M. Dudziak, O. Granichin

EXTREME COMPLEX SYSTEMS, UNCERTAIN AND UNCOOPERATIVE ROBOTIC NETWORKS, AND CONTROL STRATEGIES BASED UPON STOCHASTIC ALGORITHMS

Institute for Innovative Study,Ann Arbor, Michigan martin@instinnovstudy.org

Saint Petersburg State University, St. Petersburg, Russia oleg_granichin@mail.ru

Abstract

Deterministic control of complex systems, particular those with multiple components exhibiting high degrees of uncertainty and asymmetric behavior, is subject to both unpredictable error and computational performance limits. This is seen particularly in systems whose components (such as robots, satellites and other "agent" devices) are constrained by limited size, power and computational capacity, such as in remote operations such as space-based engineering. Stochastic approximation and randomized algorithm methods offer sound alternatives when coupled with adaptive pattern recognition and machine learning, plus experience-trained heuristic models. Heterogeneous approaches that can incorporate learning and self-correction models during remote autonomous operations offer solutions for reducing state space complexity and avoiding critical instability and catastrophe points. Experiments in aerodynamic turbulence are providing a platform and set of models that can be transferred into such diverse applications as cooperative robotics in construction, network management, biomedical monitoring, and space-based challenges such as defense from asteroid impacts.

Keywords: complex systems, uncertainty, stochastic algorithm, randomized algorithm, cooperative network, device independence, space robotics, command and control, 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 critical points into which functions within such a system may lead. Simply put, singularity events can be more sharply and irreversibly catastrophic. 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 dimensionality and the relations between parameters which may be inherently noisy or difficult to measure under any circumstances. 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.

The outcome for end-users (passengers, patients, bankers, communication networks, civil engineers) may be quite more severe in cases of critical mechanical failure, incidents of cyberhacking, or system critical points and singularities that were not projected during the design process. The increased capabilities (as well as the sharper vulnerabilities) may often be linked directly to the capabilities (and limitations) of machine learning and artificial intelligence (AI) mechanisms, coupled with the performance speeds and responsiveness of computing and communication devices for managing the individual components and composite systems. Supercomputing, high-bandwidth and AI can offer a "double-edged sword" in many respects – improved or optimal performance and beneficial results, when everything is running smoothly, or else true "crash and burn" catastrophic results when some critical point has been reached, especially if the existence of the critical points or regions in a system's performance are unknown or insufficiently predictable.

All of these issues become even more delicate and potentially severe in impact when the operations are conducted in remote environments such as orbital, lunar or interplanetary space. The majority of space-based tasks, to date, have been generally limited to singular (even composite) devices (e.g., satellite or landing rover) with limited variations in the type of interactions that may take place. As complex as have been missions to Moon, Mars, Jupiter, Saturn, 67P/Churyumov–Gerasimenko and other destinations, there have been limited and strongly constrained operations involving two or more robot devices interacting with each other and/or with manipulation-type operations involving other objects such as an asteroid or a fragment of space debris. Moreover, command and control involving human operators has been highly constrained in order to accommodate normal signal transmission delays as well as periodic and asymmetrical breaks in uplink or downlink signaling. Space robotics has, until recently, been kept quite simple in comparison to what demands are now emerging, particularly in some areas of space engineering.

The growth of interest and the emergence of capable instrumentation – coupled with the need for productivity and commercial return values - demands much more complexity in future space operations. These include space-based construction and assembly for both habitation and manufacturing, asteroid mining, and also asteroid deflection and other forms of NEO impact deterrence. This “demand portfolio” alters radically the requirements for intelligent, adaptive, and fault-tolerant control systems. Deterministic models cannot work satisfactorily when parameters cannot be identified, measured and estimated with sufficient certainty. This critical claim is directed also at such quasi-deterministic models which include Bayesian probabilitistic networks, neural networks, and other variants of both statistically-based and rule-based “machine learning.”

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.

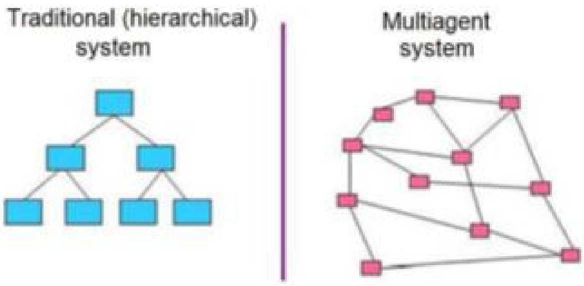

Figure 1 --- Hierarchical vs. Multi-Agent Control - but still deterministically based [1]

Such XCS-type systems are not only of a type such as multiple robots working together to construct a space station on the Moon or Mars, or to perform drilling, ballistic blasts or other forms of trajectory change for an asteroid, but such examples are among the most clear-cut cases of a class of problems that are presenting themselves for solutions and for which traditional “linear” thinking and also conventional Turing-Machine computation is running into barriers of performance and accuracy. There are many other “earth-bound” problems that approach or match the complexity, uncertainty and non-deterministic character of space-based multi-agent robotics – for example, aircraft turbulence, high-density highway traffic, global wireless network load balancing, and cardiovascular arrhythmia response.

