a space-based construction project. In the test case project, the question of how to construct a safe radiation shelter for humans, in the Near-Earth Object (NEO) region is considered. NEO material is formed into desired shapes using the radiation pressure and gradient forces experienced by dielectric objects in a standing-wave field of radio waves. The force field is produced by solar-powered transmitter/antenna carrying spacecraft, which are positioned in formation around the particle cloud to set up a resonant field of the desired mode. As a test case, formation of cylindrical shells is considered. The field level is set to induce an average particle acceleration of a millionth of an Earth-surface gravitational acceleration. Once in position, the particles are fused by solar-powered energy beams through a sintering process.

2.3.1 Recent Work

The work done to date in realising automated self-assembly in space can be best represented by the SOLAR (Self Assembly for Space Structurees) project – this is based around the FIMERS concept described in [Shen et al., 2003]. This is a system for self assembly of a space structure using Intelligent Reconfigurable Components (IRCs), and a number of free-flying **FI**bre-rope **M**atchmaker **R**obots (**FIMERs)**, is described. All the IRCs are envisaged to be equipped with GPS/Gallileo receivers and wireless communication, an on-board computer that will control the information gathering processing and communications, canonical connectors to dock with other components and FIMER units, a position and orientation sensory system, an on-board controller for topology discovery, action planning, communication with FIMERS and other IRCs and monitoring the progress of assembly, and auxiliary connections for fluid-gas pipes and electric connections so the structure can operate as a unified whole when fully assembled.

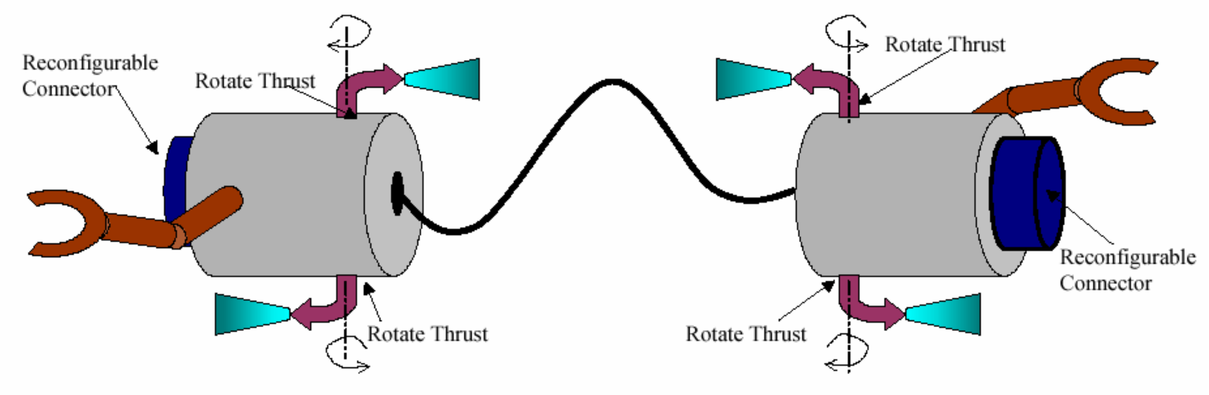

Figure 2.4 – FIMER robot with two free flying heads, adapted from [Shen et al., 2003]

The assembly of the IRCs is conceived as being mediated by one or more FIMER robots. Figure 2.4 shows a conceptual schematic of a FIMER robot. Each FIMER robot consists of a pair of robot *'heads'* attached by a thin fibre that can be reeled in or out by the heads. Each head can fly autonomously and (de)dock with any IRC or other FIMER robots. Each head is equipped with a rotational/translational thruster system, a motor to manage reeling of the fibre, GPS/Gallileo, wireless communications, a robotic manipulator arm, and a reconfigurable connector. The self-assembly process is orchestrated by the Digital Hormone Model (DHM) developed for the CONRO reconfigurable robots [Castano et al., 2002]]. Summarised simply, IRCs signal that they wish to dock with each other, and then call a FIMER for help. The FIMER heads attach one to each IRC and provides docking guidance through reeling them together. The canonical connectors will use infra-red to provide guidance signals for alignement in the docking process, as used in the CONRO system [Rubenstein et al., 2004]. Each side of the connectors will have two emitters and two receivers and are arranged in such a way that when two sides are aligned they will have maximum signal reception. The mechanics of pulling two IRCs together using the Fibre can allow simplified control of the two IRCs, naturally avoiding undesirable rotation. At this final stage, the manipulator arms on each head will be used to provide fine-grain control of the docking process. The connectors can detect their state and gathering this information allows the current topology of the structure to be determined. The IRCs then negotiate to decide on the next sequence of actions to take. The sequence of IRC assembly is embedded in the IRCs themselves. For a homogeneous system of IRCs, each IRC and it's connectors do not require unique identification and sequencing is not required. In the case of a heterogeneous set of IRCs, unique identifiers are used for each connector (for a semi-homogeneous set of IRCs, type-identifiers for generic components is sufficient).

2.3.2 Summary

This section has introduced the Fields of self organisation and self-assembly. The features present in self-assembling systems have been briefly covered, and artificial self-assembling systems (both computational and physically implemented) have been introduced. The desirability of self assembly for space applications has been outlined, and the most prominent current research into self assembly in space (the SOLAR/FIMER project) has been introduced.

3 THE EQUILIBRIUM-SHAPING APPROACH

3.1 INTRODUCTION

For a rigid-body spacecraft, a behavioural primitive (e.g. docking with another craft) will be associated with a particular control problem. There obviously already exists a large body of techniques applicable to control of rigid bodies in a free space environment[5]. Within this study, the philosophy is therefore to decouple the behavioural model that drives the agents from control techniques, which can be developed separately.

In recent literature work carried out by several groups in the field of robotics has raised the interests of space engineers for those applications in which a spacecraft has to accomplish proximity operations and has to reach, with a group of other satellites, a very tight formation, or indeed dock with those other spacecraft. The development of automated on-orbit assembly has been identified as a key requirement by work such as the HMM study [CDF, 2004]. Also, some of the advanced mission concepts being developed also rely upon the use of swarms of satellites (examples are the APIES and ANTS architectures [EADS, 2004; Curtis et al., 2000]). A fundamental component of spacecraft swarm operations involves position and velocity control. As such, the lessons learned in terrestrial robotics research would appear to highly relevant, in particular research into terrestrial robot path planning.

From path planning approaches, the artificial potential method (see section 1.1.4.5) has to date been considered as the main tool that would allow the group of spacecraft to perform as required (see [McQuade, 1997]). Work using aritificial potential fields defined in the space around the agent(s) has been performed through from terrestrial plath planning [Khatib, 1986] to spacecraft proximity and rendezvous [McInnes, 1995] and self-assembly in space [McQuade, 1997].

The artificial potential method is supposed to create in the space around the spacecraft (or the “agent” in general) a potential field that will drive the agent far from any obstacle and towards any desired target. This method is suitable to be used both for a single spacecraft and for a swarm of satellites and is capable of tackling the problem of the guidance of a vehicle in a time-varying environment. However, when combining multiple behaviours through the superposition of multiple potential fields, it is impossible to guarantee avoidance of undesired local minima. [Sato, 1993; Keymeulen & Decuyper, 1994; Chang, 1996] represent work done to get around this central problem

Work has been carried out in addition to potential function methods in order to design algorithms that allow a formation of satellite to perform reconfiguration manoeuvres in a distributed and autonomous way. For example [Ren et al., 2004; Lawton & Beard] introduced the Virtual Structure method in order to design a decentralized formation scheme for spacecraft formation flying, whilst [Campbell, 2003] applies some results from optimal control

[5] The Reader is directed to [Bong, W. (1998). Space Vehicle Dynamics and Control. AIAA Education Series] for a comprehensive overview of the field.

theory in order to design an off-board computed procedure for the design of a formation reconfiguration method.

In general all these methods have been used to design systems that have only one target configuration as a final objective. Therefore there is a general requirement for a method able to tackle the multi-target problem for a swarm of *homogeneous* agents. In such an algorithm the final position occupied by each agent in the target configuration should be chosen in an autonomous way between all the of possible ones according to the initial conditions imposed. Each satellite belonging to the swarm will be then able to autonomously decide what its final position in the target configuration will be, exchanging a minimum amount of information with the other swarm components. This kind of procedure can drive a self-assembly process of homogeneous agents in space and it clearly scales well with the increasing of the number of satellites belonging to the swarm due to the lack of explicit global coordination.

In this chapter we describe a novel dynamical systems technique to achieve this which has been termed *Equilibrium Shaping*. This procedure is able to define a kinematical field that, if followed, allows a swarm of satellites to achieve a final desired configuration in a way in which each satellite can decide autonomously what its final position in the task configuration will be. The resulting aggregation procedure is seen to be more efficient from a fuel consumption point of view thus increasing the degree of coordination of the resulting system. On the other hand the amount of data exchange between the agents will be kept low. The Equilibrium Shaping technique takes into account the gravitational force in order to obtain a desired velocity field that requires less propellant consumption to be followed.

3.1.1 Equilibrium Shaping

In this section an algorithm able to lead an arbitrary number of satellites towards a final formation by autonomously deciding which agent will get to each position of the final configuration is presented. Such a method draws the inspiration from behavioural robotics, and a model recently developed by [Gazi, 2003; Gazi & Passino, 2002], in which a kinematical field is proposed that can lead a swarm of agents to reach a stable configuration. and a method to drive the aggregation of a swarm of vehicles in a general environment is presented. The resulting procedure is made up of two different steps:

- First a desired kinematical field is imposed in the space around the agents belonging to the swarm. This kinematical field is time dependent and it assigns for each configuration, i.e. each position of each spacecraft, the desired velocity vector of each agent as a sum of different weighted contributions.
- Then an appropriate feedback signal is defined to enforce the real dynamics of each spacecraft towards the desired one.

In this way it is possible to keep the desired kinematical field design separate from the control feedback design. The velocity field used in [Gazi & Passino, 2002] is given by the sum of two different contributions, both of which are functions of the distance between two agents i and j. The first contribution introduces a linear global attraction effect whereas the second one introduces a local exponential repulsive effect, defined by:

$$g_g(\vec{x}_j) = -\vec{x}_j[c - d\exp(\frac{-\|\vec{x}_j\|}{k_1})]$$ **Equation 3.1**

This approach allows a final desired formation to be reached only if the required distance between a generic *i-j* couple of spacecraft at the end of the simulation is pre-assigned. Thus the resulting system in general doesn't have the capability of deciding autonomously where each agent should go. In order to increase the fault tolerance and the degree of parallelism of the system, the position of each swarm component in the desired final structure **should not to be pre-assigned**; this constraint becomes a particularly important feature for swarms composed of very large numbers of elements.

In that way the final formation reached would be autonomously decided by the agents according to the information that each of them can obtain by the use of its sensors and it would not be imposed at the beginning of the manouevre. The final configuration can be reached in such an autonomous manner according to a particular definition of the desired kinematical field given from the Equilibrium Shaping approach developed in this report. This technique consists in building a dynamical system that has as equilibrium points all the possible configurations suitable for the final purpose, i.e. all the agents permutations in the final desired configuration.

As example let us consider a situation in which a swarm of two satellites has to reach a final configuration made up of the two geometric positions given by:

$$\vec{x}_1 = \begin{bmatrix}1 & 0 & 0\end{bmatrix} \text{ and } \vec{x}_2 = \begin{bmatrix}-1 & 0 & 0\end{bmatrix}$$ **Equation 3.2**

If the agents are identical two final formations will be valid, one in which agent 1 is in $\vec{x}_1$ and agent 2 in $\vec{x}_2$ and one in which the final positions are inverted. The Equilibrium Shaping technique defines a desired kinematical field according to the relation:

$$\dot{\vec{x}} = \vec{f}(\vec{x}) \Rightarrow \vec{f}(\vec{x}_e) = \vec{0}$$ **Equation 3.3**

in which the $\vec{x}_e$ vector represents all the possible final formations achievable (in the example, both the final configurations in which Agent1$\Rightarrow \vec{x}_1$ and Agent2 $\Rightarrow \vec{x}_2$ and in which Agent1$\Rightarrow \vec{x}_2$ Agent2$\Rightarrow \vec{x}_1$). The desired velocity field used to obtain this effect can be written as a superposition of different contributions each of them regarding a particular *basis behaviour.*

Three behavioural primitives required for the task of assuming a formation in space (including assembly) have been defined to allow the swarm of satellites to function: ***Gather***, ***Avoid*** and ***Dock***. ***Note that this model does not take into account control of the attitude of the agents, although this is possible, and work is currently underway to extend the repertoire of behaviours to include attitude control***. The governing expressions of each basis behaviour along with some brief comments are presented below. Each contribution to the *i-th* agent desired velocity field establishes a relation with an agent if it has the *j* subscript, whereas it refers to a desired final position in the formation (hereafter a *sink*) if it has the t_j subscript:

Gather behavior This basis behaviour introduces *N* different global attractors towards the sinks of the desired formation. Therefore each agent has to know at each time where is the position of each point of the final formation to be achieved. The expression for this kind of behavior is defined as:

$$\vec{f}^{\,it_j}_{gather} = -c_j \vec{x}_{it_j} \qquad \textbf{Equation 3.4}$$

where $\vec{x}_{t_j}$ is the distance between the *i-th* agent and the *j-th* sink (t_j). This behavior can be written for each sink and for each agent and it is linear in the distance between them. So summing up for one agent the contribution of each sink it is easy to understand that all these contributions are equivalent to a single global attractor pointing towards the center of the desired formation (see Figure 3.1).

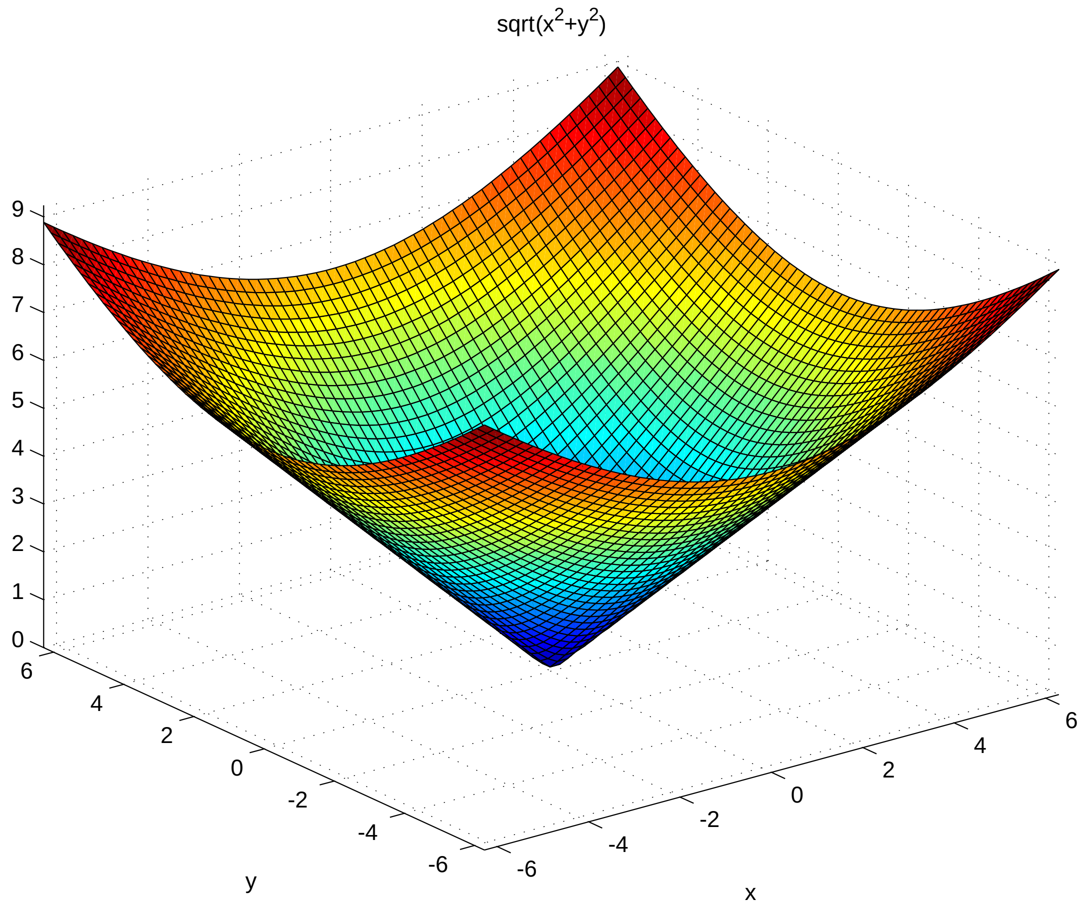

Figure 3.1 – The gather behaviour global attractor

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Avoid behavior This basis behaviour establishes a relationship between two different agents that are in proximity with each other. In such a case a repulsive contribution will assign to the desired velocity field a direction that will lead both the two agents away from each other. The expression that describes the assigned velocity for this kind of behaviour is given below:

$$\vec{f}^{\,ij}_{avoid}(\vec{x}_{ij}) = -\vec{x}_{ij}\left[b\exp\left(\frac{-\left\|\vec{x}_{ij}\right\|}{k_1}\right)\right] \qquad \textbf{Equation 3.5}$$

In this relation $\vec{x}_{ij}$ is the distance between the two agents that are proximate and k_1 is a parameter that describe the sphere of influence of this contribution, i.e. at what distance this behavior would have a non-negligible effect. In order to maintain the symmetry between all the agents the *b* parameters of the avoid behavior have all the same numerical value.

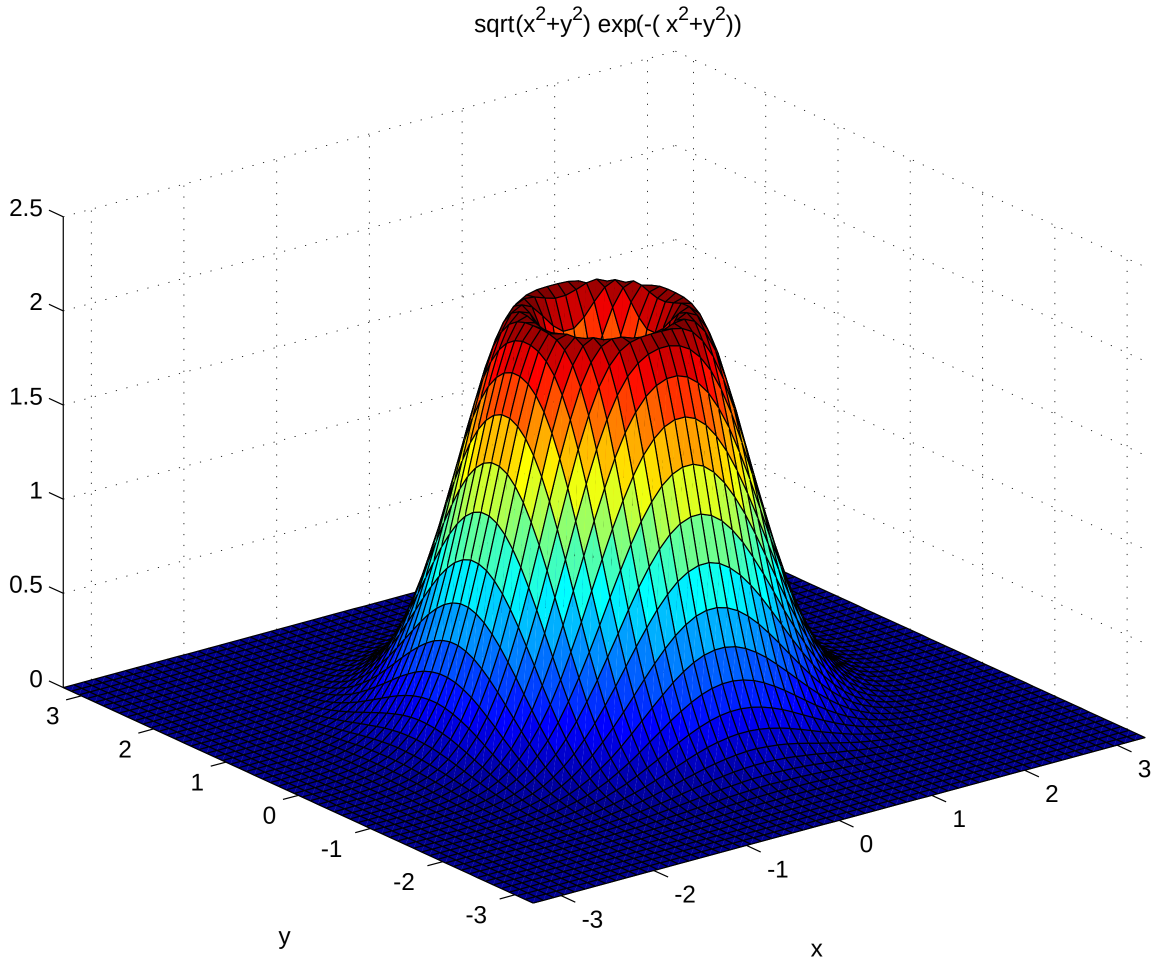

Figure 3.2 – The avoid behaviour

Dock behaviour This last basis behaviour expresses the local attraction of each agent towards each sink. The component of the desired velocity field due to this behaviour has a non-negligible value only if the agent is in the vicinity of the sink. The parameter *d* determines the radius of the sphere of influence of the dock behaviour. The expression for this basis behaviour is:

$$\vec{f}^{\,ij}_{dock}(\vec{x}_{it_j}) = -\vec{x}_{it_j}[d_{it_j}\exp(\frac{-\left\|\vec{x}_{it_j}\right\|}{k_2})] \qquad \textbf{Equation 3.6}$$

in which again $\vec{x}_{it_j}$ is the distance between the *i-th* agent and the *j-th* sink t_j and k_2 is the radius of the sphere of influence of this behavior. The values of the weighting parameters can be different for any sink.

