Multi-Scalar Multi-Agent Control for Optimization of Dynamic Networks Operating in Remote Environments

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***Abstract*— Multi-agent control systems have demonstrated effectiveness in a variety of physical applications including cooperative robot networks and multi-target tracking in high-noise network and group environments. We introduce the use of multi-scalar models that extend cellular automaton regional neighborhood comparisons and local voting measures based upon stochastic approximation in order to provide more efficient and time-sensitive solutions to non-deterministic problems. The scaling factors may be spatial, temporal or in other semantic values. The exercising of both cooperative and competitive functions by the devices in such networks offers a method for optimizing system parameters to reduce search, sorting, ranking and anomaly evaluation tasks. Applications are illustration for a group of robots assigned different tasks in remote operating environments with highly constrained communications and critical fail-safe conditions.**

I. Introduction

Keywords: complex systems, uncertainty, stochastic algorithm, randomized algorithm, cooperative network, device independence, space robotics, command and control, multi-target, artificial intelligence, machine learning

Multi-agent networks and autonomous systems including mobile-capable robots become more common in life-critical applications such as mass transportation, military and security operations, manufacturing, healthcare, and public infrastructure management. Such systems are increasing in their capabilities and diversities of tasks that can be performed, including unattended tasks that can be life-saving when performing optimally and according to design. Stabilization, cooperation within confined physical and operational environments, and solutions to turbulence are among the types of problems that are addressable and desirable, thus compelling the argument for introducing more robots and more AI (artificial intelligence) into critical infrastructure and life-support systems.

However, there are also vulnerabilities that derive from the inherent high dimensionality of any system state space and the appearance of critical points into which functions within such a system may lead. Simply put, singularity events can be more sharply and irreversibly catastrophic. Certain singularities may be triggered by the inability of the control system in a relevant portion of the network of devices to detect anomalies and variances which could otherwise be met with a counterbalancing response that would compensate for the variance and enable the critical state to be avoided [9]. This inability may be the result of a deterministic sampling algorithm or a dependence upon certain heuristics; this has been one of the classic criticisms of neural network based pattern classifiers and recognizers [12].

The goal of reducing a complex state space is a challenge in any environment where there can be uncertainty or fuzziness with regard to that part of the state-space where anomalies and masking events may occur and further disturb or inbalance the relations between parameters which may be inherently noisy or difficult to measure under any circumstances. A "masking event" can be virtually any parameter p or set of values $\{p_1, p_2, p_3 \ldots\}$ that causes a minimization of system resources (computational or otherwise) that in turn decreases the ability for response to some other Δp_i where such variances may cause critical points to emerge within the same or other portions of the state-space [15].

Risks of system instability and criticality are further exacerbated by conditions that can be introduced from external agents and unpredictable configurations into which even a well-designed and well-tested system (e.g., aircraft, rail, satellite, wireless network) may be placed. External-origin disorders and failures increase in relation to not only complexity within a control system model and its physical and computational implementation, but also in response to other paths to vulnerability [1, 6].

II. Multi-Agency

Multi-agent models offer a significant "first-tier" move away from dependence upon traditional hierarchical and deterministic control schema, as illustrated in Figures 1-2. Such models may be very effective in many applications (mechanical and manufacturing/assembly systems, management and reporting structures) where the re4lations among nodes in both horizontal and vertical relations are stable. However, many systems, both physical and

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informational, have precisely the dynamism and non-linearity that can lead to a breakdown of effective control if there are anomaly behaviors undetected and insufficiently responded to within the network.

It is thus argued here that a new type of thinking about command and control is necessary, and with it, a new type of computing architecture as well, for the types of machines and systems that offer such dual-impact concerns which may be termed "Extreme Complex Systems" or XCS. However, this new cybernetics and new computation is not simply a move into multi-agent parallelism, which is still inherently deterministic (in most architectures; Figure 1). We suggest, on the basis of formal and experimental results, that stochastic, randomized, and non-parametric-dependent modeling may be often more effective for stable control of such "XCS" environments, but even further, there can be an important value in operating at multiple scales of network composition.