We make a distinction here from other forms and levels of complexity in both natural and artificially-engineered systems. By XCS we mean those types of systems which are inherently hard to formulate into models and algorithms to process such models, by virtue of the uncertainties and stochastic, random-like natures of their parameters, and through the complex relationships and inter-dependencies among those parameters. Computationally, these may be NP-hard problems, but not necessarily so. Instability and insufficiency within a given control system may be not only due to the calculations that must be performed in order to ascertain values and even value ranges for such parameters. Limitations on physical hardware and long-distance communications, for instance in aerospace as well as high-speed rail, subsurface sea, and high-density highway traffic, curtail the ability to perform calculations that even in “polynomial time” may vastly exceed the time limits for answers, for decisions on course correction.

An XCS environment 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:

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

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. Again, these problems become exacerbated by factors such as physical distance (light-years or simply “light-minutes”), bandwidth competition, and asymmetric threats (e.g., cyber-hacking). Furthermore 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.). 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 connecting port, for example, or a location for either placing or retrieving some object (e.g., drilling or removing a machine part or a sample from an asteroid surface). 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 or “wait-mode” states
- 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 with reverse thrusters, etc.
- 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 (Figure 2). In the experimental case described here, this randomization is performed with wing-flap adjustments in response to randomly sampled pressure readings.

The Local Voting (LV) control protocol developed by Granichin et al [1] is one such model. It operates with a nonvanishing step-size for conditions of significant uncertainty and external disturbances [2]. The objective is to detect changes that may be insignificant in most cases but which can be

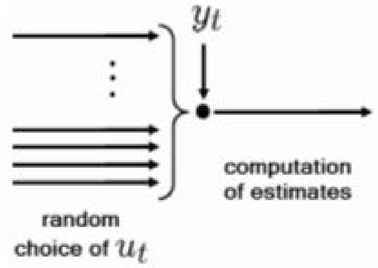

Figure 2 – Random selection of estimation and control coupled with learning and optimization of choice [1]

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], [4]) 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 [5] to track the changes in the parameter drift using the simultaneous perturbation stochastic approximation [6].

An experimental platform has been developed [1] (Figures 3-6) which addresses one major problem in aerodynamic stabilization during turbulence, focusing upon wing surface pressure points as the key observable parameter. This may be considered as a prototype for use of the LV protocol to other applications including the interactivity among a group of cooperating robots, or the dynamics of one or several robots manipulating an unwieldy, relatively amorphous and free-standing object, such as an asteroid or other object in low-gravity or zero-gravity (e.g., "space-debris" in near-earth orbit). In such a case the "turbulence" is not present in a classic aerodynamic or hydrodynamic phenomenon but there are comparable dynamics in the forces exerted between the target object and the robot apparatus operating with it. Simple joining of satellites, robots, and manipulation of fixed-geometry parts in zero-G space offers challenges that are "extreme" in comparison to those in an earth-gravity or planet-gravity region, and the demand for computational simplicity and speed (other than what can be provided by impractical "supercomputers" or machines requiring cryogenic environments (e.g., contemporary "quantum computers") becomes mandatory.

Consider a wing structure whose surface is covered with actuators that serve as mini-wingflaps, each coupled with a pressure sensor, such as illustrated in Figure 3. 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.

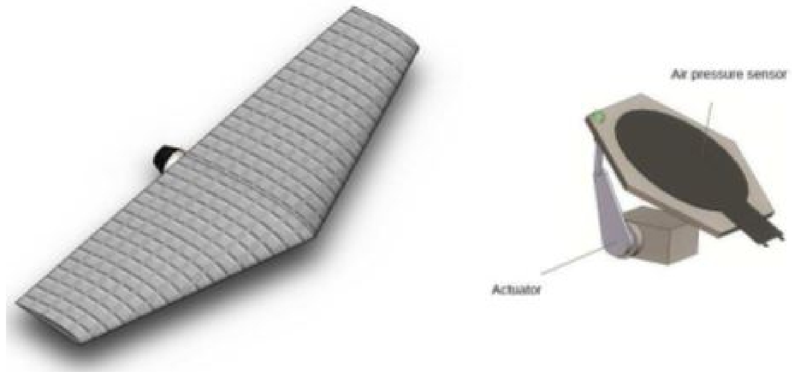

Figure 3 --- "Wings with feathers" [1]

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 Local Voting 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.