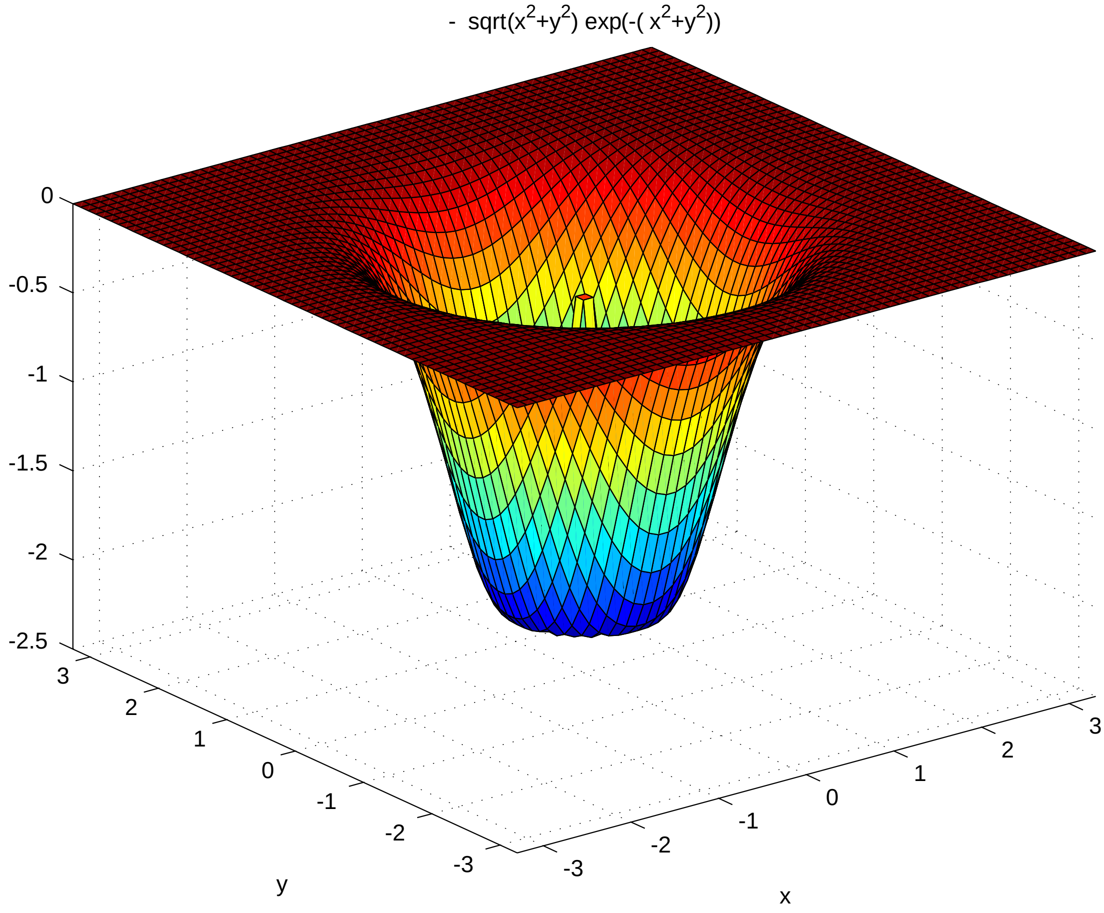

Figure 3.3 – The dock behaviour

Having defined behavioural primitives for each member of the spacecraft swarm, it is now necessary to decide on the form of the *Action Selection Mechanism* that is used to decide which behaviours are expressed at any particular time. In this problem, as with potential function and other dynamical systems approaches, we choose a simple action fusion architecture, whereby we define the velocity field for each configuration of spacecraft simply by summing the contribution from each of the basis behaviours:

$$\vec{v}_i = \sum_j \vec{f}^{\,ij}_{avoid} + \sum_{t_j} (\vec{f}^{\,it_j}_{gather} + \vec{f}^{\,it_j}_{dock}), i = 1...N \qquad \textbf{Equation 3.7}$$

This strategy leads to build a dynamical system driven by the set of equations written below, which can be sketched in the simple form:

$$\dot{x} = \vec{f}(\vec{x}; \underline{\lambda}) \qquad \textbf{Equation 3.8}$$

The resulting dynamical system is obtained as a function of some parameters $\underline{\lambda} = \lfloor c_{it_j} \quad d_{it_j} \rfloor$ that can be evaluated in order to impose that all the final desired configurations are equilibrium points. If $\vec{x}_e$ is the final target configuration to be achieved the relation that has to be fulfilled in order to impose the existence of such equilibria can be written in the compact form

$$\dot{x} = \vec{f}(\vec{x}_e; \underline{\lambda}) = 0 \qquad \textbf{Equation 3.9}$$

and it is the so-called *Equilibrium Shaping* formula that is written below as a function of the distance between two different sinks each of them occupied by an agent $\vec{x}_{e\,t_i t_j}$:

$$\sum_j \left[b \exp\left(\frac{-\vec{x}_{t_i t_j} \cdot \vec{x}_{t_i t_j}}{k_1}\right) - c_{it_j} \exp\left(\frac{-\vec{x}_{t_i t_j} \cdot \vec{x}_{t_i t_j}}{k_2}\right) - d_{it_j} \exp\left(\frac{-\vec{x}_{t_i t_j} \cdot \vec{x}_{t_i t_j}}{k_2}\right) \right] \vec{x}_{t_i t_j} = 0 \qquad \textbf{Equation 3.10}$$

$i = 1.....N.$

This equation is a linear system made up of *3N* scalar equations in *2N* unknowns where the unknowns are the weighting parameters $\underline{\lambda}$. If a regular formation or a planar formation are the target configurations, the number of independent scalar relations becomes $\leq 2N$ and the solution of the Equilibrium Shaping formula can be found. This system in theory can be designed for each agent and can be thus considered as the "subjective" view of the *i-th* spacecraft. In this way for a system of *N* satellites it is possible to write *N Equilibrium Shaping* formulas each of them representing the subjective kinematical field of each agent. In Figure 3.4, Figure 3.5, Figure 3.6, Figure 3.7, and Figure 3.8 some examples of swarms of *N* agents reaching regular formations are presented. The lines displayed in these figures are the desired trajectories that each agent has to follow in order to reach the final desired configuration and as such represent the solution of the path planning problem given by the velocity field.

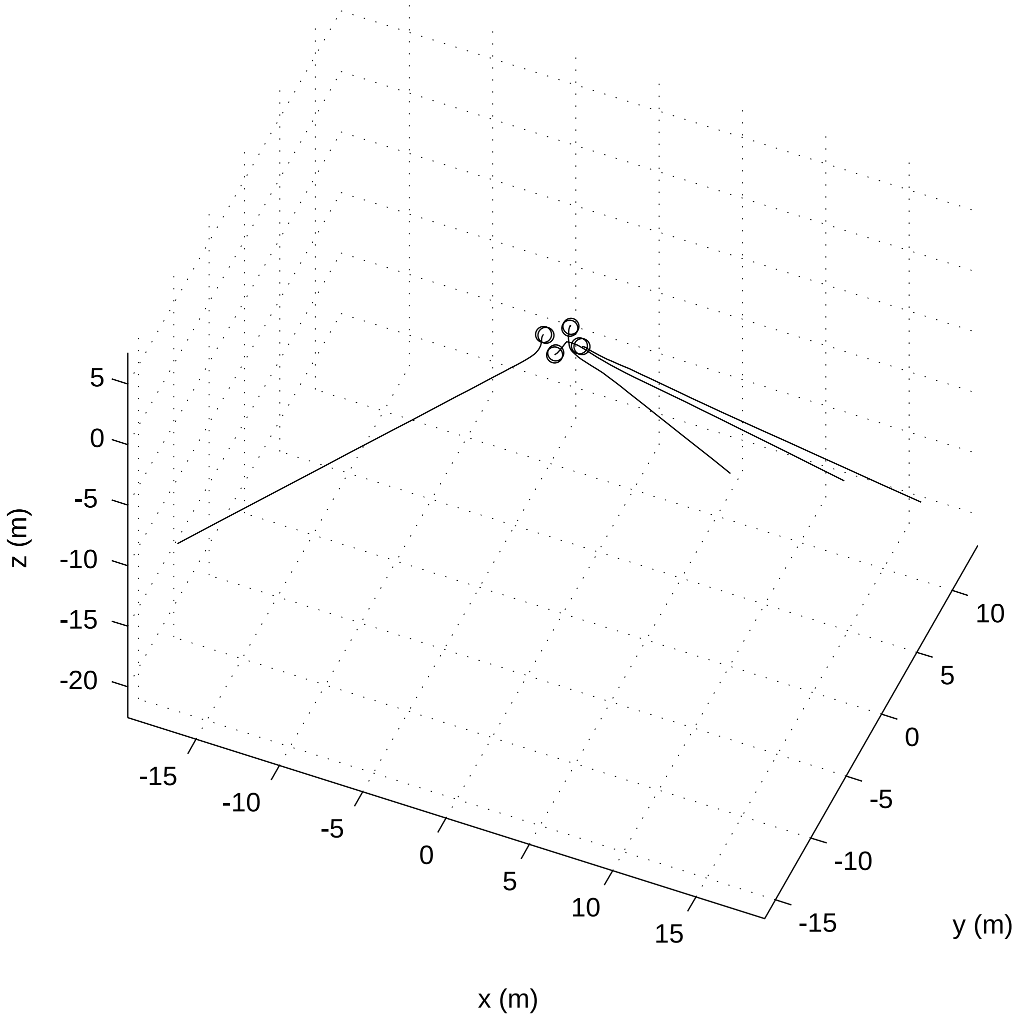

Figure 3.4 – Trajectory plot for a group of four spacecraft

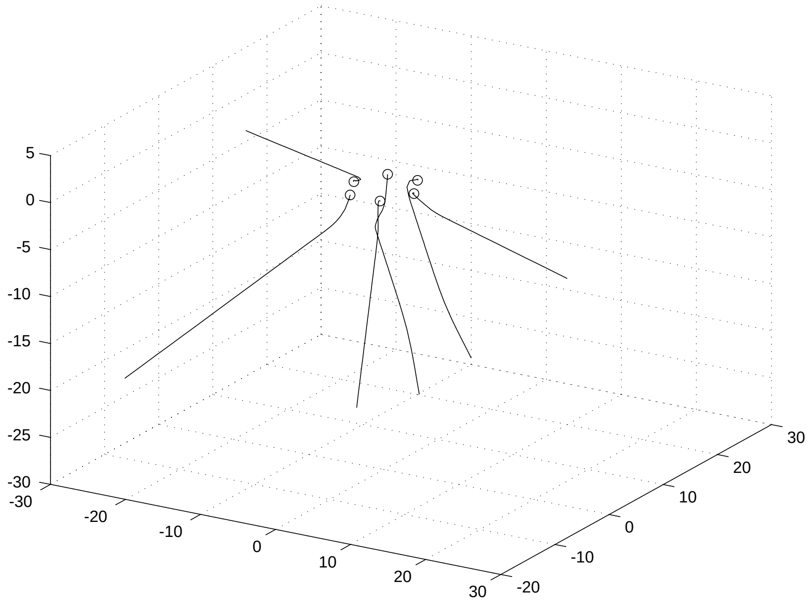

Figure 3.5 – Trajectory plot for a group of 6 spacecraft assuming a regular hexagonal formation

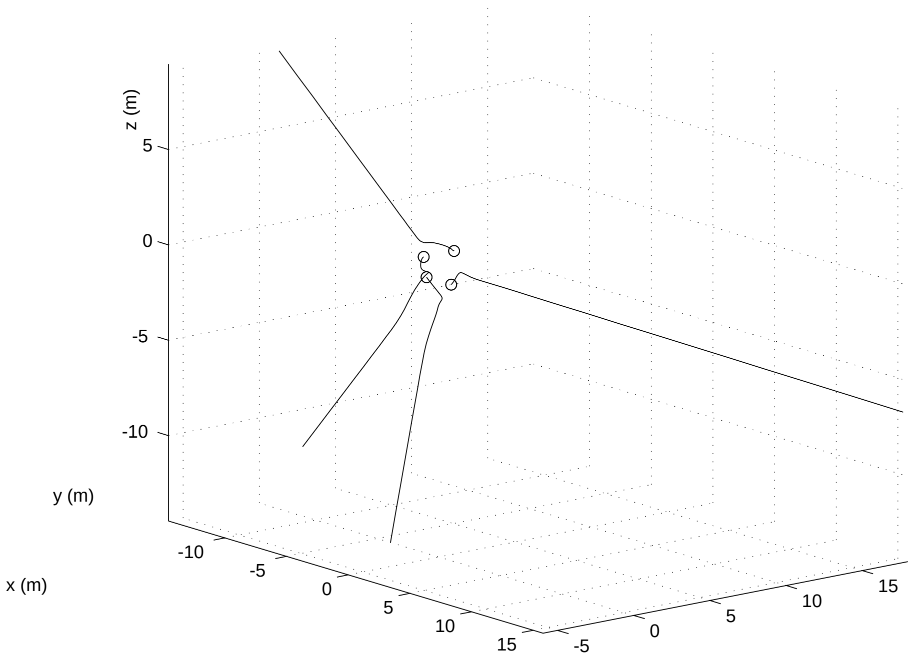

Figure 3.6 – four spacecraft adopting a formation

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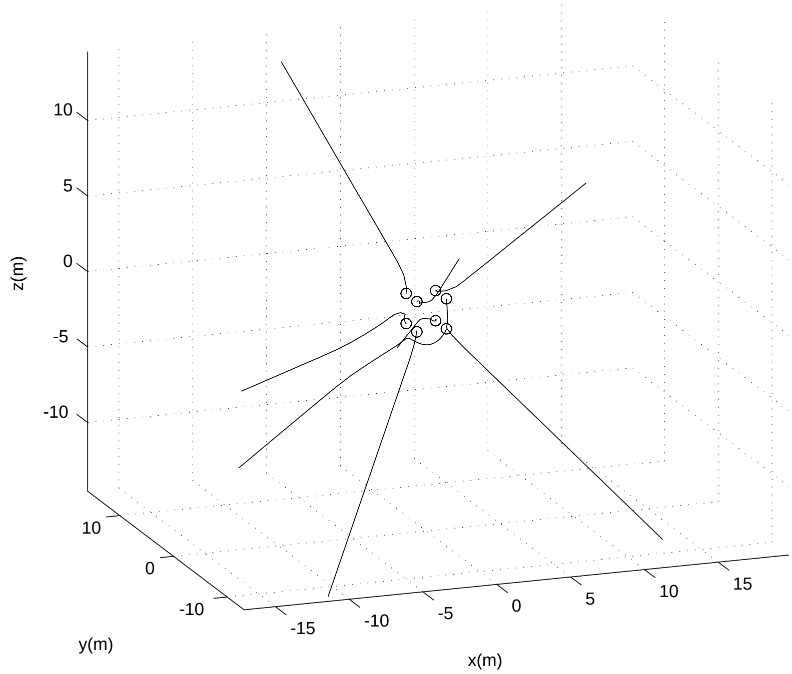

Figure 3.7 – 8 spacecraft adopting a regular cube formation

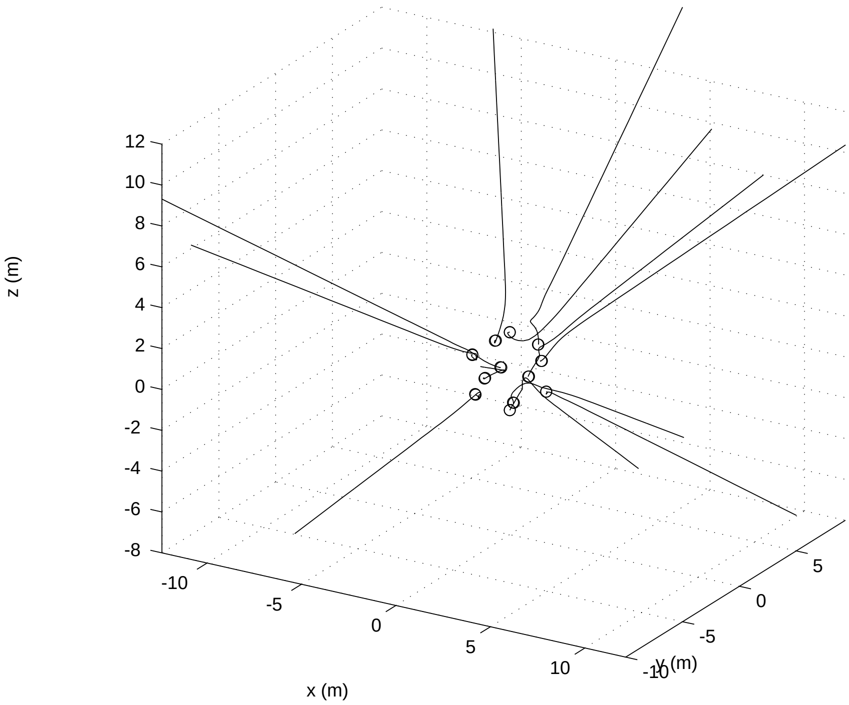

Figure 3.8 - Trajectory plots for a swarm of 12 agents

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During the simulations *emerging* behaviours may be observed due to the interaction between the basis behaviours. These behaviours include waiting for other agents to adopt their position, and coordinated avoidance between agents.