III. MULTI-SCALAR SUB-NETS

The scales consist of subnet groups which themselves consist of lower-scale sub-nets that are evaluated and treated as nodes within the higher-scale entity and which may be processed also in a stochastic manner. This may consist of randomly skipping over large segments of a network when, for instance, the probability of there being any significant activity on the part of the sub-nets and their elements is low. This action would serve to favor dedicating system resources (e.g., sensors, processors, electrical power) toward more (likely) critical tasks such as two components (e.g., robots operating cooperatively in space with an asteroid or EVA astronaut) that are in a resource-critical engagement. For instance, in Figure 1, any subset of the multiagent system at right may be grouped together and treated as a unit, with the likely proviso that there must be at least one arc connecting any given node to another node within the overall system. At a maximal-scope scale, all of the nodes may be subsumed within the higher-order functionality and logic (including heuristic-type rules applied) as a single "unit." But typically the groupings will constitute less than complete membership of all agents in the system.

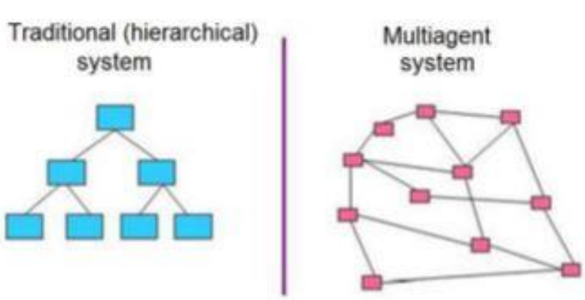


Figure 1 --- Hierarchical vs. Multi-Agent Control - but both still deterministically based [1]

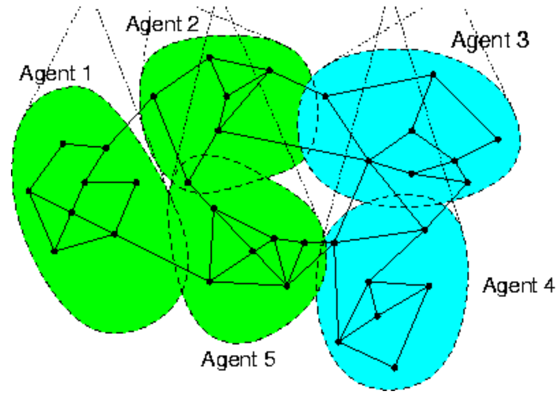


Figure 2 --- Multi-Agent Control - but maintaining static agent sub-net structures and scales [1]

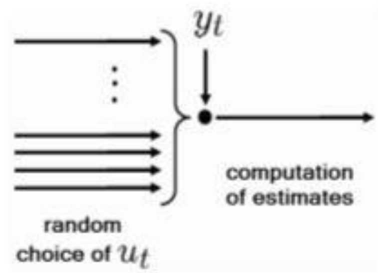


Figure 3 – Randomized estimation and control coupled with learning and optimization of choice [1]

Such an XCS-type system can be considered as having an unknown and uncertain structure, where that structure s_k changes in time instances $t_0, t_1, t_2, \ldots$ The task of understanding how s_k changes at specific instances t_i and in response to certain parameter changes may not be computationally achievable, certainly within finite time intervals when change (adaptation) is required in order to avoid catastrophic critical values. The path forward to understanding how changes and how to adapt in terms of a control system may be realized by a technique of dividing the state space into regions, clusters, or cellular networks. Clustering of the state space may be understood as:

$$X_{sk} = \{X_1, X_2, \ldots, X_{n(sk)}\} : X = \cup_{i=1,2,0\ldots,n(sk)} X_i, \quad (1)$$

where $X_i \subset X$

The goal from a cybernetic perspective becomes then one of identifying changes within dynamically defined regions or clusters, making use of simplified sampling and adaptation, avoiding the computationally intensive and deterministic methods which can be less resilient to unexpected and non-linear behaviors, and impractical from the standpoint of practical engineering, especially in the case of microscopic-sized or ultra-light devices.