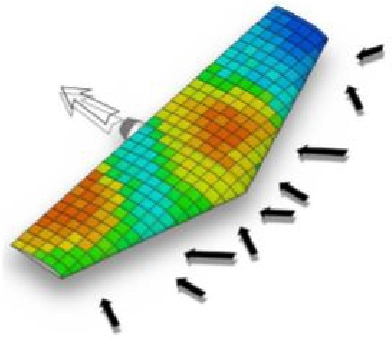

Figure 4 --- Wing sensor field under turbulence [1]

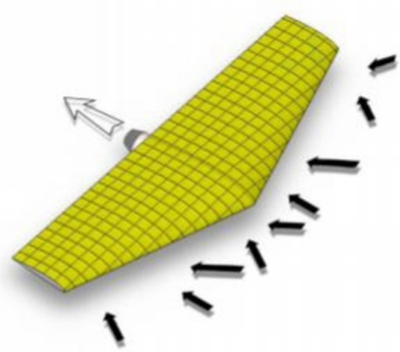

Figure 5 --- Wing consensus state under turbulence [1]

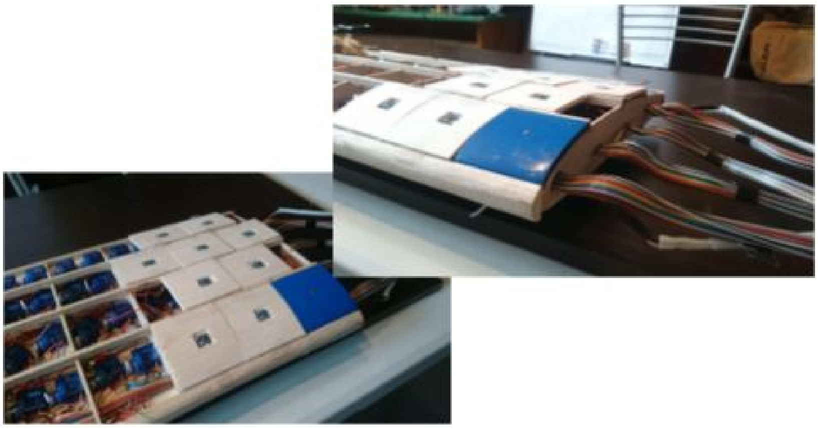

Figure 6 – Experimental Wing Sensor Platform [1]

In this given experimental case the LV clusters are statically defined by the geometry of the sensor-actuator units (Figures 3 and 6). However, stochastic approximation and randomized sampling and perturbation is not limited to a static architectural model of the given system, but quite to the contrary. A conventional aircraft wing, and the entire vessel, constitutes a static geometry – the wing has a defined and permanent geometry. In other applications and tasks the LV regions need not be uniform, nor static, in their geometry. For instance, consider cooperative agents working with interchangeable components (such as tool fittings) in physically dynamic environments with unpredictable kinetics (such as an asteroid in the process of being mined or split into fragments with the intention of reducing impact threats to Earth or some other habitation). It is possible to create different "dynamic" maps of LV cellular regions and also larger assemblies of clusters, with different geometries that correspond to how the system is being affected by its environment at any given time period.

Within XCS operations there are critical time intervals for such adaptations that can avert an critical "singularity" event affecting the entire system. Adaptation of wing surfaces (and potentially also other components) in an aircraft to atmospheric turbulence requires that decisions be made regarding adjustments of multiple actuators. 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. Drawing from the illustration of wing adaptation to turbulence - adjustment of several "feather" actuators, in a way that has an adverse or otherwise non-beneficial effect on the overall system, will (generally) be more easily correctable and offset by other adjustments, in contrast to a system-wide adjustment that may be irreversible.

A Thought-Experiment with "Cosmic" Implications

Consider a network of 10, 20, 50 or more robot devices, each powered by an ion propulsion engine, each equipped with a toolset that may consist of drills, impactors, chisels, cables and grappling hooks, and apparatus for placing ballistic charges. These form a cooperative team of robots working on an asteroid (perhaps 10m – 20m in approximate diameter) traveling in space, perhaps even on a potential collision course with Earth. There is limited opportunity for use of massive or physically cumbersome supercomputing, and real-time human or even AI control from Earth may be completely out of the question. The objective is to alter the asteroid's trajectory or to otherwise reduce its capacity for surface impact or for a severe air burst with consequences for human life Earth. Tunguska and Chelyabinsk offer two actual case histories within the past century-plus.