3.1.1.1 Modifying for a Gravitational Field

In the absence of a gravitational field, the velocity field field designed in the previous section allows the spacecraft to reach the final formation following trajectories that are straight lines in long part of the simulation (i.e when only the ***gather*** behaviour has a non-negligible value). In a field-free space, this is of course appropriate and efficient. However, in field-space, the desired velocity field should be modified to take into account and exploit the natural trajectories that exist between two points on different orbits. The desired velocity that accomplishes this will here be found by substituting the linear ***gather*** behavior defined by equation 4.4 with a new one. The starting point for the design of the new ***gather*** behaviour is the system of Hill's Equations (see Equation 3.11):

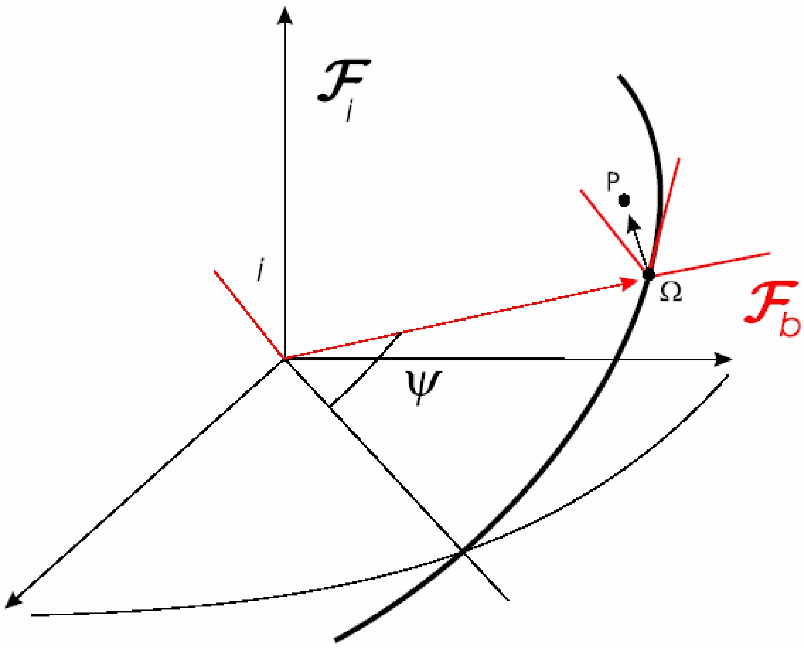

Figure 3.9 – two spacecraft on different circular orbits

$$\begin{cases} \ddot{x} - 2\omega\dot{y} - 3\omega^2 = 0 \\ \ddot{y} + 2\omega\dot{x} = 0 \\ \ddot{z} + \omega^2 z = 0 \end{cases} \qquad \textbf{Equation 3.11}$$

These equations have as their solution the following relation:

$$\underline{\dot{q}} = \begin{bmatrix} 4-3\cos\tau & 0 & 0 & \sin\tau & 2(1-\cos\tau) & 0 \\ 6(\sin\tau-\tau) & 1 & 0 & 2(1-\cos\tau) & 4\sin\tau-3\tau & 0 \\ 0 & 0 & \cos\tau & 0 & 0 & \sin\tau \\ 3\sin\tau & 0 & 0 & \cos\tau & 2\sin\tau & 0 \\ 6(\cos\tau-1) & 0 & 0 & -2\sin\tau & 4\cos\tau-3 & 0 \\ 0 & 0 & -\sin\tau & 0 & 0 & \cos\tau \end{bmatrix} \underline{q}$$ **Equation 3.12**

in which:

$$\underline{q = [\xi \quad \eta \quad \zeta \quad \dot{\xi} \quad \dot{\eta} \quad \dot{\zeta}]}$$ **Equation 3.13**

is the non-dimensional state space vector with the parameters describing the relative position and velocity of a deputy satellite (*P* in figure) with respect of a chief (Ω) satellite in a circular orbit and $\tau = \omega t$ where ω is the orbital angular velocity. The transition matrix can be written in a block form obtaining the following relation:

$$\begin{bmatrix} \rho \\ \dot{\rho} \end{bmatrix} = \begin{bmatrix} A(\tau) & B(\tau) \\ C(\tau) & D(\tau) \end{bmatrix} \begin{bmatrix} \rho_0 \\ \dot{\rho}_0 \end{bmatrix}$$ **Equation 3.14**

that gives at each instant τ the value of the velocity and the position of a satellite that starts from ρ_0 with a velocity $\dot{\rho}_0$. Relation 3.14 can now be used in order to define a new gather behavior that could allow each agent to exploit the gravity field in order to reach the final desired configuration. In fact if one wants to impose that a satellite will reach a certain point ρ_d in the relative space in a certain time τ_d, the following relation has to be valid:

$$\rho_d = \rho(\tau_d) = A(\tau_d)\rho_0 + B(\tau_d)\dot{\rho}_0$$ **Equation 3.15**

This relation assigns for each position in space ρ_0 and each desired time τ_d a desired velocity vector:

$$\vec{v}_d = \dot{\rho} = B^{-1}(\rho_d - A(\hat{\tau}_d - \tau)\rho)$$ **Equation 3.16**

in which $\hat{\tau}_d$ is the time at which at the beginning of the simulation the agent is supposed to reach the position ρ_d. In order to track the natural trajectory the resulting desired velocity vector depends explicitly on the time. This contribution can be added to those obtained by Equation 3.5 and Equation 3.6 and in order to build the final desired kinematical field that the swarm has to follow. Since at the end of the assembly procedure each spacecraft will probably operate in a condition in which it is close to the other swarm components it is not possible to allow the spacecraft to have high velocities in that situation. Furthermore Equation 3.16 becomes singular as long as *t* approaches the $\hat{\tau}_d$ value. For both these reasons the agents are not permitted to follow the natural trajectories until the end of the formation acquisition. To implement this we divide the desired kinematical field into two different sections: (i) far from the desired final configuration, in which the gather behavior takes into account the gravitational force and (ii) close to the desired final formation, in which space can be linearised and considered flat. The geometrical shape of the edge of these two different zones of the space can be easily set as a sphere of a radius that can be decided by the system designer.

3.1.2 The Control Strategy

Having defined a kinematical field to provide the spacecraft with their desired velocities, the second step required is the development of a control law able to enforce the desired kinematical field. In this section different feedback laws will be derived and discussed. The first control strategy derivation starts from the definition of a velocity-to-be-gained vector $\vec{v}_g^{\,i}$ that represents at each time the difference between each agent's actual $\vec{v}^{\,i}$ and desired velocity $\vec{v}_d^{\,i}$. The objective of the control is to drive the velocity to be gained vector to zero. From now on each quantity will be related to each agent but, in order not to make the notation used more difficult the *i* apex will be omitted. If one defines the following Lyapunov function for each agent:

$$V = \frac{1}{2}\vec{v}_g \cdot \vec{v}_g \qquad \textbf{Equation 3.17}$$

the velocity to be gained vector is seen to decrease along the trajectories followed by each agent if:

$$\dot{V} = \dot{\vec{v}}_g \cdot \vec{v}_g < 0 \qquad \textbf{Equation 3.18}$$

The time derivative of $\vec{v}_g$ during the motion is obviously $\dot{\vec{v}}_g = \dot{\vec{v}}_d - \dot{\vec{v}}$. Substituting in this relation the momentum balance of each spacecraft:

$$\dot{\vec{v}} = \vec{u} + \vec{f}_{in} \qquad \textbf{Equation 3.19}$$

where $\vec{f}_{in}$ is the external inertial acceleration and $\vec{u}$ is the acceleration due to control force, the following expression can be obtained:

$$\dot{\vec{v}}_g = \dot{\vec{v}}_d - \dot{\vec{v}} = \dot{\vec{v}}_d - \vec{u} - \vec{f}_{in}$$ **Equation 3.20**

The expression of the time derivative of the desired velocity along each agent trajectory is found to be, using the chain rule:

$$\dot{\vec{v}}_d = \frac{\partial \vec{v}_d}{\partial t} + \frac{\partial \vec{v}_d}{\partial \vec{r}}\vec{v} = \frac{\partial \vec{v}_d}{\partial t} + \frac{\partial \vec{v}_d}{\partial \vec{r}}(\vec{v}_d - \vec{v}_g)$$ **Equation 3.21**

In the outer kinematical field the agent is supposed to follow the ballistic trajectory defined by the gravitational ***gather*** behaviour. The time derivative of the desired velocity then becomes:

$$\frac{d\vec{v}_d}{dt} = \vec{f}_{in} + \frac{\partial \vec{v}_d}{\partial \vec{r}}\vec{v}_g$$ **Equation 3.22**

[Battin, 1987] and the resulting total time derivative of the velocity to be gained is, according to equation 3.16:

$$\dot{\vec{v}}_g = -\vec{u} + \frac{\partial \vec{v}_d}{\partial \vec{r}}\vec{v}_g = -\vec{u} - B^{-1}A\vec{v}_g$$ **Equation 3.23**

If the following control feedback is introduced:

$$\vec{u} = -\kappa\vec{v}_g - \dot{\vec{v}}_d - \vec{f}_{in}$$ **Equation 3.24**

in which $\kappa > 0$ is a parameter that can be used to define a particular thrust strategy, the time derivative of V is rendered definite negative:

$$\dot{V} = -\kappa\vec{v}_g \cdot \vec{v}_g < 0$$ **Equation 3.25**

and $\vec{v}_g$ is set to decrease along the trajectory followed by the agent. The control feedback seen in Equation 3.24 is a continuous control that can be obtained using as an actuator for example an electric engine. The $\kappa > 0$ parameter can be used to select the best thrusting strategy to drive $\vec{v}_g$ to zero as can be seen in Figure 3.10. In particular if $\kappa \to 0$ the control strategy is to thrust in the direction of the velocity to be gained vector regardless of the contribution to the $\vec{v}_g$ due to the uncontrollable terms $\dot{\vec{v}}_d$ and $\vec{f}_{in}$. A different strategy can be achieved if the thrust direction is chosen in order to align the time derivative of the velocity to be gained vector with the $\vec{v}_g$ vector itself, as expressed in the following relation:

$$\dot{\vec{v}}_g \times \vec{v}_g = 0$$ **Equation 3.26**

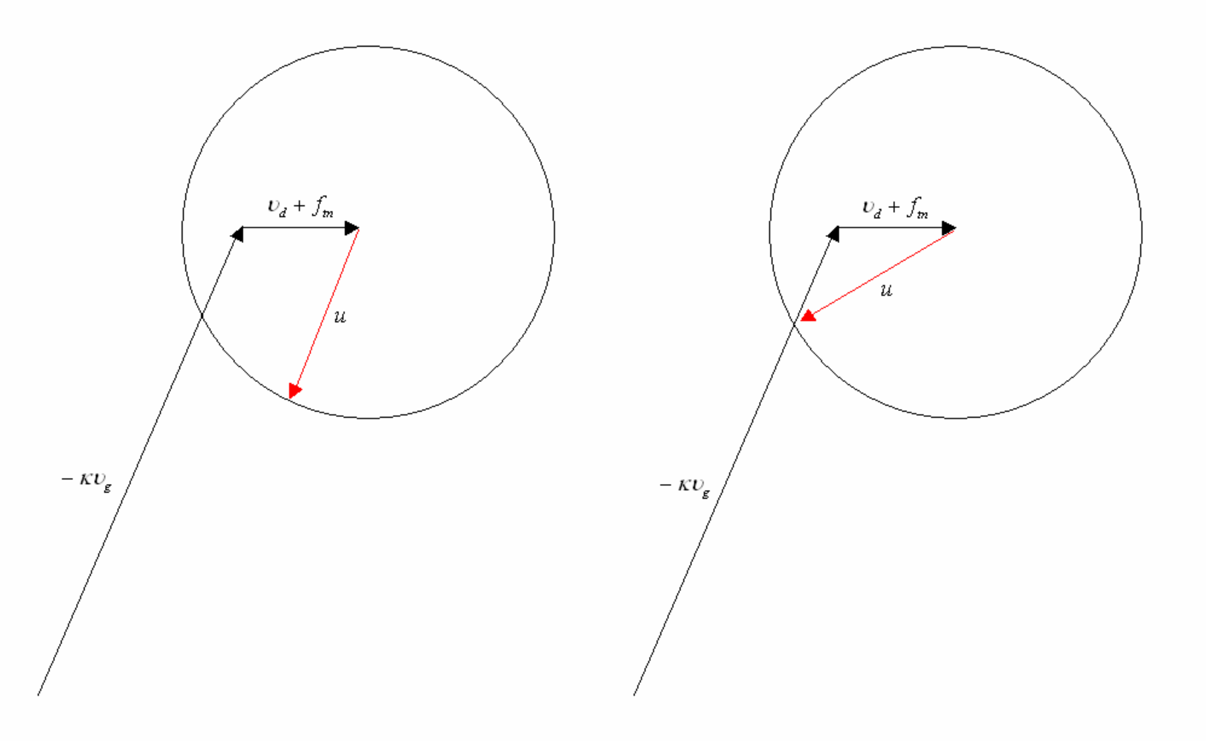

Figure 3.10 – The cross product steering law

This strategy, named cross product steering, has been introduced by Battin, and it can be implemented by finding that value of κ for which (see Figure 3.10):

$$(-\kappa\vec{v}_g + \dot{\vec{v}}_d + \vec{f}_{in}) \cdot (-\kappa\vec{v}_g + \dot{\vec{v}}_d + \vec{f}_{in}) = u_{sat}$$ **Equation 3.27**

where u_{sat} is the saturation considered for the thrust vector modulus. The procedure here used in order to derive Equation 3.24 is equivalent to the one introduced in the sliding mode control theory. In such a theory from the equation of motion written for a generic agent (Equation 3.19) and from the definition of a generic desired kinematical field:

$$\vec{v}_d = \vec{g}(\vec{r})$$ **Equation 3.28**

an *N*-dimensional sliding manifold over which the motion of the satellite is supposed to take place is defined as:

$$\vec{s} = \vec{v} - \vec{g}(\vec{r}) = \mathbf{0}$$ **Equation 3.29**

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A sufficient condition for the sliding mode to occur is then set to be:

$$\vec{s} \cdot \dot{\vec{s}} < 0 \qquad \textbf{Equation 3.30}$$

and it can be imposed by using the following feedback signal for the control thrust:

$$\vec{u} = -u_o sign(\vec{s}) - \vec{f}_{in} \qquad \textbf{Equation 3.31}$$

The procedure used to derive Equation 3.31 is obviously equivalent to the one used to derive Equation 3.24 as long as the $\vec{s}$ variable is recognized to be equal to $\vec{v}_g$. This remark establishes a trait d'union between the sliding mode control theory and the control strategies based on the definition of the velocity-to-be-gained vector.
A third thrusting strategy can be obtained starting from the definition of an artificial potential function $V(\underline{x})$ in which x is the state vector describing the motion of the whole swarm of satellites. In our case the function that has minimum points in all the possible agents' permutation of the final desired configuration is:

$$\phi = \frac{1}{2}\sum_i \vec{v}_i \cdot \vec{v}_i + \sum_i b \sum_{i \neq j} \phi_{ij}(\vec{r}_i, \vec{r}_j) + \sum_i \sum_{i \neq j} \phi_{it_j}(\vec{r}_i, \vec{r}_{t_j}, \underline{\lambda}) \qquad \textbf{Equation 3.32}$$

where the functions ϕ_{ij} and ϕ_{it_j} are defined as:

$$\begin{aligned} \phi_{ij} &= \exp\left(-\frac{\| \vec{x}_{ij} \|^2}{k_2}\right) \\ \phi_{it_j} &= -d_{it_j} \exp\left(-\frac{\| \vec{x}_{it_j} \|^2}{k_2}\right) - \frac{1}{2} c_{it_j} \| \vec{x}_{it_j} \|^2 \end{aligned} \qquad \textbf{Equation 3.33}$$

and the parameters $\underline{\lambda} = \lfloor c_{it_j} \quad d_{it_j} \rfloor$ are obtained from the Equilibrium Shaping technique. The swarm will reach the final formation avoiding the inter-vehicles collisions if the $V(\underline{x})$ will decrease during the motion. The agents controls are then chosen such that the rate of descent of the potential function is rendered negative definite:

$$\dot{V}(\underline{x}) < 0 \qquad \textbf{Equation 3.34}$$

If a control feedback:

$$\vec{u} = -\kappa[\vec{v}_i - \nabla V(\vec{x}_i - \vec{x}_j)] + \nabla V(\vec{x}_i - \vec{x}_j)(1-\kappa) - \vec{f}_{in}$$ **Equation 3.35**

the time derivative of the potential function is found to be:

$$\dot{V} = -\kappa\vec{v} \cdot \vec{v}$$ **Equation 3.36**

which is definite negative as long as κ is chosen definite positive. All the control strategies proposed in this section are able to steer the swarm towards the desired formation. The first two are seen to be equivalent from a conceptual point of view whereas the last one relies upon a slightly different approach in which a Lyapunov control is applied to a global potential function rather than to the error between a desired kinematical field and the real velocity. At this point of the discussion it is possible to understand how the procedure to reach the target formation will look like:

(i) A powered part in which the velocity to be gained vector is driven to zero and in which a ballistic trajectory is entered. (ii) A coasting phase in which the engine is switched off and each spacecraft follows a natural trajectory towards the centre of the desired final formation. In this part of the approaching procedure each agent considers in the evaluation of the desired velocity field only the contributions related to the avoid behaviour. If a possible-collision condition occurs then the engines are lighted on and the spacecraft abandons its natural trajectory to perform the collision avoidance. As long as a non-dangerous distance between the two colliding agents is reached, then each agent will come back to the first phase in order to drive $\vec{v}_g$ to zero. As each agent enters the flat-space sphere the engines are activated, and the thrust vector enforces each agent to follow linear trajectories. The discontinuity introduced in this way can be easily reduced to be zero by changing the radius of the sphere and the time required at the beginning of the simulation to reach the centre of the desired formation, τ_d. The last phase is the one in which the agent is close to the desired final formation and decides what will be the position to be assumed.

It is important to notice here that the final formation can be achieved only if every agent is in a "sink". For this reason, since it cannot be predicted if all the agents will arrive at the same time at the edge of the flat-space sphere, it is possible that an agent will be obliged to change the decision it made moving towards another "sink". This "global behaviour" is one of the most important results obtained with the Equilibrium Shaping technique and it allows a formation to be reached in space without requiring the establishment of any communication between the agents.

3.1.3 Simulation Results

In this section the results obtained from some simulations are presented. The first simulation will show the real trajectories of a swarm of satellites reaching a final regular formation with a 6m radius starting from a random configuration. Each spacecraft belonging to the swarm starts at an average distance of 1000*m* from the centre of the final configuration. These conditions have been chosen as they are considered to be representative of the second

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phase of a generic rendezvous procedure in which a spacecraft is supposed to move from a distance of around 1000*m* towards a distance of 6-3*m*. The saturation value used for the thrust acceleration modulus is set to be 0.005 ms^{-2}. This value is representative of the modulus of currently available electric propulsion systems and is not a decisive issue for the results obtained, as long as the desired velocity field is well designed. The simulation total time is 15000*s* and the time after which the final formation is achieved is seen to be 10430*s*. In Figure 3.11 and Figure 3.12 the real trajectories followed by the spacecraft belonging to the swarm are displayed. Figure 3.11 represents the motion of the swarm of satellites following the outer kinematical field while Figure 3.12 displays the motion of the swarm in the volume in which a flat space is considered. For these simulations the centre of the desired formation is on a geostationary orbit.

In Figure 3.13 the thrust profiles of each spacecraft are showed. These show that the most fuel expensive phases of the whole procedure are at the very first seconds of the simulation in which the ballistic trajectory is entered and at the entrance into the flat-space sphere. In this second phase the agent has to choose what will be its position in the final configuration and so it has to thrust in the direction of the decided task. In Figure 3.14 a bar diagram is presented in which it is possible to see what are the total Δv required by each spacecraft to achieve the final formation. The maneouvre considered here shows a good distribution of the control effort required for the accomplishment of the desired task and requires an average Δv to the swarm component of about 0.8 ms^{-1}.