Networks of both mobile and stationary robots and other autonomous or semi-autonomous devices are often characterized by uncertainty in data reporting, sharing and analysis within the network. These problems become exacerbated in an operating environment such as interplanetary space by factors such as physical distance (light-years or simply "light-minutes"). In more familiar terrestrial applications, there are performance and communication reducers of bandwidth competition, and also asymmetric threats to data integrity (e.g., electromagnetic disturbance, and deliberate cyber-hacking).

More significant in the operational context of a cooperative group of robots, for instance, there can be problems of conflict or "un-cooperativity" which pertain to conflicting agent goals and sharing of resources such as energy (fuel, accessory equipment and supplies, etc.). In terms of clustering of the state-space, adherence to a fixed-scale representation of the elements comprising that space and the membership of the sub-net groupings therein, will create the risk of either elevating or diminishing certain agent goals to points (levels, ranks) that are inappropriate for a new phase of the system's behavior and (in the case of a robot team assigned a set of tasks) the completion of the mission objectives.

In Figures 4-6, an organized "community" of potentially heterogeneous robots is operating to maneuver and alter the trajectory of an object such as a small asteroid. Each unit and each grouping of *n* units taken together may be considered as a sub-net, acting in both cooperation and/or competition at any point in time, for both system resources and for mechanical positioning, balancing, and collision avoidance, all of the parameters for such determinations being based upon extremely non-linear dynamics imposed by the behavior of the target (in this case a hypothetical asteroid sized from 15m – 1000m in average diameter).

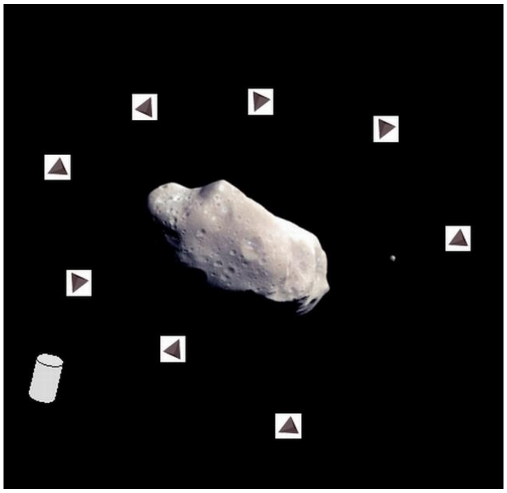


Figure 4 -- Robot pre-configuration in vicinity of target asteroid for trajectory displacement– stage 1

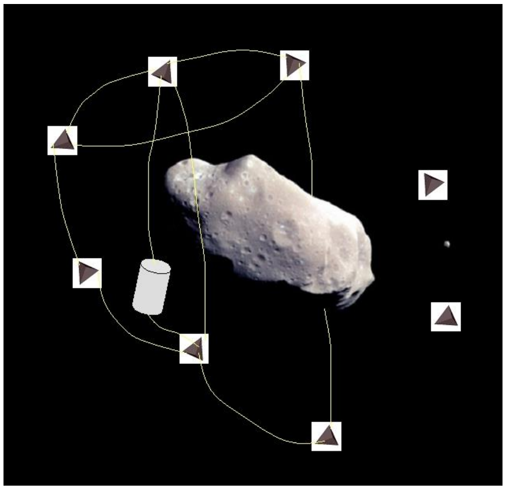


Figure 5 -- Robot deployment of tether-net around target asteroid for trajectory displacement– stage 2