Consider the stochastic approximation and randomized algorithm methods being applied within a sensor-motor control system that is intended to optimize the cooperation among several robots to orient the asteroid rock and to configure the positioning of robots and tools for a variety of engineering tasks. The range of operations spans from drilling to use of ballistics, kinetics, gravitation mass adjustments and the use of nets and tethers. All of these decision processes ultimately depend for their possible successful completion upon the control of multiple units in what amounts to being a turbulent, dynamic, uncertain environment in which there are many critical points within the overall system state space, and wherein there is a high degree of uncertainty, noise, and unpredictability. The "turbulence" is not involving air, water or any physical "fluid" but it involves the movements and positioning of multiple bodies, the largest and most massive being the least controllable and adjustable (namely, the asteroid object). During all of this process there are two major limits that have critical "countdowns" - the amount of time that can be expended operating the robots, because they all have finite fuel and power reserves, and the amount of time before a projected Critical Point of the asteroid's movement, namely a point beyond which there will be irreversible consequences of impact or atmospheric burst.

Control functions may be distributed across virtual as well as literal physical surfaces and spaces. An aircraft wing and fuselage surface has distributed forces and air pressures which can be measured as points, then as cellular neighborhoods, then as increasingly larger regions. Parallel and competing analysis can provide sets of points where adjustments should be made that will offset pressures positively or negatively and lead to a stable laminar flow, the goal state for the plane in flight. The same model can be applied to the virtual space of robots manipulating amorphous shapes that have 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. The suggestion made here is that 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. 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. Flies and mosquitoes fly very well and avoid obstacles and threats. Synchronized swimmers and dancers do not rely only upon knowing the score and the choreography. Infants learn to handle balls and toys first with touch, then with eyes, and last of all comes learning via discourse, logic, and formal arithmetic. Food for Thought, in a world increasingly dominated by Extreme Complex Systems.

[1] O. Granichin, T. Khantuleva, O. Granichina, "Local Voting Protocol for the Adaptation of Airplane's 'Feathers' in a Turbulence Flow," 2017 American Control Conference, May 24–26, 2017, Seattle, USA.

[2] N. Amelina, A. Fradkov, Y. Jiang, and D. Vergados, "Approximate consensus in stochastic networks with application to load balancing," IEEE Trans. on Information Theory, vol. 61, no. 4, pp. 1739–1752, 2015.

[3] J. Tsitsiklis, D. Bertsekas, and M. Athans, "Distributed asynchronous deterministic and stochastic gradient optimization algorithms," IEEE Transactions on Automatic Control, vol. 31, no. 9, pp. 803–812, 1986.

[4] M. Huang, "Stochastic approximation for consensus: a new approach via ergodic backward products," IEEE Transactions on Automatic Control, vol. 57, no. 12, pp. 2994–3008, 2012.

[5] O. Granichin and N. Amelina, "Simultaneous perturbation stochastic approximation for tracking under unknown but bounded disturbances," IEEE Trans. on Automatic Control, vol. 60, no. 6, pp. 1653–1658, 2015.

[6] J. Spall, “Multivariate stochastic approximation using a simultaneous perturbation gradient approximation,” IEEE Trans. Automat. Control, vol. 37, no. 3, pp. 332–341, 1992.

[7] O. Granichin, N. Amelina, “Simultaneous perturbation stochastic approximation for tracking under unknown but bounded disturbances,” IEEE Transactions on Automatic Control, 2015.

[8] O. Granichin, K. Amelin, “Randomized control strategies under arbitrary external noise,” IEEE Transactions on Automatic Control, 2016.

[9] M. Dudziak. Parallel Replicative Neural Networks for Cooperative Robot Systems, NATUG-90, Santa Clara CA, April 1990.

[10] M. Dudziak. Spaceships To Planet Earth: Designing Systems for Space that Sustain Life on Earth. Dupont Summit, Washington DC, Dec. 2015.

[11] I. Ermolov, V. Gradetsky, M. Knyazkov, S. Sobolnikov. Cooperative Motion Planning of Autonomous UGVs for Mobile Reconfigurable Communication Networks, Proc. of IEEE-RAS-IARP Joint Workshop on Tech. Challenges for Dependable Robots in Human Environment, IROS2013 WS, Nov. 3, 2013, Tokyo, Japan

[12] A.S. Yushchenko, K.V. Ermishin. Collaborative Mobile Robots – A New Stage of Robotics. Proc. Intl. Scientific and Technological Conference EXTREME ROBOTICS. Nov. 24-25, 2016, St. Petersburg, Russia.

[13] M. Chacin, A. Mora, K. Yoshida, “Motion control of multi-limbed robots for asteroid exploration missions,” IEEE International Conference on Robotics and Automation, 2009. ICRA '09, Kobe, Japan.

[14] F. Matsuno, Y. Oosako, “Control of an asteroid sample return robot during contact based on complementarity modeling,” Procs. of the 40th IEEE Conf. on Decision and Control, 2001, Orlando, Florida.

[15] J. Bellerose, A. Girard, D. Scheeres, “Dynamics and Control of Surface Exploration Robots on Asteroids,” : Optimization & Cooperative Ctrl. Strategies, LNCIS 381, pp. 135–150, Springer-Verlag, 2009.