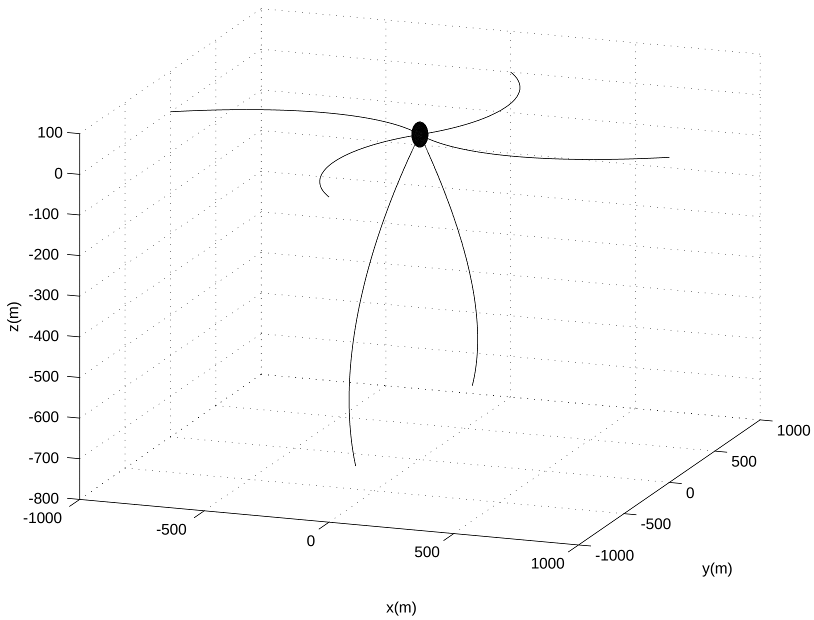

Figure 3.11 – plot showing the ballistic phase of the spacecraft trajectories

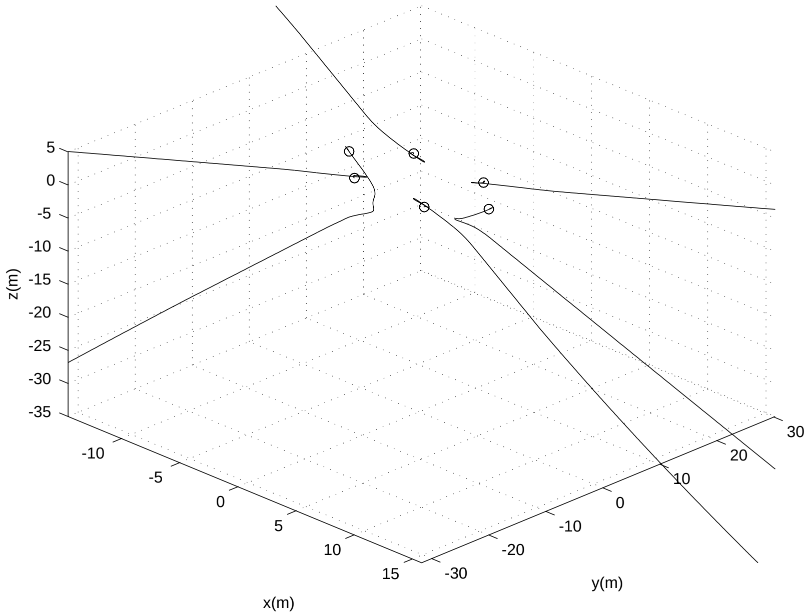

Figure 3.12 – plot showing the flat-space phase of the spacecraft trajectories

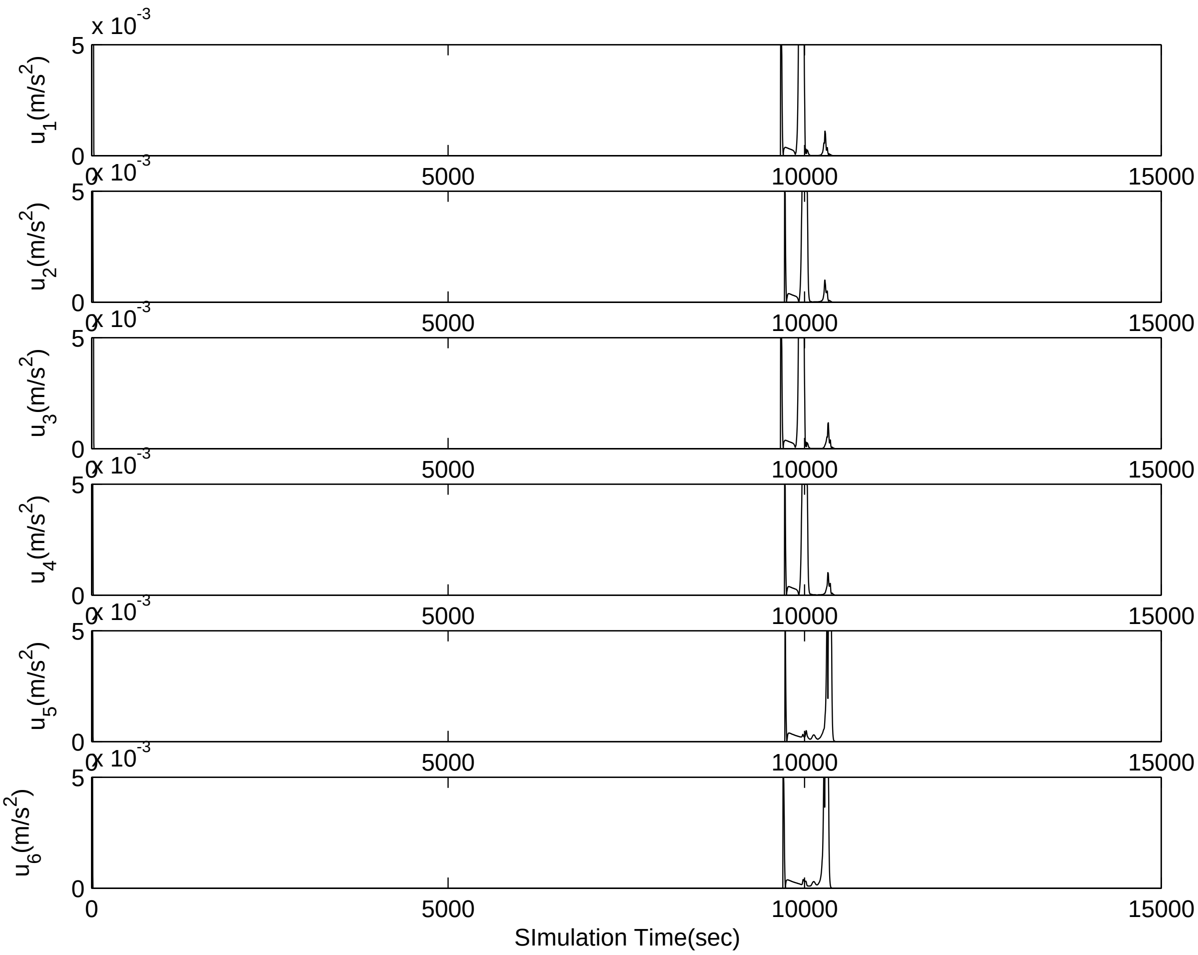

Figure 3.13 – Thrust histories for the six agents in the test simulation

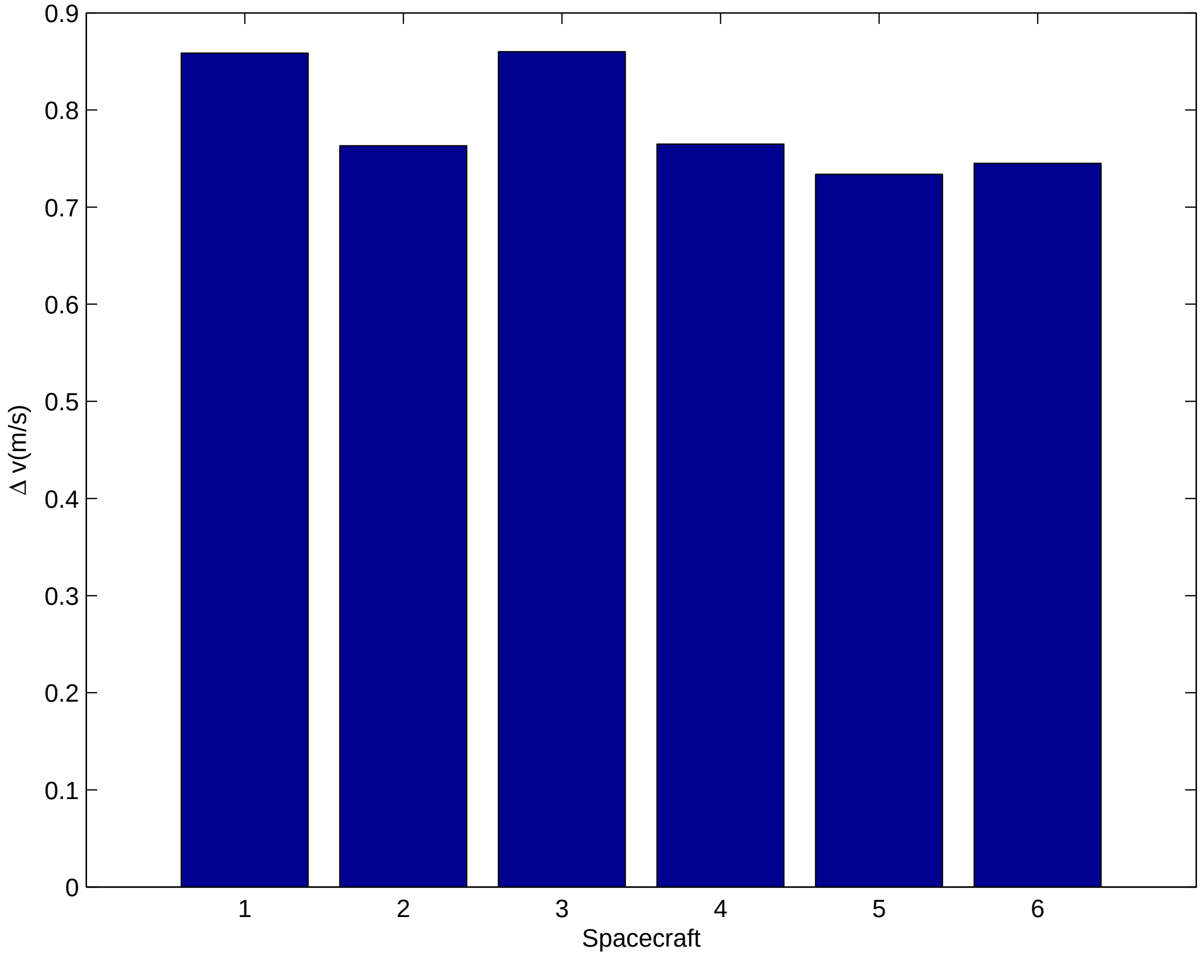

Figure 3.14 – Total delta V for each of the six spacecraft in the test simulation

In Figure 3.15 a simulation in which the initial and final conditions are the same with respect of the previous one but in which the gravitational force is not considered, is presented. In this case the total Δv required is larger as can be observed. This increase of Δv required to follow straight trajectories has been observed to become larger if the process takes place in lower altitude orbits.

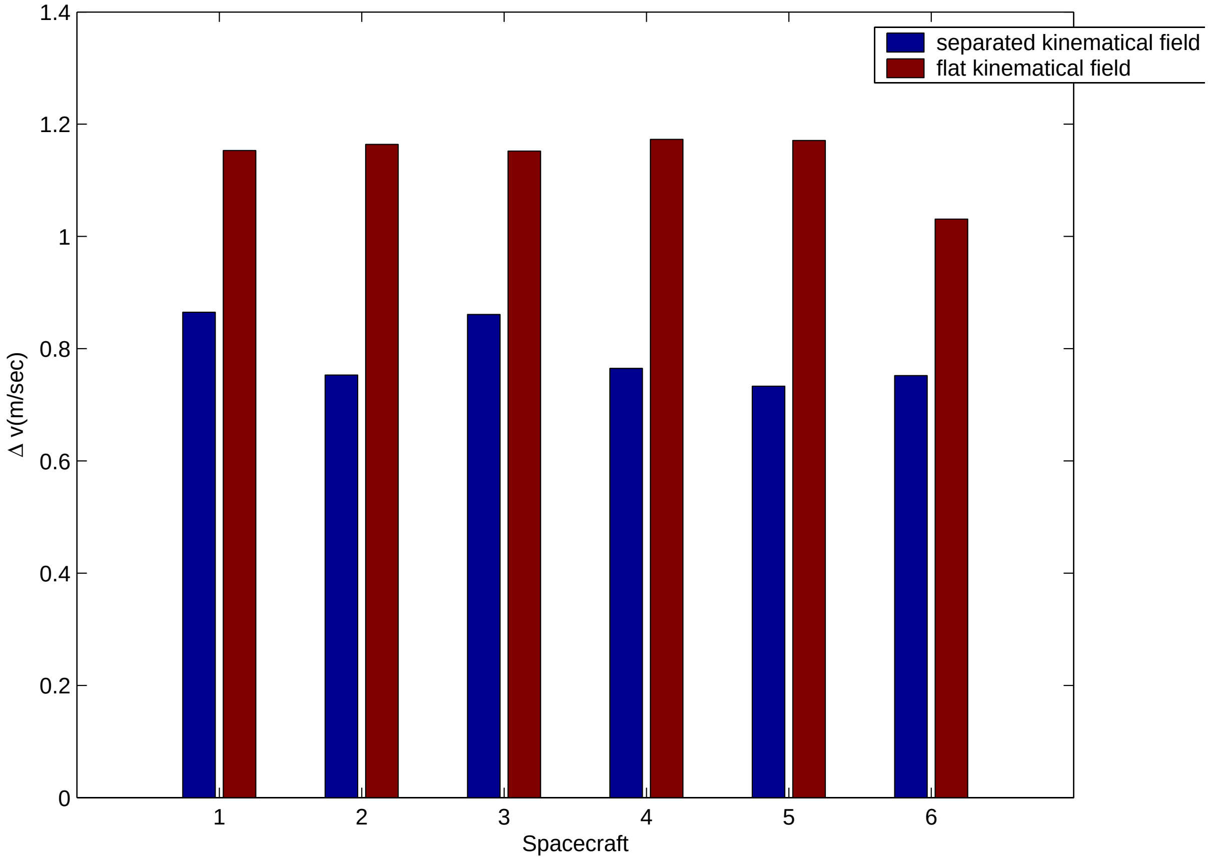

Figure 3.15 – comparison between total delta V of each spacecraft between the flat and separated kinematical fields

Figures 3.16 to 3.19 show captured still storyboards from simulations of self assembly produced using MATLAB/Simulink and the VRML toolbox (these are available as movies on the ACT website http://www.esa.int/gsp/ACT/biomimetics/index.htm). In Figure 3.16 the assembly of 7 homogeneous agents into a regular hexagonal structure is shown: Figure 3.17 and Figure 3.18 show respectively the curved and flat space phases of formation acquisition by a group of 7 agents in a gravitational kinematical field (in fact these images correspond to the test-case simulation described earlier). Figure 3.19 shows an interesting case where a regular formation is adopted by 7 agents, with an extra redundant agent that enters a stable minimum point outside of the target configuration: one of the agents in the formation is destroyed/incapacitated (in this case by an asteroid), and the redundant agent automatically moves in to replace the missing agent. This provides a good example of the type of uncoordinated, emergent behaviour that is possible with this technique.

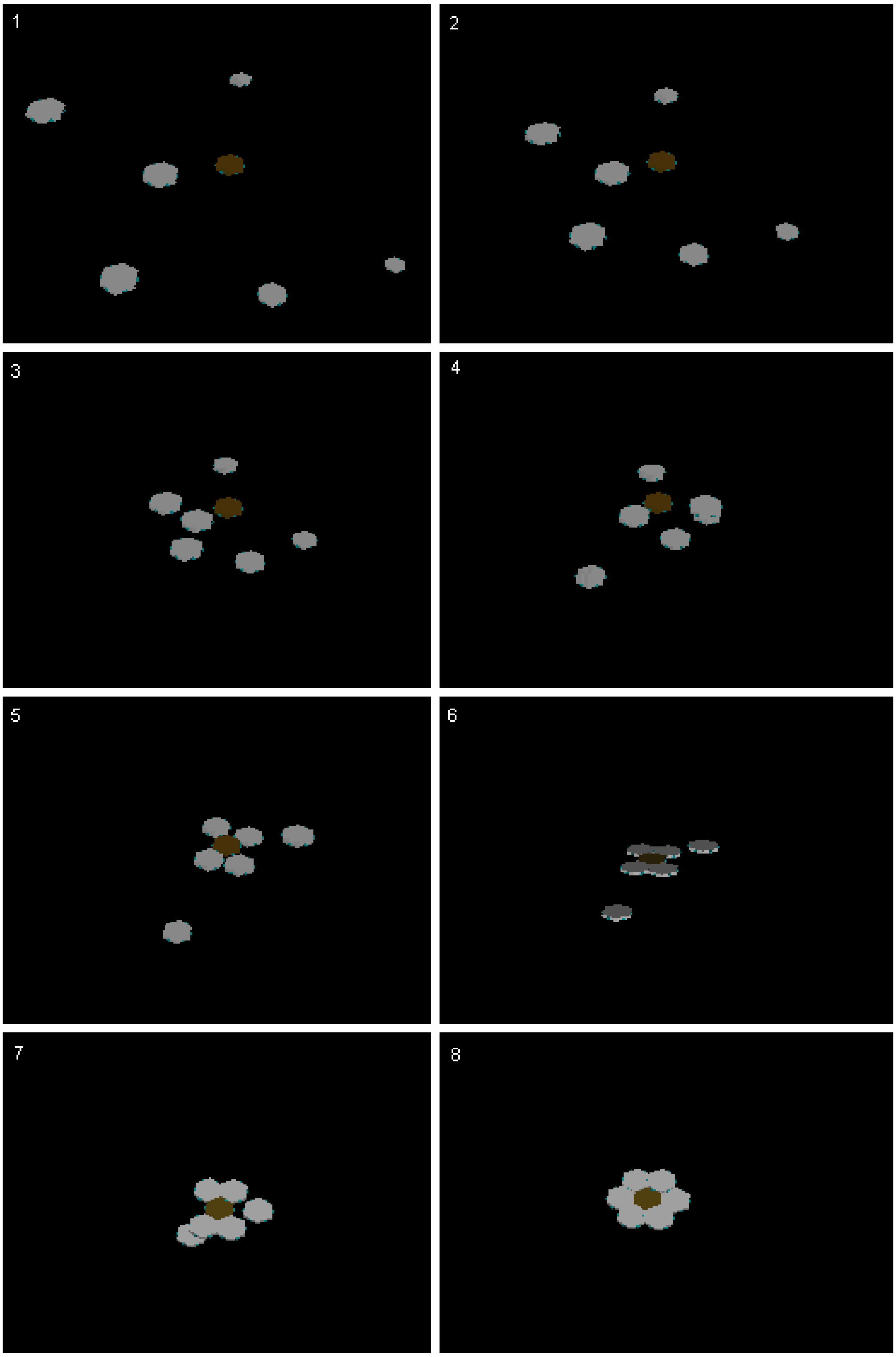

Figure 3.16 – Sequential storyboard of 7 agents assembling into a regular hexagonal structure