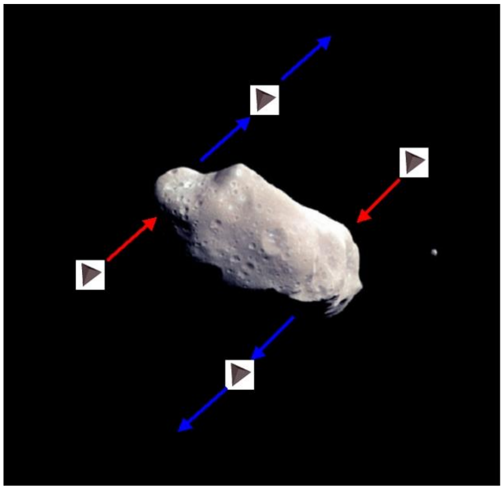


Figure 6 -- Robot deployment of tether-net around target asteroid for trajectory displacement– stage 3

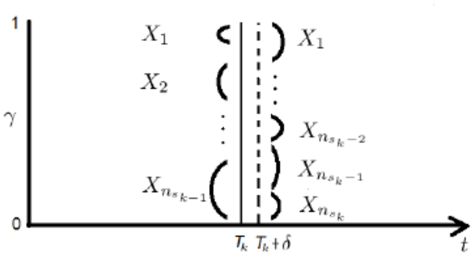
The three stages illustrated abstractly above can be understood in terms of the formation and deformation of dynamic structures at different scales; e.g., micro-, meso- and macro-levels (figure 8). A combination of internal feedback plus external control input will lead to a progressive discretization within the state-space, and the resulting new structures can be significant for the future process of control that seeks to optimize qualities such as physical stability, resource management, and performance of specific mission tasks for the system (in the example of asteroid redirection, thus, the successful trajectory modifications being accomplished by the "squadron" of robots assigned to the mission, with the tools and fuel at their disposal, etc.)

The dynamic equations for the clustering of the state-space (eq. 1) can be expressed as

$x_i = \_g_i (\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_{n_{sk}}; u; w; q_{sk}); \; i = 1,2 \ldots, n_{sk};$ (2)

where $\underline{x}_i$ is a set of integrated x_g on cluster X_i ,
q_{sk} is a finite set of \current" parameters

This in turn leads to changes in the state-space structure that may be represented thus quantitatively and visually:



$$\delta << \zeta = \min_k |T_{k+1} - T_k|$$

Figure 7 – State-space structure dynamics

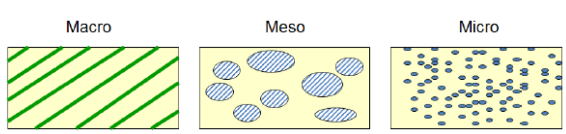


Figure 8 – State-space structure morphology

This can also be described in terms of load-balancing problems, but the problem becomes more complicated as the autonomy and independence of the agent subsystems increases. Competition over resources can include inadvertent competition for access to a physical resource such as a port or fastener, or a tool to be employed by one of the robot units. The overall mission task of the robot network ("team") may be further complicated by a combination of other factors, all of which carry elements of uncertainty and undecidability – for example:

- fuel/power consumption during repositioning
- maintaining a steady position relative to another moving object
- irregular and "wobbly" motion of some target object (e.g., asteroid or fragment thereof)
- collision avoidance and consumption of fuel
- performing work tasks within a prescribed period (e.g., sufficient access to sunlight for solar panels)

The principle challenge with XCS is the issue of undecidability about critical points and regions, also known as singularities. A general or comprehensive model of interaction within distributed and non-stationary spaces that does not allow for the appearance and even dominance of critical points can lead to catastrophic results (mathematically and physically). Failure to observe minute variations and gradient changes can lead to irreversible situations.

However, such minute variations may be measured and analyzed much faster through attention to local neighborhoods and cellular-type regions or fields of data. This path has led to new approaches using sets of localized models that have simpler and potentially faster computational loads and which can be conveniently mapped to parallel architectures. Such models are characterized by asymmetric, stochastic methods for sampling, estimating, and assessing predictive values for regions in a data space where changes may otherwise be unobserved within constraints of computational time.