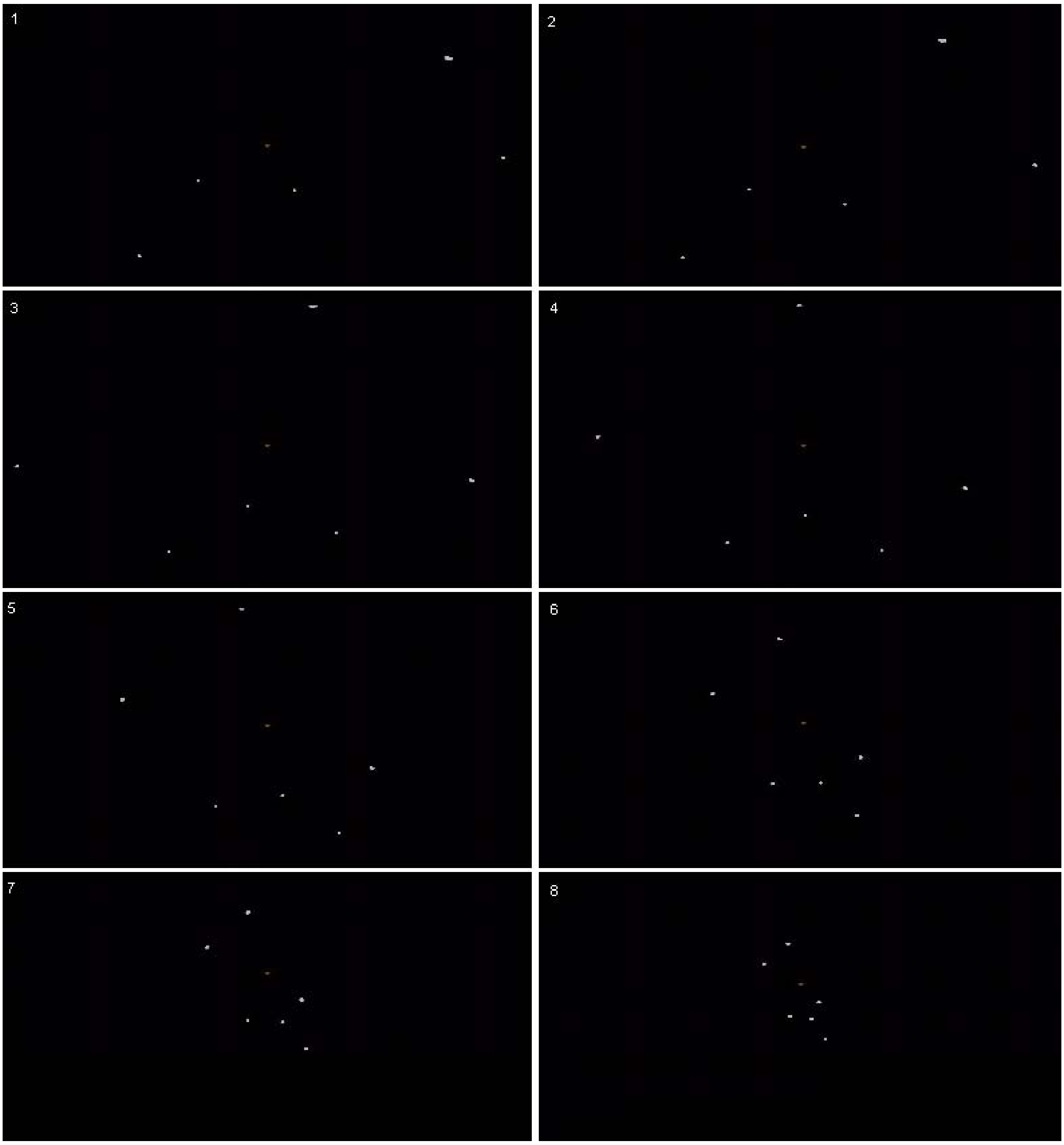

Figure 3.17 – The ballistic phase storyboard for 7 agents adopting a regular hexagonal formation

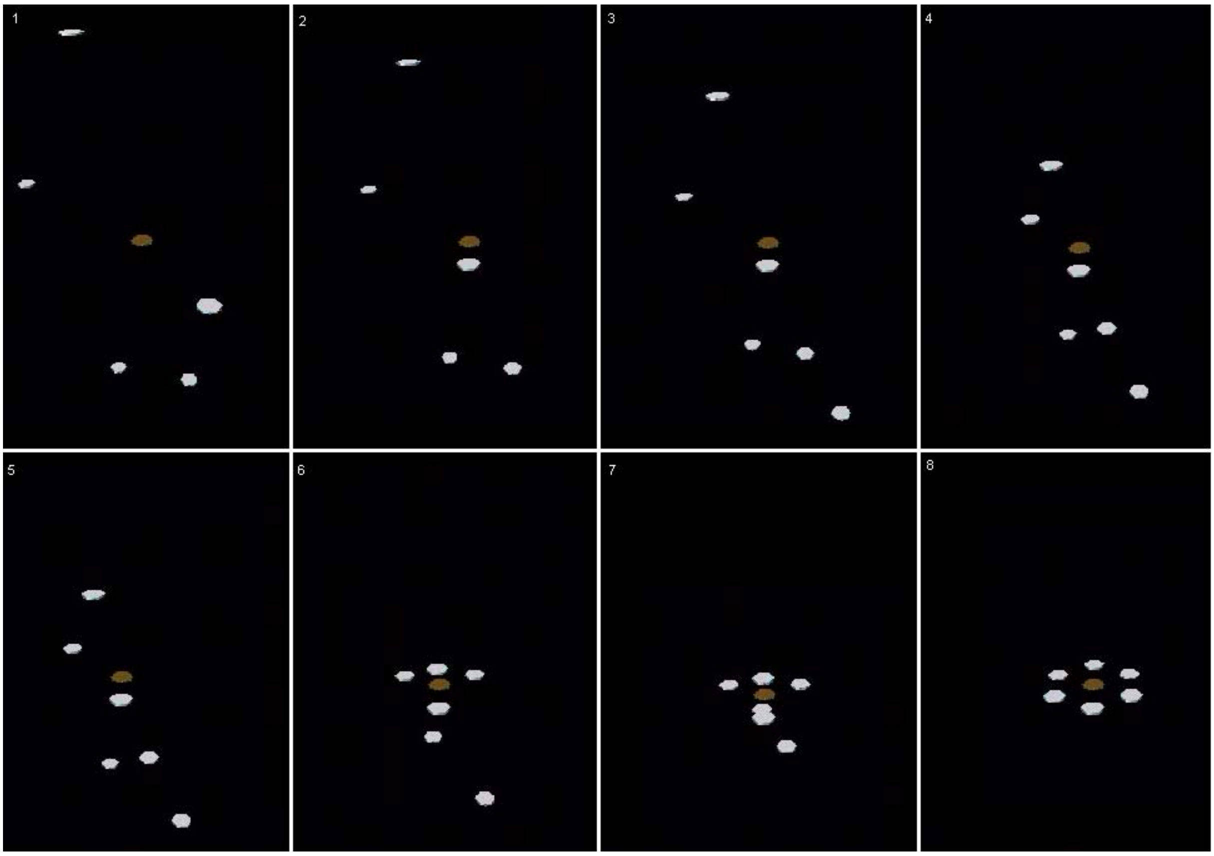

Figure 3.18 – The flat-space phase storyboard for 7 agents adopting a loose regular hexagonal formation

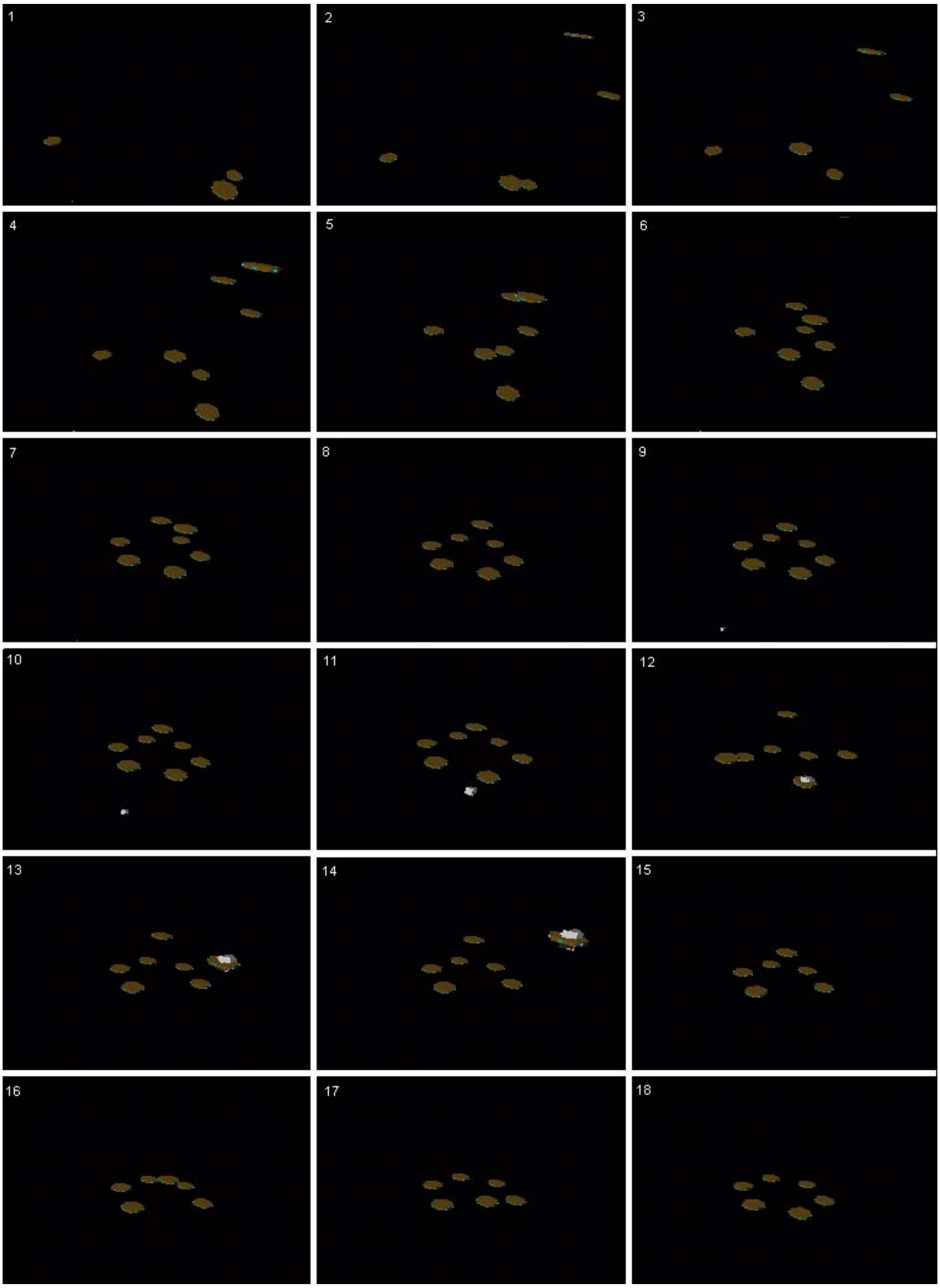

Figure 3.19 – Storyboard showing automatic redundancy of a formation of spacecraft

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In the remainder of this section some results will be presented in order to discuss the performances of the different control strategies proposed in section 1.5. The comparison between these different thrusting strategies is made within a simulation in which a flat kinematical field is imposed and with zero initial velocities and random initial positions spread over a sphere of radius 30*m* as the initial conditions. The six spacecraft belonging to the swarm are homogeneous and have the same characteristics considered previously. The comparison has been performed by tuning the parameters κ and u_0 in order to obtain the same total mission time of 1135 secs. In Figure 3.20 it is possible to see that the velocity-to-be-gained thrust strategy leads to Δv savings and to a better distribution between the agents of the control effort required for the whole maneouvre.

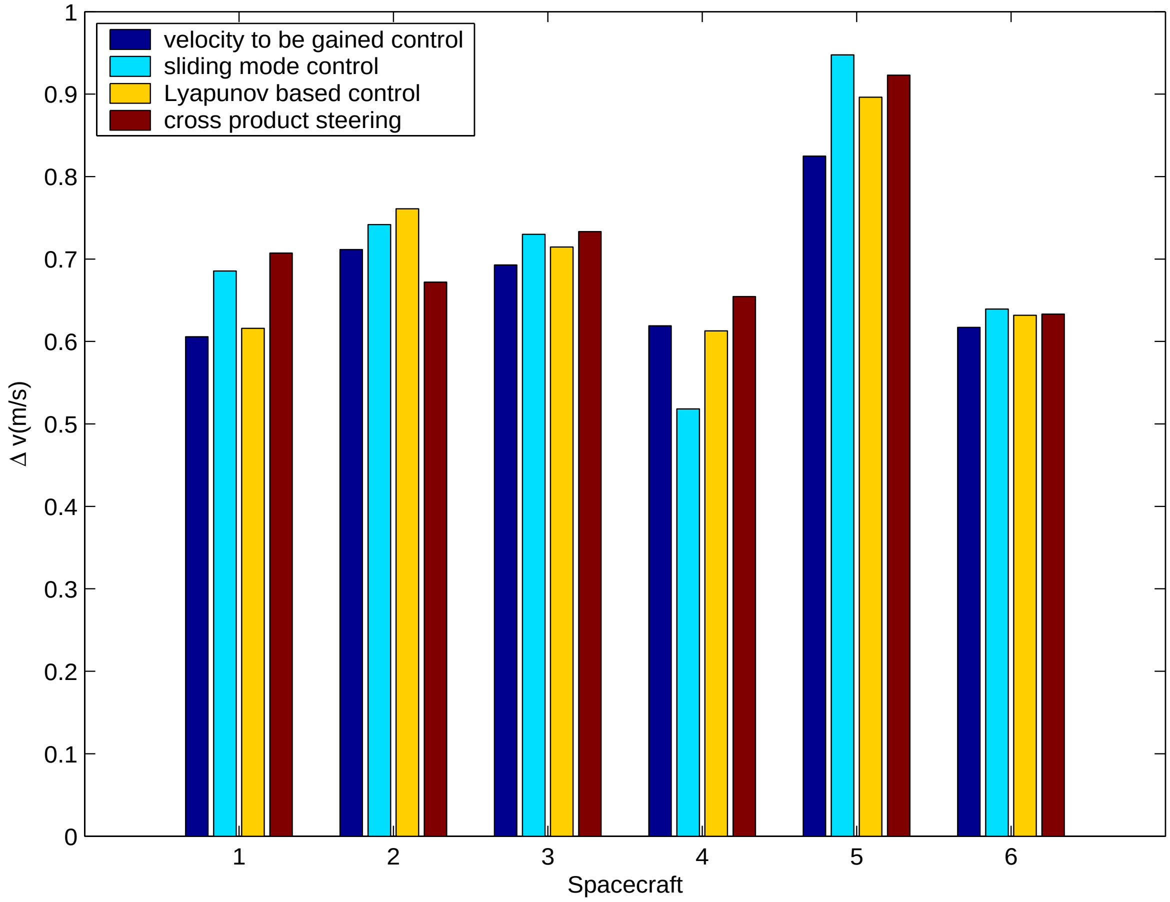

Figure 3.20 – Comparison between the different control laws for the first simulation

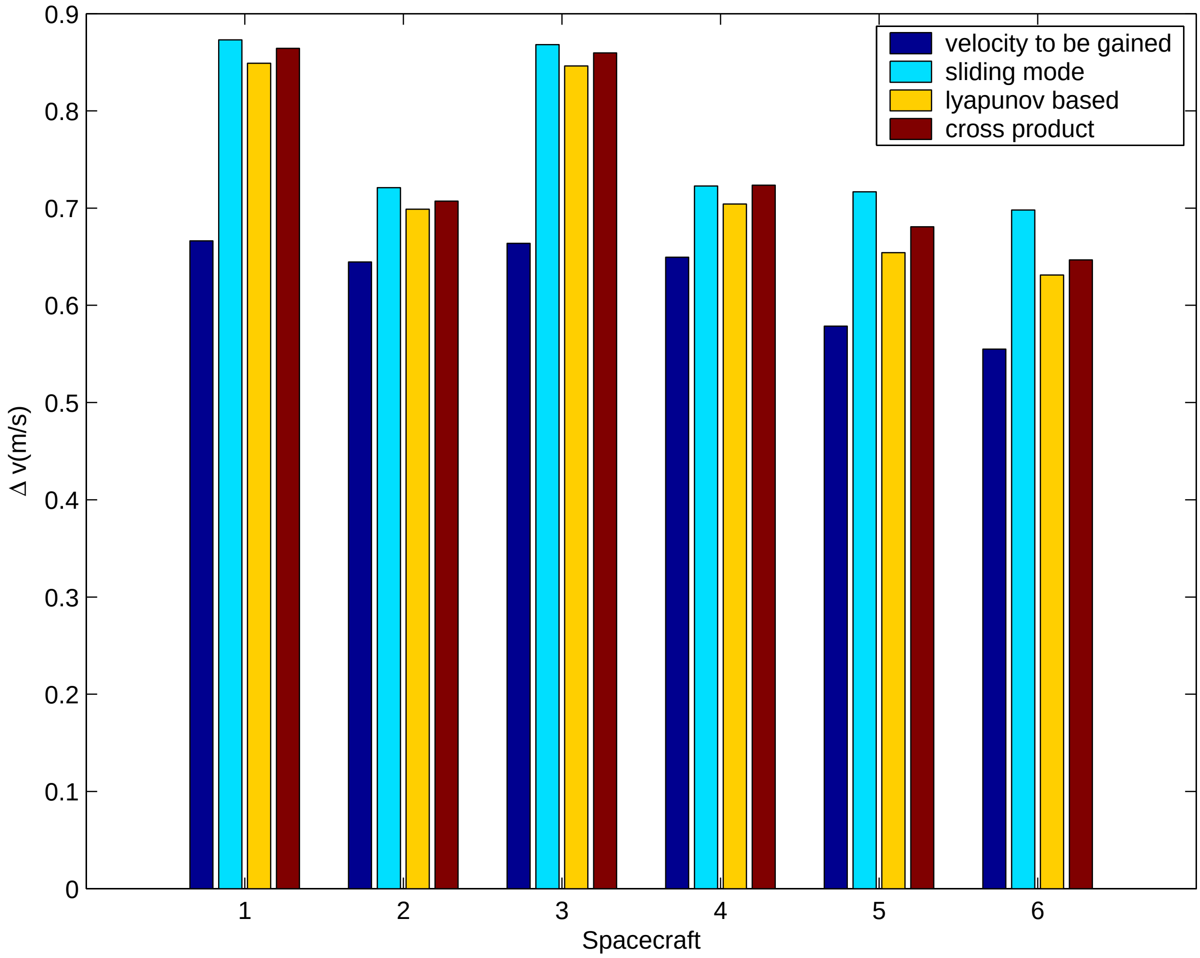

Figure 3.21 – Comparison between the different control laws for the first simulation

3.1.4 Local Minimum Avoidance Procedure

The model developed up to now does not ensure that the swarm of spacecraft will reach one of the final desired configurations. The target configuration may not be achieved due to the occurrence of local minima, i.e. equilibrium configurations that are different from the desired ones. In this section a procedure that will allow the swarm to avoid settling into undesirable local minima is introduced. This procedure exploits the particular nature of a system composed of many agents in order to release it from an undesired equilibrium position without increasing the level of communication exchanges between the agents. This procedure (sketched in a compact form in Figure 3.22) is autonomously run every time each agent of the swarm is in a position in which the evaluated desired velocity vector $\vec{v}_d = 0$. In that situation the agent checks if the occupied position is in one of the sinks of the final formation. If not the agent starts changing the parameters λ in the space of the solutions of Equation 3.10 in a random way. The process is iterated in order to find that set of parameters

λ that make the currently occupied position unstable, whilst keeping the final desired one stable.