Stochastic programming is one framework for modeling of optimization problems that involve uncertainty in both the identity and interrelationship of parameters and in their values at given instances and configurations. Whereas deterministic optimization problems are formulated with known parameters, real world problems almost always include some unknown parameters. One of the approaches for solving such problems, when the parameters are known only within the certain bounds, is called the robust optimization. Here, the goal is to find a solution, which is feasible for all such data and is optimal in some sense. Stochastic programming models are similar in style, but take the advantage of the fact that probability distributions governing the data are known or can be estimated. The goal here is to find some policy that is feasible for all (or almost all) the possible data instances and minimizes the expectation of some decision functions and the random variables. More generally, such models are formulated, solved analytically or numerically, and analyzed in order to provide useful information to a decision-maker. The approximation techniques are then extensible to randomized selection and trial (an interpolation process) of algorithms for adjusting system parameters.

The Local Voting Control (LVC) protocol developed by Granichin et al [2, 6] is one such model. It operates with a nonvanishing step-size for conditions of significant uncertainty and external disturbances [8, 9]. The objective is to detect changes that may be insignificant in most cases but which can be indicative of developing conditions that could have irreversible effects. This stochastic gradient-like (stochastic approximation) method has also been used before in other works (see, e.g. [3-5]) but with a decrease to a zero step-size. Usually, the stochastic approximation is studied for unconstrained optimization problems, but the above-mentioned results stimulated the development of new approaches to track the changes in the parameter drift using the simultaneous perturbation stochastic approximation [6].

Consider an experimental platform which can demonstrate the extension of the LVC model to multi-scalar measurements and evaluations. This experiment involves a wing structure whose surface is covered with sensor-actuator pairs that serve as mini-wingflaps, each coupled with a pressure sensor, such as illustrated in Figure 9. Each sensor-actuator unit may be considered as an active agent in a computational network. However, sampling – and motor response – can be performed asynchronously and asymmetrically – this derives from the use of the stochastic approximation methods. This also enables parallel processing, asynchronously and asymmetrically, at different scales (orders) of complexity and set-membership among the elements (action-parameters) in the overall system.

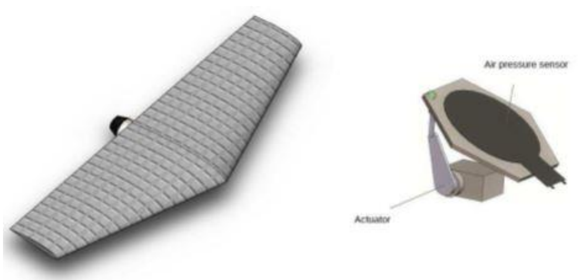


Figure 9 --- "Wings with feathers" [2]

Let x^i_k be the integrated pressure deviation for "feather" a^i – data derived from sensor measurement

Agent dynamics may be described as: $x^i_{k+1} = f (x^i_k, u^i_k), i \in N = \{1,...,n\}$

Observations: $y^i_k = x^i_k + \xi^i_k$

The LVC Protocol is given by:

$$u^i_t = \alpha \sum_{j \in N^i_k} b^{i,j}_k (y^j_k - y^i_k)$$

Consistent behavior (consensus): $x^i_k \approx x^j_k$, $i,j \in N$

In a turbulent flow environment, with no responsive adjustments to the sensor-actuator units, LV readings across the wing surface will resemble a "kaleidoscope" effect among the regions, as shown in Figure 4 below. All actuator units "feathers") in the wing remain unadjusted and with no change in orientation in response to changes in applied external pressures. The consensus "goal" state (illustrated in Figure 5) provides for uniform or within-threshold values from all LV "cellular regions" (clusters) during turbulent conditions, achievable in this case through servo-controller adjustments of the sensor-actuator "feather" units.