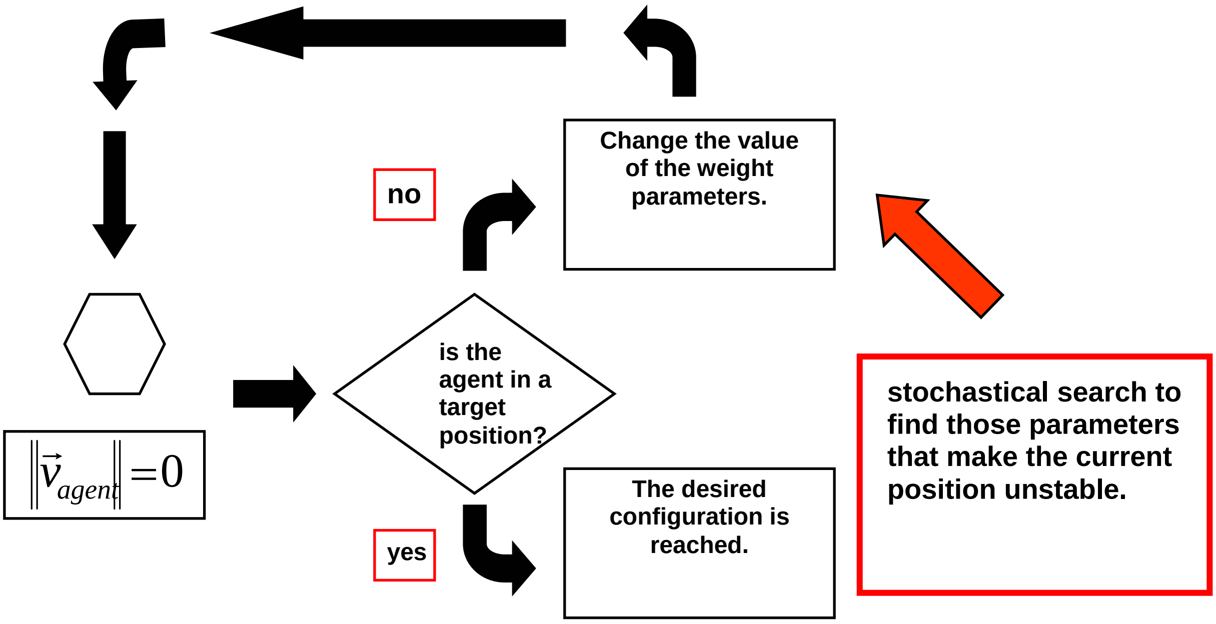

Figure 3.22 – Local minimum avoidance procedure

3.1.5 Summary

The Equilibrium Shaping Technique has been presented. The technique employs a dynamical systems approach where three basis behaviours (gather, avoid, dock) are described by suitable functions which are then summed to provide an equation the solution to which will define the kinematical field to be followed by the agents. Adherence to this kinematical field can then be achieved through the use of suitable steering laws. Some test simulations have been presented to verify the performance of the technique, using four steering laws: velocity-to-be-gained, sliding-mode, Lyapunov and cross-product steering. It has been shown that the Equilibrium Shaping Technique allows effective path planning for a swarm of *N* spacecraft into a desired formation, and that swarms of spacecraft employing the technique exhibit emergent behaviours such as waiting for other agents to pass. The technique is robust and very scaleable.

4 ASSEMBLY ARCHITECTURES

4.1 INTRODUCTION

In the last section the Equilibrium Shaping technique has been derived. This procedure is able to solve the problem of autonomous path planning for a swarm of *N* spacecraft. This technique is a tool that can be easily plugged into algorithms that can allow self-assembly of large structures in space under more constrained conditions. In this section we describe incorporation of the Equilibrium Shaping Technique into the *Transition Rule Set* scheme [Jones & Mataric, 2003] to allow sequentially constrained assembly of structures from homogeneous components. We also describe the *master-slave architecture* (which incorporates the TRS), allowing the use of separate 'slave' agents to assemble a structure, and the *sub-assembly architecture* allowing for increased parallelism in the assembly of very large and periodic structures.

4.1.1 The Transition Rule Set

The Equilibrium Shaping Technique as it stands is sufficient for a formation/assembly where sequence of the components entry into the equilibrium points is not a constraint. This is obviously the case for all situations where a formation (i.e. the elements are still separate in their final configuration) is the target. However, for self-assembly applications, we can envisage situations where sequentiality of the asssembly process is required. For example, in the 'growth' of a large structure, we can imagine the requirement that assembly proceeds from a central component, with elements 'snapping' on in sequence as the structure is built. The TRS [Jones & Mataric, 2003] is a simple technique for controlling the assembly of an arbitrary structure from a swarm of homogeneous components. The TRS involves the definition of a matrix of 'Transition Rules', which specify when (sequentially) and where components can attach themselves to the structure. Each element is designated a particular state variable (not neccesarily unique), and the connection points on the structure can be defined in an arbitrary manner. In the following very simple example we consider the construction of a shape from four blocks (Figure 3.23). The connection points on the structure are simply labelled N, S, E and W (North, South, East and West). The first element is termed the seed, the element which forms the basis of the structure, and has a state value of '1'. New elements can then dock with the seed according to the rules held within the transition rules matrix. For example in the figure the first rule is that another element can only dock with the W connection point of an element with state '1'. Once a rule is obeyed, it is switched off, and typically (though not always) accompanied by a state change of the connected elements (in this example, the state of the seed changes from '1' to '2'. New transition rules then become available, and construction proceeds.

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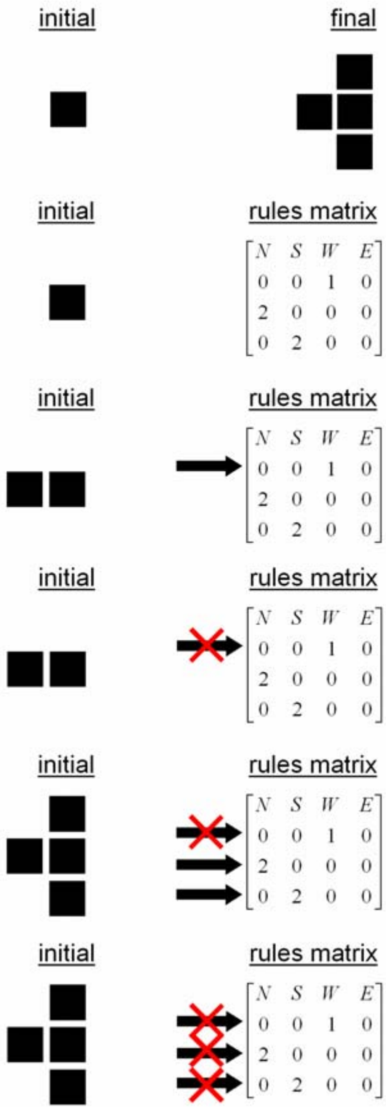

Figure 4.1 – A simple example of the TRS process

The TRS can be combined with the Equilibrium Shaping Technique to allow arbitrary structure to be built, simply by using the Equilibrium Shaping Technique to coordinate the movement of structural elements to the connection points. Note that within the TRS there still exists the ability to fully exploit any parallelism that may exist in the assembly of the structure (by the releasing of several identical rules at the same time, as is the case given in the example figure 3.23), and that the Equilibrium Shaping Technique is naturally able to exploit this parallelism.

4.1.2 Master-Slave Architecture

The master slave configuration can be considered for systems which are made up of very large numbers of components. It is used as the assembly architecture for the SPS concept presented later in chapter 0. In this method only a small (optimised for the mission in hand) amount of agents belonging to the swarm has actuation capability. This allows a large reduction in the number of engines required by the whole system. In the master-slave configuration the swarm is heterogeneous and divided into two different groups: (i) the *agents*, that are not able to autonomously move in space, and (ii) *slaves,* which have the ability to actuate, and dock with the *agents*.

The architecture presented here is based upon two different tools: a Transitional Rules Set method, and the Equilibrium Shaping technique. The transitional rules method allows description by a graph of a generic structure in space and is able to provide, at each assembly step, a set of rules that a swarm has to follow in order to build the target structure. The Equilibrium shaping technique drives each docking procedure allowing different groups of agents to achieve different formations in an autonomous way. In Figure 4.2 the proposed algorithm is presented. In the first phase a seed, i.e. the central structural element, releases the rules to be followed according to the Transitional Rules Set method. Then the seeds chooses what are the closest agents that can achieve the rules released and each agent chooses what is the closest group of slaves that can help it to fulfil the rules. At this point a first equilibrium shaping procedure is called that leads each group of agents to dock to each slave. In this way the agents will acquire moving capabilities. Then a second equilibrium shaping procedure will plan the path of the swarm of agents towards the actual structure.

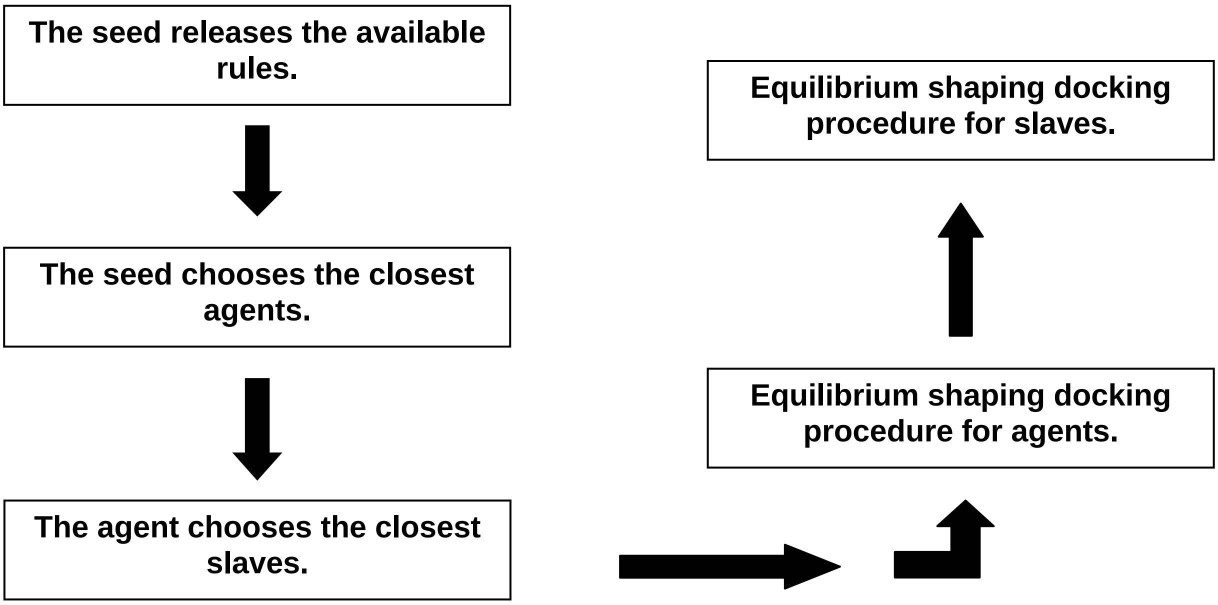

Figure 4.2 – Master/Slave Architecture outline

4.1.3 Sub-Assembly Architecture

The sub-assembly procedure can be used when the target structure that has to be achieved is regular in space and also periodic. In this architecture the swarm components are divided into two different groups: the *agents* and the *seeds*. Both these two groups achieve a final desired configuration relying upon the Equilibrium Shaping technique. The *seeds* follow trajectories obtained from an equilibrium shaping technique with a large radius of influence, i.e. at a large scale. In the other hand the agents are related to a particular seed and they are deemed to reach a formation around it according to a different equilibrium shaping technique performed at a smaller scale. The trajectories followed by each group of agents can be thought to take place in the relative space of each seed and so for each group of agents it is possible to find the absolute velocities as a sum of two different components, a relative velocity and a drift velocity:

$$\vec{v}_a^{\,i} = \vec{v}_{rel}^{\,i} + \vec{v}_{drift}^{\,i} \,.$$

The relative velocity of the components of the *i-th* group is given as a result of the equilibrium shaping technique applied to it whereas the drift velocity is the outcome of the same technique applied to the *i-th* seed.

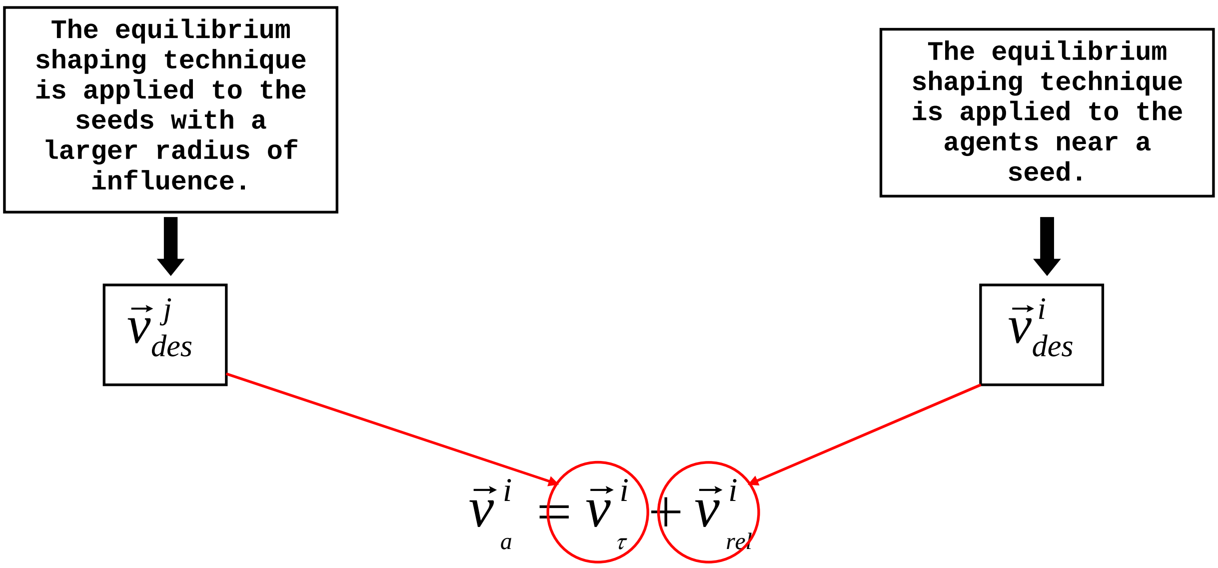

Figure 4.3 – Schematic of the sub-assembly architecture

4.2 SUMMARY

A selection of architectures has been presented that would incorporate the Equilibrium Shaping Technique and allow the assembly of arbitrary structures composed of homogeneous elements in space. All the architectures would scale well due to the swarm intelligence approach that has been employed. The Equilibrium Shaping Technique can be easily incorporated into a wide variety of architectures, and we can envisage develop of architectures involving the Equilibrium Shaping Technique that allow the assembly of arbitrary structures composed of heterogeneous elements.

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5 CONCLUSIONS AND FUTURE WORK

5.1 CONCLUSIONS

A robust, scaleable and highly adaptable technique for the assembly of structures in space has been developed, taking inspiration from the newly emerging biomimetic paradigm of *swarm intelligence*. The technique allows robust and parallel path-planning for a swarm of *N* spacecraft into an arbitrary formation through a dynamical systems approach that involves the definition of an kinematical field within which the agents operate. Actuation of the elements within this kinematical field is then effected through using suitable steering laws.

The technique has been tested through simulations using a variety of steering laws, and has been shown to allow robust acquisition of formations, and exhibits the *swarm intelligence* properties of emergent behaviours and robustness. Furthermore it can be easily incorporated into wider control architectures to allow assembly of structures in space under more constrained conditions, for example when the assembly process is sequentially constrained, and/or the structure is composed of heterogeneous elements. Some possible architectures have been described.

5.2 FURTHER WORK

This work leaves many questions unanswered. The work described here only considers the problem of spacecraft translation in the formation/assembly process. However, in a similar way to definition of the velocity-field described in this report, attitude control of the component spacecraft of the swarm can be approached in the same fashion through the definition of a quaternion-field that dynamically assigns to each position within the space a desired attitude. Again this could then be effected using suitable attitude control techniques (for example quaternion feedback control).

Considering the requirements imposed upon the agents as they assembly, we can intuitively understand the desired attitude behaviour of swarm elements in the varying situations they inhabit. This allows us to define three attitude basis behaviours:

Slot behaviour: This behaviour drives the agent to assume the target attitude associated with a sink when in the proximity of the sink. This is obviously a required element of a docking procedure, where a particular relative orientation between elements will be required to allow connector elements to function.

Cruise behaviour: This basis behaviour drives the agent to align it's principal thrust axis along the direction of motion.

Sidle behaviour: This basis behaviour drives the agent to adopt an attitude that results in it presenting a minimal cross-section to other agents in the vicinity.

An important part of future work will be to develop the quaternion-field control to allow full translational and rotational control for the agents.

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Additionally, the application of the Equilibrium Shaping Technique within swarm contexts other than assembly should be evaulated, e.g. for an exploration role of a swarm of agents amongst Saturns' Rings.

ADDENDUM: REFERENCE SYSTEM STUDY

5.3 INTRODUCTION

In this section we describe the conceptual design of an assembly scheme for the formation flying instance of the Integrated Symmetrical Concentrator (NASDA Reference system) [Mori et al., 2001], [Oda & Mori, 2003] SPS concept. This assembly scheme makes use of the agent-slave automated assembly scheme developed in section 3. The conceptual design of the system allows for a significant reduction in the total launch costs of the SPS system. This is achieved through injection of the array elements into MEO, where they then raise themselves by solar sailing to GEO. Here they are met by slave teams which serve as the thrust actuators for the assembly process. The slaves also gradually embed themselves into the array structure during construction in order to provide station-keeping and geometry maintenance of the completed reflector structure.

5.4 REFERENCE SYSTEM DESCRIPTION

The target system for this study is one of the primary reflectors of the formation flying instance of the Integrated Symmetrical Concentrator (NASDA Reference system) [Mori et al., 2001], [Oda & Mori, 2003] – shown previously in Figure 2.2. A conceptual image of the concept is shown in Figure 0.1. The formation flying concept [Takeichi et al., 2003]] of the ISC removes the requirement for the connecting boom and rotational mechanism between the primary reflectors and beaming section by separating the sun-pointing and earth-pointing segments of the structure, and placing them on parallel, non-identical orbits (see Figure 0.3). The Sun-pointing reflector and the Earth-pointing EGT are treated as separate structures. The EGT is on the common GEO, and the reflectors use a combination of solar pressure and active thrust to achieve and maintain orbits perpendicularly separated from the GEO plane. As a result, the 'orbits' of the reflectors are parallel to the GEO and have the same radius. The reflector area required for this 1GW class SPS concept is around 14 km^2 in total, which consists of two 2.5 km by 3.5 km elliptical primary reflectors. Consequently it is likely that each reflector will be composed of a very large (~100s) number of elements.

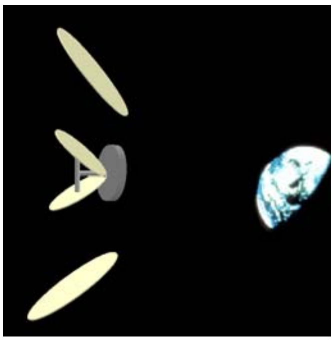


Figure 0.1 – Conceptual art of the free flying integrated symmetrical comcentrator concept (adapted from [Mori et al., 2001])

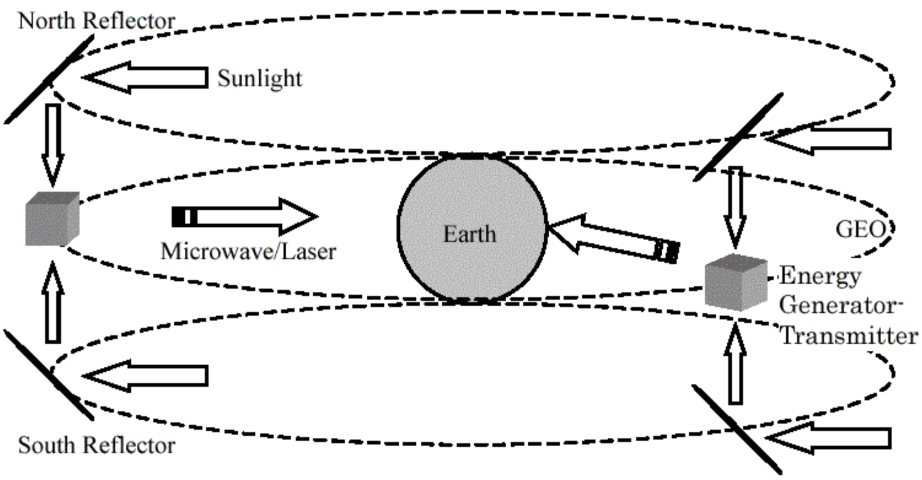


Figure 0.2 - SPS Formation flying configuration (adapted from [Mori et al., 2001])

The altitude of the primary reflector orbits (defined as the distance above and below the GEO orbit path of the EGT) is determined by the balance between the vertical component of the solar pressure and the acceleration caused by the orbital motion, which tends towards oscillation of the two reflector components about the GEO path. Additionally the pitch angle of the reflector (angle of the reflector structure relative to the GEO path – see Figure 0.3) must vary to accommodate changes in the tilt angle of the incident sunlight with the seasons (for the northern reflector this equates to a pitch angle requirement of 56.7° and 33.3° for Summer and Winter solstices respectively).