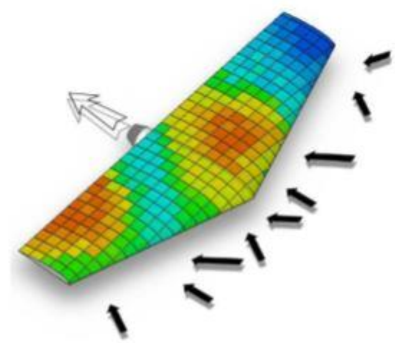


Figure 10 --- Wing sensor field under turbulence [2]

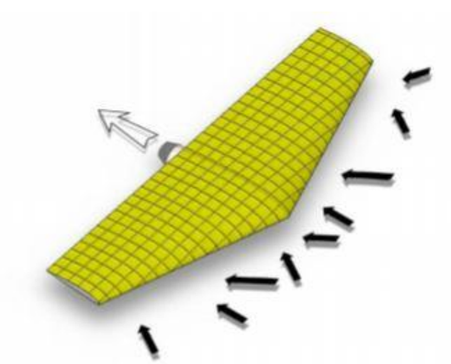


Figure 11 --- Wing consensus state in turbulence [2]

Within XCS operations there are critical time intervals for such adaptations that can avert an critical "singularity" event affecting the entire system. Randomized alterations to small regions (clusters) of the system space have two unique advantages over models that attempt to comprehensively address the entire system. First, results can generally be achieved faster and with fewer computational resources. This is significant for mobile, remote and compact device platforms (such as satellites and other space vehicles, robotic or otherwise). Secondly, and very significantly, errors in the decision process – which can be frequent in beginning stages of a cybernetic system adaptive learning process – will be more localized, more containable, and more easily correctable, than errors which affect large sectors of some system performance.

IV. CONCLUSION

A complex system may have many unobservables among those parameters deemed significant for determining the next steps in any control process. This becomes more complex as the number of discrete elements in the system increase or act in combined cooperative and competitive cycles with respect to one another.

Control functions may be distributed across virtual as well as literal physical surfaces and spaces. A network of robots manipulating amorphous shapes such as asteroids or rocks in space or on the lunar surface will operate with each robot element having multiple axes of motion and angular momentum. There are goal states which involve positioning of devices and avoidance of collision impacts including those that could occur between the cooperative robots. For some levels of extreme complexity, a rethinking of what we mean by "control" and by "learning" and indeed by "intelligence" is required, and in this process, also, a rethinking of how we can perform the computations that are required to operate multiple motors in parallel.

This rethinking includes a revisiting of what is meant by both terms, "uncertainty" and "freedom." Both are essential to control. There must be sufficient freedom of motion in different directions and this implies that there will be uncertainty with respect to how some component can move. ("Motion" here is certainly not restricted to 3D physical motion but can be understood figuratively as well, in terms of moving into, over, within different semantic spaces.)

This is also a rethinking of what is meant by terms such as "stochastic" and "random" in the context of control. Generally something "random" seems to be a quality to avoid in matters of control. But definiteness and rigidity in a control structure can lock a system or its parts into a dynamic that will result in failure or at least loss of efficiency and optimal performance. We are only at the beginning of what appears to be a revolution in how we think about computability and control, but the key may be found in looking at the simpler ways that some tasks are done in Nature, in Biology, more than at any other example. "Life itself" makes a strong case for doing some actions by trying out purely random varieties and then evaluating – on more than one scale of meaning at a time – which ones are probably going to be more suitable for the goals at hand – which themselves may be multiple and in competition with one another. Ultimately decisions do get made, by microbes and humans and then there is the challenge of how the system can adapt to the changed environment it has helped to create for itself. The adaptive element is the kernel and heart of intelligence, and the thing that makes the difference between repetition of the same mistakes or advancement to a new level of understanding, mastery, and control.

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