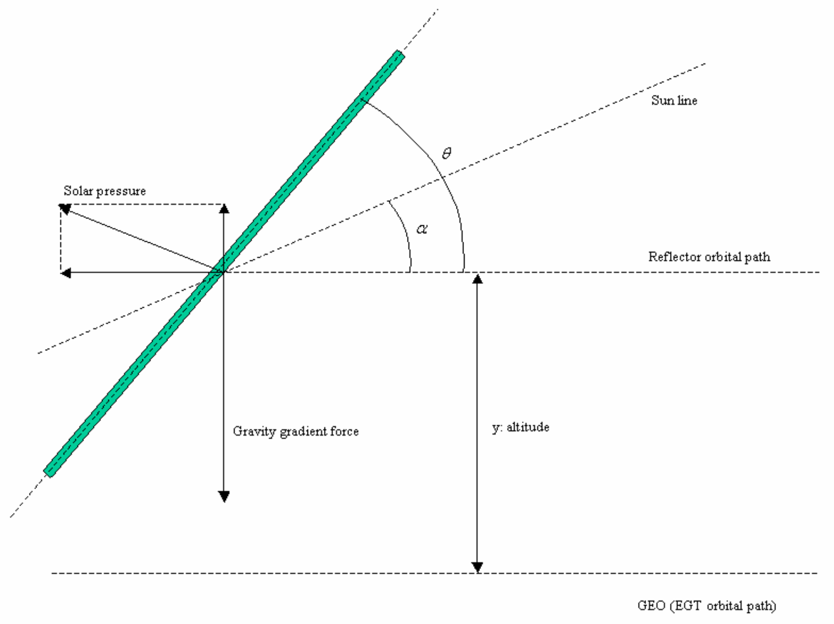


Figure 0.3 – Reflector orbit geometry (adapted from [Takeichi et al., 2003])

The vertical separation (y) of the reflector from the EGT is determined by the ratio between the specular and diffuse reflectance of the reflector material (analogous to solar sail efficiency) and the mass per unit area of the reflector structure (analogous to solar sail assembly loading). More effective specular reflectance and lower assembly loading will result in a larger separation distance. In [Takeichi et al., 2003], a separation requirement of $2000\,m$ is set: to achieve this separation passively, an assembly-loading for the reflector structure of around $100\,gm^{-2}$ is required.

As some structural control will be necessary, this assembly-loading may not be achievable (due to the presence of thrusters units within the structure), and the solar pressure will be insufficient to raise the reflector far enough away from the GEO line. In this case there will be a requirement for active orbit maintenance using thrusters. In any case, orbital pertubations are experienced due to solar pressure and gravity gradient forces. Solar pressure will result in periodic drifting of the longtitude of the structure, and gravity-gradient torque will induce two major effects: a non-zero average of the y component, and periodic variations in all three axes. Both these effects would require active thrust control to offset.

Active orbit raising and maintenance to the parallel GEO orbit for the reflectors, through using the thrusters to simultaneously raise the orbit, and negate gravity-gradient effects, is shown to add only a few percent to the total propellant requirement to counter solar pressure, and is therefore feasible for this concept. To meet these control requirements, thrust vectors are required parallel (and opposite) to, and perpendicular to (in both directions) to the solar pressure vector. This could theoretically be achieved most easily by the placement of thrusters around the periphery of the structure. However, because of the vast non-rigid planar area of the reflector structure, the behaviour of the reflector under applied forces is likely to be membraneous in nature, with forces applied at a single point resulting in structural deformation propogating through the structure in a very complex manner. Therefore the requirement for geometry maintenance and control (for fine focusing) is likely to be met by actuators embedded throughout the reflector structure. Thrusters will be required on both sides of the reflector planar surface.

5.5 Assembly Scheme

The essential features of the reflector assembly scheme are shown in Figure 0.4. Initially, reflector elements are injected into a MEO orbit. These elements then separate from each other and deploy, and begin the spiral up towards GEO. Immediately prior to their arrival, slave units and other required infrastructure (fuel tanks etc.) are delivered directly to the desired orbital position of the SPS array. When the elements arrive the slave teams then provide the actuation capability for the elements to assembly into the final reflector structure. During assembly the slaves embed themselves into the structure.

Selection of the MEO orbit injection height is sufficiently high to allow avoidance of the high-energy proton environment of the Van Allen belts – the sail material, once deployed, must avoid extensive damage due to charged particles - 9000km. This would allow avoidance of the worst of the proton flux (which can reach 400 MeV): the peak electron flux occurs at higher altitudes, but is less of a problem due to the much lower momentums involved.

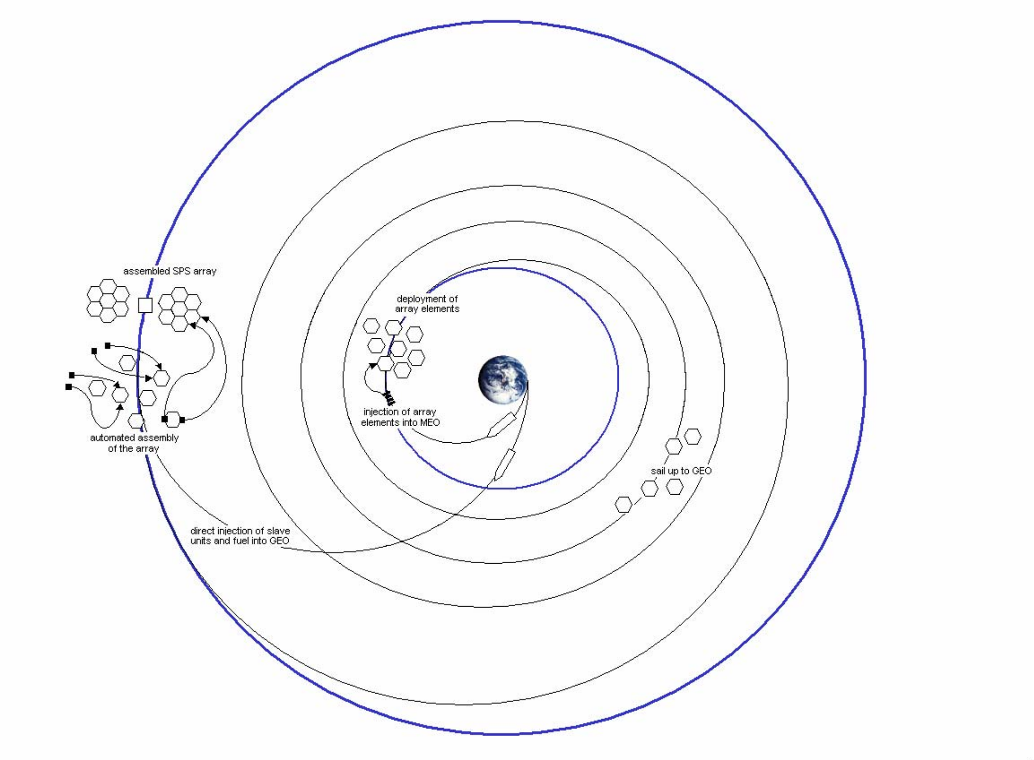


Figure 0.4 – Basic schematic of the reflector launch and assembly process

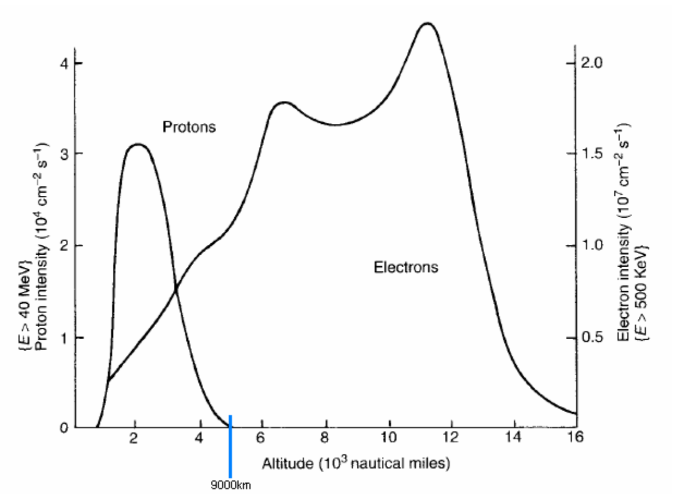
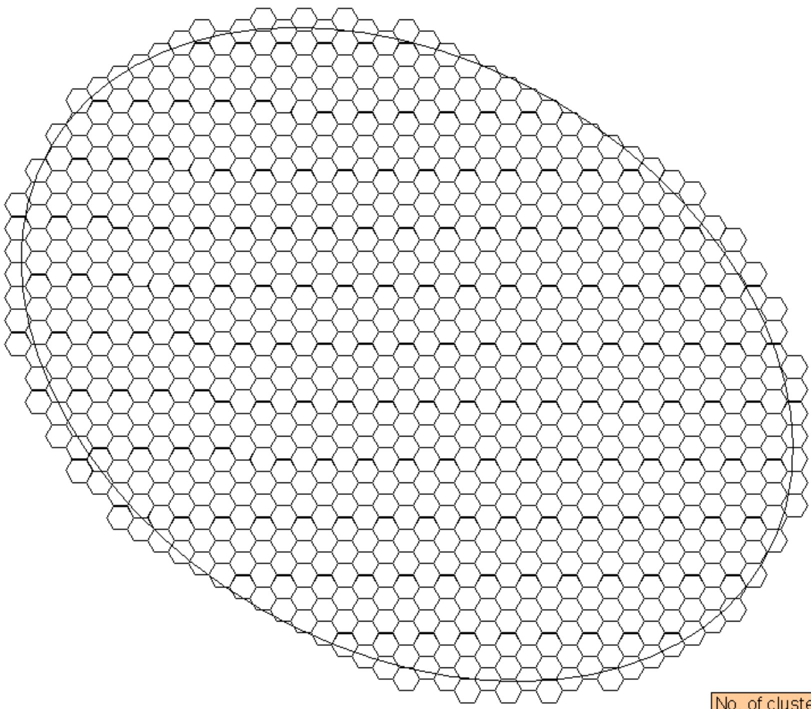


Figure 0.5 - Van Allen belt proton and electron intensities as a function of altitude

The following conceptual design follows from initial choices concerning the launch system used and the dimensions/geometry of the deployed array elements. These initial design choices are:

(i) Hexagonal array elements with a characteristic dimension of 100 m. This is estimated from a quote from [McKinnes & Eiden, 2000]. For a 2.5 km by 3.5 km elliptical reflector, this results in a requirement for approximately 850 array elements. Figure 0.6 shows one possible configuration composed of 861 elements and a total surface area of 7.456 km^2.

Configuration #1



No. of clusters	861
No. agents in 1 cluster	1
No. of elements	861
Array Area	7456478.727

Figure 0.6 – Possible configuration for one primary reflector composed of hexagonal elements with a characteristic dimension of 100 m.

(ii) Use of the Energia launch system (Figure 0.7). Only a superheavy lifter such as Energia would be suitable due to the huge number of array elements required. The Energia launcher design is capable of lifting 88,000 kg into LEO, and 18,000kg into GEO (with the Energia Upper Stage - EUS). The external payload fairing has a payload bay area of 37 m by 5.5 m, although the available length is reduced by the presence of the RCS/EUS.

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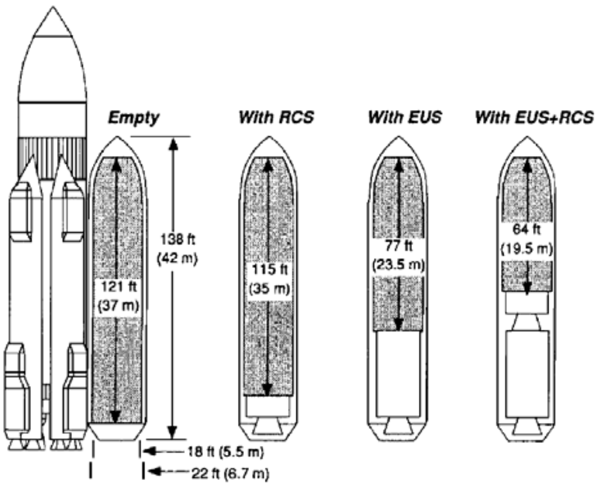

Figure 0.7 – The Energia launch system

5.5.1 Individual Array element Design

The design criteria for the reflector array elements of this SPS concept are identical to those for solar sails – low mass per unit area (high assembly loading), high specular reflectance (high sail efficiency), and stowability in a tight volume. Because of the identical set of requirements between array elements and solar sails, it was decided to investigate the feasibility of reflector elements doubling as solar sails for a sailing transfer up to the SPS construction site from a lower orbit. Such a strategy could potentially reduce significantly the number of launches required to place an SPS platform into position.

After initial consideration of the likely mass and volume associated with one array element compared to the mass/volume constraints of the Energia fairing, it is apparent that the payload capacity constraint of Energia in this instance is volumetric rather than massive. It is necessary to maximise the packing of array components to the greatest extent possible in order to achieve the most use of the payload mass capability. The array element geometry chosen to achieve this is hexagonal, comprising a central hub from which stem 6 rigid booms, as shown in Figure 0.8. This does not maximise the ratio of reflector area to boom length (maximised by a square sail configuration). However, hexagonal elements were considered primarily for packing purposes within the fairing, as their initial shape more closely conforms to a circular form.

Plan and side views of the stowed array element are shown in Figure 0.10. 6 extendable booms are guided during deployment from the stowed boom rolls by the outer edges of the hexagonal structure. On the boom tips are mounted the connector elements that allow docking with other array elements – These are envisaged to consist of sexed connectors for one-sided reflector elements, or perhaps canonical hermaphroditic connectors if two-sided reflector elements are used.

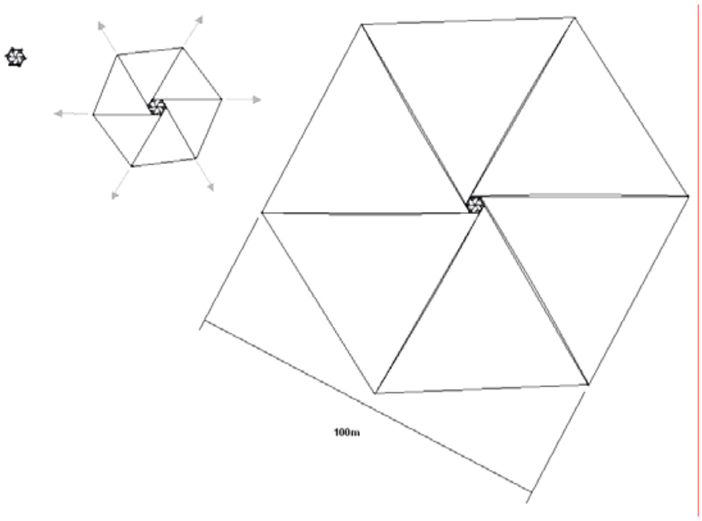

Figure 0.8 – Basic array element deployment sequence

The deployment mechanism of the element makes use of Carbon Fibre Reinforced Plastic (CFRP) snap-boom technology, developed by DLR [Herbeck et al., 2000] for solar sail deployment. The boom is formed from two hemispherical halves that are joined at tapered edges – this results in a cross-section that approximates to a circle, and therefore has good structural stiffness and resistance to buckling. For stowage, the two hemispheres are pressed together to form a flat plate of material which can then be rolled, giving excellent packing density (see Figure 0.9). Deployment simply consists of unwinding the boom material off the roll, at which point the compressive forces holding the two halves together are removed, and the circular cross-section is regained.

In this case the sail material is Aluminium coated Kapton film, which has a thin-film density of $0.006 kgm^{-2}$. Reinforcement of the sail material occurs along the edges to prevent rips. This reinforcement may be more along the outer edge to help maintain the hexagonal geometry of the element.

Figure 0.9 – DLR CFRP boom technology

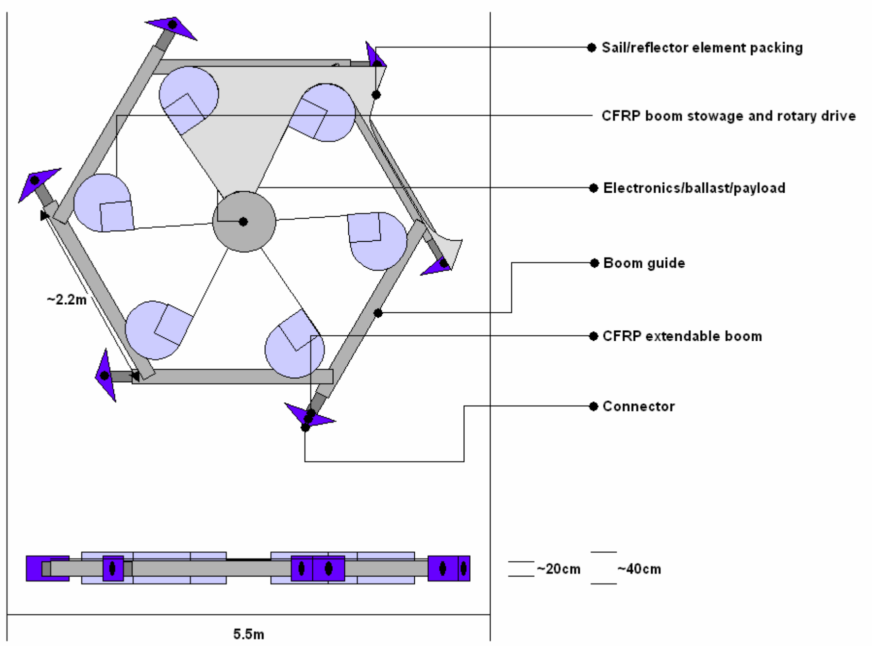

Figure 0.10 – Top and Side view Schematic of a stowed array element

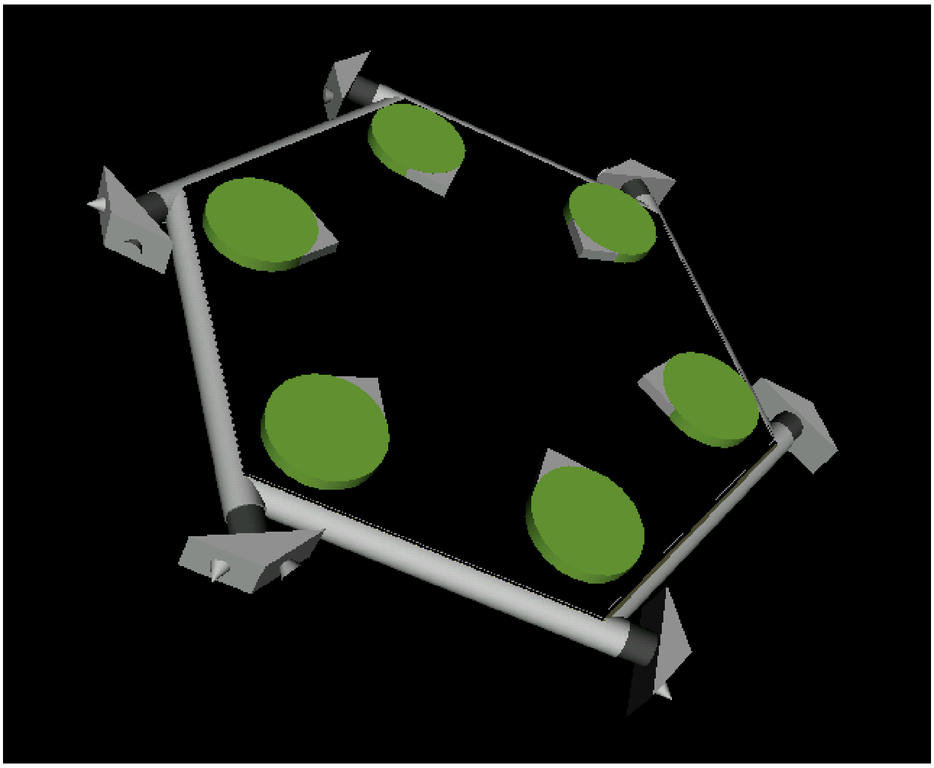

Figure 0.11 – VRML image of an individual stowed array element

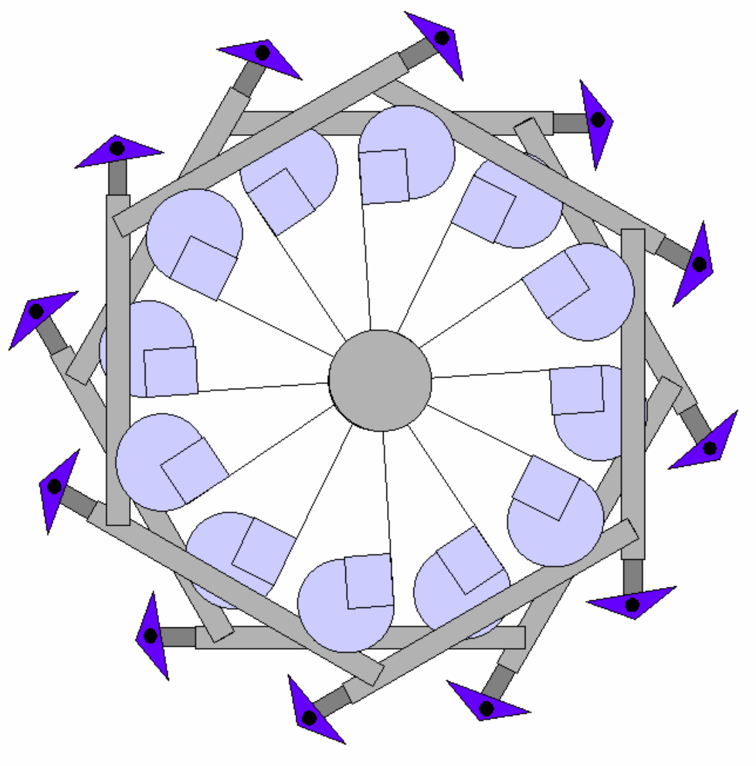

Figure 0.12 – Plan view of two stowed array elements in stack orientation

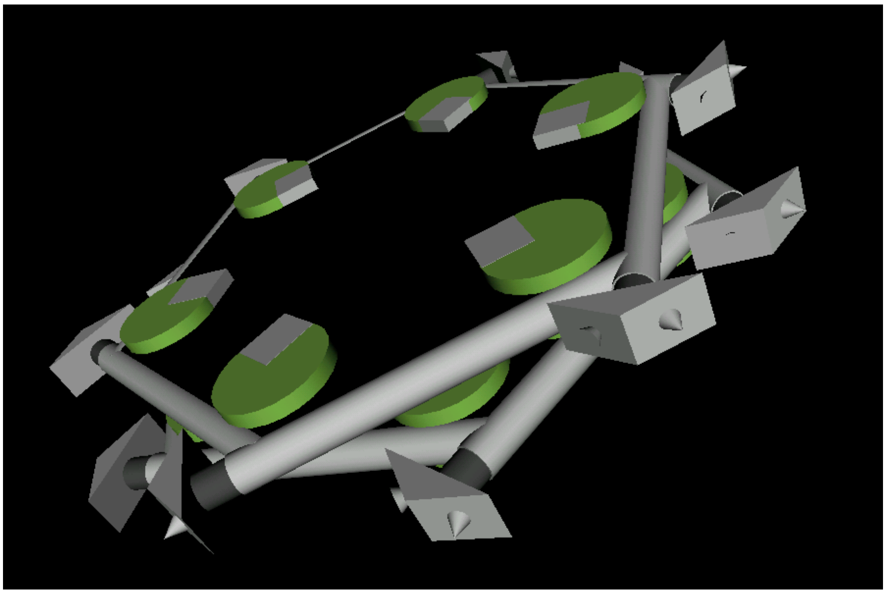

Figure 0.13 – rotated stacking of two stowed array elements

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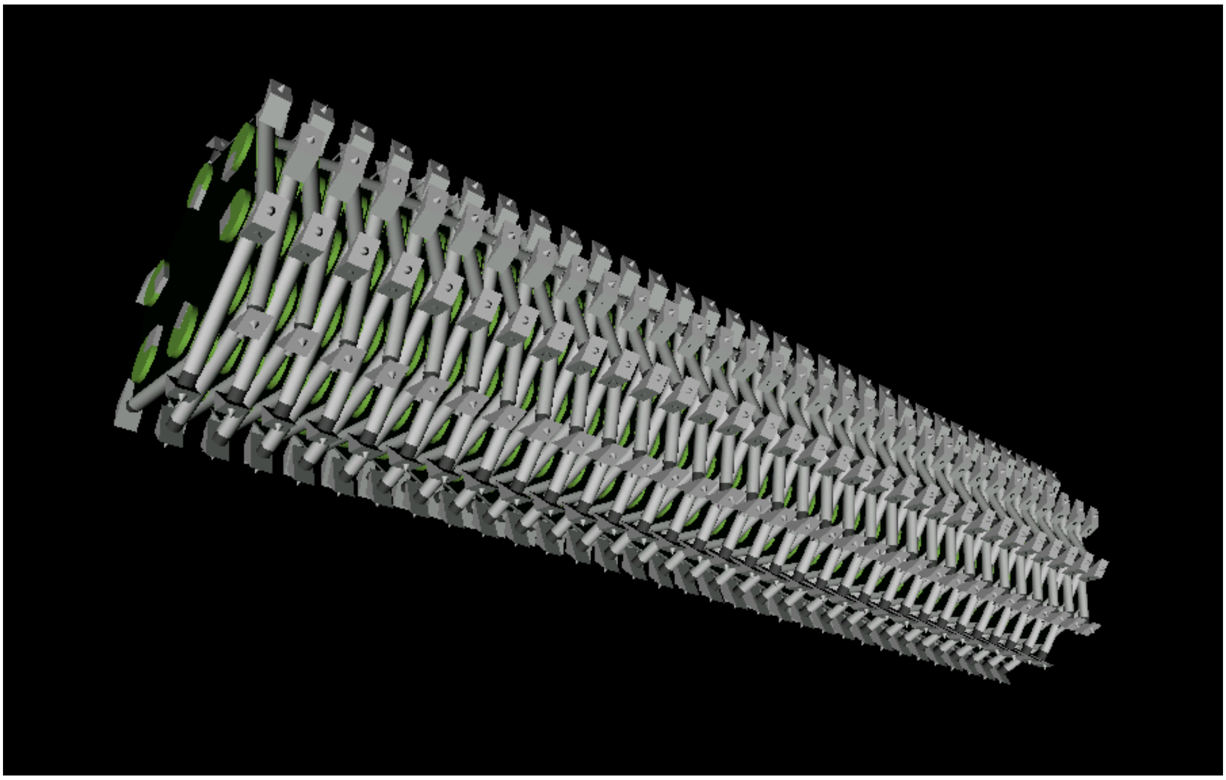

Figure 0.14 – VRML image of 64 stacked array elements for integration into the Energia fairing

A simple approximation was made of the boom length by considering concentric circles of boom packed within each other, the radius of the circles decreasing by the major thickness of the boom at each revolution. A simple expression to describe the approximate length of the rolled boom under such a configuration can be derived as:

$$l \approx \pi\left[2rn - n(n-1)t\right] \qquad \textbf{Equation 0.1}$$

where *l* is the total approximate length, *t* is the major thickness of the roll (i.e. the highest thickness), *r* is the radius of the outer roll and *n* is the number of rolls. The inner diameter of the rolled boom (indicating the radius of the rotary drive) is obviously given by $r - nt$. The largest arbitrary dimension associated with the stowed array elements is the width of the packed boom, and it's surrounding casing. A boom diameter of $20\,cm$ has been estimated as reasonable in this study. Alternating stowed elements can be rotated by 30 degrees in order to pack the rolled booms more effectively. Stacking in the manner shown in Figure 0.13 and Figure 0.14 allows the characteristic packing height of the elements to be maintained at around $0.3\,m$.

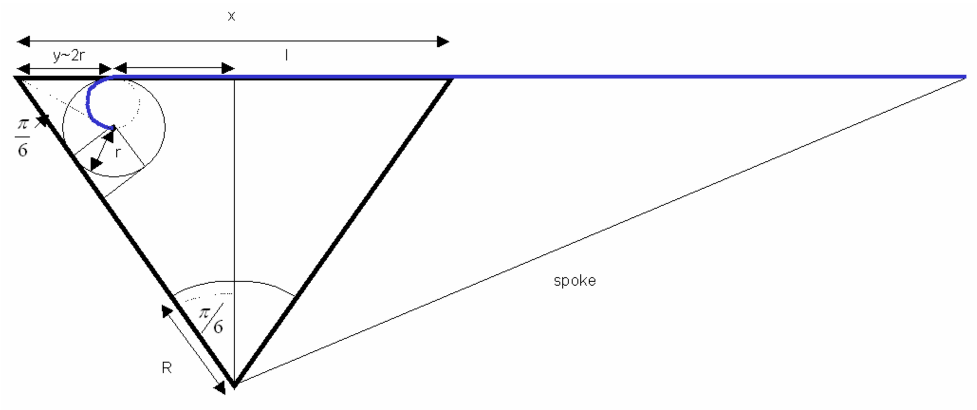

Figure 0.15 – Geometry of one hexagon sextant and boom length/sail stowage estimation.

Simple consideration of the geometry of the element (Figure 0.15) allows the required Boom length to be approximated by:

$$l \approx \frac{\pi r}{2} + \left(\frac{x}{2} - \frac{r}{\tan \frac{\pi}{6}} \right) + \sqrt{spoke^2 - \left(x \cos \frac{\pi}{6} \right)^2} \qquad \textbf{Equation 0.2}$$

To approximate the linear density of the boom, it has been scaled with the new length requirement. This is equivalent to scaling with r^2 (linear density is proportional to r^2), thus allowing the longer boom an equivalent resistance against buckling load, which scales with length. This yields a new linear density approximation of 0.256 kgm^{-1}. The required radius of the boom is unknown, as nothing could be found in the literature, so we have taken 0.2 m as a reasonable value. This gives a flat stowed width of somewhat more than $0.1\pi\ m$ (to take into account the plate joins. In addition to this is the requirement for the boom rotary drive coupling to the drive motor, which will by necessity extend beyond the boom roll. Therefore we have allowed a boom stowage height of 0.4 m to accommodate this.

The required amount of boom that must be rolled is the required boom length minus that part which is not rolled during stowage – in this instance this is 1.5 m (2.2 m boom guide length – 0.7 m for the boom stowage radius. This gives a figure of 57.166 m that needs stowing. The boom storage cylinder of cross-section radius 0.35 m can easily accommodate this: for example 33 revolutions of a boom with a characteristic upper thickness of 3mm, starting from an outer radius of 0.33 m, will stow a boom length of over 58 m, with an inner radius of over 13 cm for the rotary drive.

Again from Figure 0.15 sail/reflector packing area is approximately given by:

$$A \approx h\left[\frac{x^2}{2\tan\left(\frac{\pi}{6}\right)} - r^2\left(\frac{3}{4}\pi + 1\right) - \frac{\pi}{3}R^2\right]$$ **Equation 0.3**

Where R is the radius of the payload bay area (assumed circular). For a payload/instrumentation bay of radius 0.5 m, this yields a sail stowage area for one sail segment of around 0.515 m^2: this equates to a sail material packing density of 16.816 kg per m^2. This would appear from a mass perspective to be achievable. However, this study has not taken into account the method of folding the sail, and this will have to be carefully considered.

We have assumed AL3003 for the main structural material of the element (density $1700 kgm^{-3}$), with a characteristic thickness of 1 mm of the boom guides, plates and partitioning between sail stowage areas. The electronics, antennae, direct sensing equipment and ballast mechanism (or other attitude control mechanism) have been given a total mass of 20 kg. The connectors at the ends of each boom have been given a mass of 8 kg each (taken from a CONRO connector precedent, with a 33% extra margin to accommodate the requirement for attachment to the boom and sail). The boom and sail masses have been calculated using their respective planar and linear densities ($0.006 kgm^{-2}$ and 0.256 kgm^{-1}).

Overall Mass characteristics			
element	number	individual mass/kg	total mass/kg
boom guide	6	7.483085205	44.89851123
bottom plate	1	9.353074361	9.353074361
top plate	1	9.353074361	9.353074361
sail stowage partition/support	6	2.16	12.96
payload/ballast/electronics	1	20	20
connector	6	8	48
boom	6	12.28975867	73.73855199
boom rotary drive (inc. housing)	6	6.5	39
triangular sail element	6	8.660254038	51.96152423
One array element			309.2647362

Table 0.1 – Estimated mass breakdown for one array element

This mass breakdown gives a sail loading of 36 gm^{-2}, which is a very high loading for a solar sail (current technology objectives for sail loading are around 10 gm^{-2} [Herbeck et al., 2002]). However, this value is good enough for our requirement (sail-up to GEO from 9000 km) as we shall see.

5.5.1.1 Slave elements

For direct assembly, it would be possible for each array element to possess actuator elements, for example at a minimum of two points on the edge of the structure. With just two actuators per element, this would avoid multiple actuators at connector sites, but would still mean one thrust unit at each connection point in the final structure: this would probably be unnecessary. Furthermore, the sail up strategy of this concept precludes the direct integration of thrust actuators into the element structure, as this would lead to an unacceptably high sail loading during the sail-phase.

W can address both these problems by decoupling the thrust actuation required for assembly and orbit maintenance from the elements, and directly injecting the thrusters (as slave teams) directly into GEO. There they would then act to autonomously dock the array elements, by docking with the array elements and temporarily acting as their actuators. As this proceeds, the slaves would gradually embed themselves in the structure to in order to provide the station keeping for the free-flying reflector. In this way it is apparent that the number of thrust units is potentially very much reduced: the number required can be optimised to the number required for maintenance of array geometry and station keeping

In this short study we are unable to consider the structural strength of the deployed booms, or the ability of the end connectors to transmit forces (and hence effect and maintain geometry changes) throughout the structure. The optimal strategy for actuator placement would presumably involve high numbers of slave units at the periphery of the reflector to maximise the moment of their action. We cannot comment on the number or position of slaves that need to embedded within the structure. However, as a first approximation, one slave unit per 7 array elements has been chosen as a starting figure: this leads to a requirement for 123 slave units in total for the reflector.

5.5.1.2 Packing

For the Energia fairing with EUS, approximately 67 array elements could be integrated (assuming there is an unusable $2\,m$ space at the leading tapered edge of the fairing, and a characteristic packing height of $0.32\,m$). This corresponds to a mass of around 21 tonnes, which is only 3 tonnes more than the GEO payload capacity of the launcher. Extrapolation from a performance chart in [Isakowitz et al., 2000] reveals that Energia (with the existing EUS design) could lift approximately 55-60 tonnes into a $9000\,km$ circular orbit. The current EUS therefore overperforms massively for this concept.

We can envisage a redesign of the EUS such that the number of array elements delivered to $9000\,km$ per launch is optimised – i.e. reduce the EUS size and capability to allow more array elements to be carried per launch. For this study we assume a redesigned EUS which increases the available payload bay length to $30\,m$ (the EUS length is reduced by $8.5\,m$ - approximately 45% of it's length excluding the nozzle). This allows 94 array elements to be stowed (assuming the same packing height as before), which gives a mass of $29071\,kg$. As a first order approximation we assume that the delivery capacity of the EUS is proportional to the volume of the body: thus the resized EUS is capable of delivering this payload to a 9000 km circular orbit.

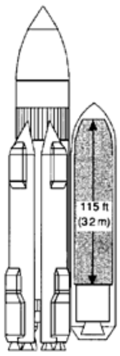

Figure 0.16 – The assumed Energia configuration

5.5.1.3 Orbital Transfer

To establish the feasibility of the concept it is necessary to estimate the time the array elements would require to spiral up from the 9000 m MEO orbit to GEO. There exist a growing number of studies on the optimal orientation of a sail to the sun-line to allow minimum-time transfers, for example [Hartmann et al., 2004; Swartwout, 2004], based around the maximisation of instantaneous rate of increase of total orbital energy (MIRITOE). However, these are not considered in this short study. We estimate the trip time more simply by considering the conventional wisdom that energy input to a sail trajectory should be positive wherever possible, and that the sail should be feathered for zero-energy input at all other times [Sands, 1961]. For a circular orbit, this gives the simple sailing strategy whereby the sail is oriented normal to the sun-line for the half-orbit where it is moving away from the sun, and parallel to the sun-line for the half-orbit where the sail is moving towards the sun. If we consider an approximate relation for the orbital transfer in which the thrust is alligned with the element velocity vector we obtain:

$$\dot{a} = \frac{2v}{\mu} f a^2 \qquad \textbf{Equation 0.4}$$

after integration this gives:

$$\Delta t = \left(\frac{1}{a_i} - \frac{1}{a_f} \right) \frac{\mu m_T}{2 \bar{v} \bar{f}} \qquad \textbf{Equation 0.5}$$

with

$$f = P_{eff} A \cos(\theta)$$ **Equation 0.6**

Where P_{eff} is the effective solar radiation pressure at $1\,AU$ (the product of $P = 4.56 \times 10^{6}\,Nm^{-2}$ at 1AU and the sail efficiency factor), and θ is the angle between the solar sail velocity and the sun-line. For the sail strategy mentioned above, the average force exerted on the sail by the sunlight, assuming a perfectly reflecting sail surface, during one orbital period is given by:

$$\bar{f} = \frac{2PA}{\pi}$$ **Equation 0.7**

in this instance this is $0.02513\,N$. For the array element design described previously, with a sail loading of $36\,gm^{-2}$, this yields a transfer time from $9000\,km$ MEO orbit to GEO of 1.11 years (406 days). Because the trip-time is inversely proportional to the sail efficiency, this transfer time will of course be somewhat larger for less efficient sail surfaces. For a sail surface efficiency of 0.75, the trip time would extend to 540 days. Nonetheless, this would not appear prohibitively long to invalidate the concept when compared to the likely length of the construction campaign of the SPS concept, which would likely extend to several years (one possible complication to this approach is the recent interest within the SPS community of using sail material that acts as a band pass filter for those segments of the solar spectrum that cause excessive heating at the EGT – the high UV and infra-red components of the spectrum. Using a sail material that is transparent to parts of the solar spectrum will of course reduce the amount of momentum that is transferred to the sail and increase the trip-time).

During the transfer period, we can also evaluate the torque required to maintain the required attitude against gravity gradient effects. The average gravitational torque acting on the element during a whole period can be evaluated from the following formula (which considers the gravitational torque only in the orbital plane):

$$\vec{M} = \frac{3\mu(B-A)}{\pi r_0^3}\hat{h}$$ **Equation 0.8**

where *A* and *B* are the moments of inertia of the solar sail out of plane and in plane respectively, and is the orbital radius. The max torque exerted during the transfer period is $0.1634\,Nm$. A deployable ballast mass system that allows sailcraft rotation around any axis through the centre of mass and parallel to the sail plane [Angrilli & Bortolami, 1990] could be envisaged to counter this gravitational torque. However, a ballast system would not be able to provide the angular velocity required for the rapid (ideally instantaneous) feathering maneouvres that occur at the points where the trajectory pass the sun-line. This requires more investigation.

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5.5.2 Assembly

Table 0.2 shows a basic comparison between the number of launches that would be required for this construction concept as compared to the case where the array elements are directly inserted into GEO. Insertion into GEO reduces the payload capacity to that of the Energia+EUS configuration, thereby reducing the number of elements that can be stowed per launch. A 50% increase in the number of array element launches would thus be required, increasing the total number of launches required for the reflector just under 25%.

Launch Campaign	Sail-up	Direct
Number of elements per launch	94	58
Number of slaves per launch	90	90
Element launches required	10	15
Slave launches required	4	4
redundancy launch	1	1
Fuel resupply launch	1	1
Total launches	16	21

Table 0.2 – Number of launches for the sail-up strategy compared to number for direct injection of array elements

5.5.3 Conclusions

A brief outline of a novel SPS construction concept based on the use of solar-sail technology has been presented. The general scheme of the concept has been defined, and some preliminary calculations concerning some of the more critical parameters have been performed. The concept has been shown to reduce the number of launches required by a significant amount, and hence could be an important step in reducing the total cost of an SPS system.

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