Working notes on a developmental approach to autonomous spacecraft and the recovery of the Hubble Space Telescope

Michael L. Rilee

L-3 Communications GSI, Largo, MD 20774
NASA/GSFC, Mailstop 695.1, Greenbelt, MD 20771
Michael.Rilee@L-3com.com

Steven A. Curtis, John E. Dorband, Cynthia Y. Cheung, Jacqueline J. LeMoigne

NASA Goddard Space Flight Center
Mailstops 695, 931, 695.1, 935, respectively
Greenbelt, MD 20771
Steven.A.Curtis@nasa.gov, John.E.Dorband@nasa.gov, Cynthia.Y.Cheung@nasa.gov, Jacqueline.J.LeMoigne@nasa.gov

David E. Lary,

UMBC/GEST NASA Goddard Space Flight Center, Mailstop 900.3, Greenbelt, MD 20771
David.J.Lary@nasa.gov

and

Hamse Y. Mussa

Molecular Informatics Centre, Unilever Centre, University of Cambridge, Cambridge, England, UK
hym21@hermes.cam.ac.uk

Abstract

At NASA's Goddard Space Flight Center (GSFC), we have been developing the means to create space and surface systems that are active participants in their environment rather than being merely visitors that withstand space's hazards as our extended remotely controlled tools. Central to this work has been the development of the Autonomous Nano-Technology Swarm (ANTS) mission architecture and the Neural Basis Function/Synthetic Neural System (NBF/SNS) which are included among the subjects of several GSFC provisional patent applications. These are scalable systems with non-linear dynamics built in to deal with irregularity, uncertainty, and unpredictability in their environments. NBFs are a synthesis of low- and high-level approaches to system control in which specialized components are embedded in an Evolvable Neural Interface (ENI) that mediates information flow through the system. Individual system behaviors are driven by individual NBFs, and more complex behaviors are composed by linking multiple NBFs through the ENI. Conflict resolution and ontological mapping between NBF components occurs primarily within the ENI which is genetically evolved and trained to perform these resolutions and mappings. This built-in flexibility is especially important for space systems which currently operate only within very narrow margins of safety. The first NBF is being developed to demonstrate that independent reactive low-level attitude and propulsion control and a heuristic high-level navigation executive can ground themselves and achieve mission goals in the context of a Hubble Space Telescope (HST) recovery scenario.

Synthesizing the autonomic and the heuristic

We are taking a developmental approach to the problem of developing an extensible, evolvable, and trainable control system that can scale to advanced systems. Individual specialized components are developed in simulation in which they are evolved to fit the mission context and trained to show mission-appropriate behaviors. Adaptability is built in from the beginning and provides a means for the control system to adapt to off-nominal performance, system degradation, and module replacements that happen during space system operations. This built-in adaptability also allows control components called Neural Basis Functions to be added to enrich system behavior (Curtis et al. 2000). Such capabilities would greatly enhance space system survivability and greatly ameliorate integration and test problems. The approach we are taking would also help us address a key problem facing space system control, namely the explosion of detailed specification required to handle the future's complicated systems. Our approach represents a dramatic departure from current standard practice that requires precise and rigid control over every degree of freedom available to the space mission architect, and the minimization of uncontrollable variables. Such a design philosophy is not appropriate for developing robust and reliable systems for the irregular and dynamic environments that are our next destinations in space.

The space systems required to meet the challenges being posed by our goals for space exploration are growing more sophisticated and complex. With current approaches to space system implementation, the margin for error or deviation from nominal mission plans is extremely small. This fact drives up costs and drives down our tolerance for risk, irregularity, and spontaneity. At Goddard Space Flight Center, by considering advanced mission concepts such as the Autonomous Nano-Technology Swarm Prospecting Asteroids Mission (ANTS/PAM) and then looking at today's capabilities, we have outlined pathways from near-term to far-term capabilities (Curtis et al. 2000; Curtis et al. 2004).

In this work, we describe our initial efforts to develop an approach for implementing richer and more complicated space systems than are currently possible. Spacecraft operations is a critical component of mission architecture and is a key limiting factor, particularly for systems with large numbers of components, multiple spacecraft, or that are intimately coupled with their environment like planetary rovers or asteroid surveyors.

Autonomic Systems

In biological systems, a great deal of control is performed at an autonomic level. These are functions and behaviors that are handled outside of conscious control. These are functions such as breathing, heartbeat regulation, and balance: i.e. the essential control functions that govern the homeostatic balance of life. In many ways, biological autonomic control functions solve very difficult problems balancing many competing environmental and system parameters. These solutions may not be optimal, but they have been successful and adaptable enough to bring about the diversity of life we see today.

The autonomic systems that we have been developing are based on nonlinear oscillators acting as simple nervous systems called nervous nets first developed by Mark Tilden (Rilee et al. 2004). In these systems actuators and sensors are tightly coupled with the nervous net. The nonlinear oscillations of the nervous net provide control signals to the actuators that provide desired low-level behaviors such as balance or walking. This control strategy can be very robust, even if the system takes on unexpected states, because the nonlinear dynamics of the nervous system can automatically and chaotically search its state space for desirable states or limit cycles. Thus we are constructing systems whose built-in dynamics maintain a particular kind of balance or motion. For these systems, whatever logical calculus is applied to a given situation is "hardwired" into the system itself.

Though biological autonomic systems seem to feature a low-level synthesis of control, sensing, and actuation, we are not limited to this approach. As computer performance has increased, the capability, complexity, and sophistication of control software has increased. The telecommunications industry, among others, has driven technologies that have improved reliability and robustness with implementations of multi-module redundancy and replacement capabilities. Remote and distributed software maintenance is commonplace today. Some spacecraft instrumentation today features a "plug-and-play" autonomy for important, but narrow functions. With these advances, one can use what essentially amount to algorithmic or heuristic approaches to system automation and control and mimic what biological autonomic systems do as part of their fundamental nature.

Heuristic Systems

By heuristic systems we mean those that use ratiocination as a means to control their behavior. Symbolic reasoning using various forms of logical inference is the foundation of these approaches. Expert systems are the typical examples of heuristic systems and may draw on a wide variety of algorithms, e.g. neural net or fuzzy logic. For environments and systems that have logical patterns in the problems that arise during missions, heuristic systems can perform quite well.

There are two costs for the use the array of the tools of reason or deliberation: (1) some reference must be made between the symbols used by the reasoning system and the reality being reasoned about, and (2) reasoning works best with simple systems and does not scale well to highly complex or irregular systems. In an engineered system, a model in a symbolic reasoning system can be made to reflect with great precision the reality of that system. However, uncertainties and lack of knowledge can cause model and reality to differ, and reconciling and eliminating these differences is a long standing problem in model-based robotic control. If these differences are not recognized and reconciled, the system may perform inappropriate actions with catastrophic consequences.

Synthesis via the Evolvable Neural Interface

Thus we have two ways a robot might determine what happens next. In psychological terms, on one hand there is an intuitive (low-level) approach in which responses are essentially hardwired into the control systems themselves. On the other hand there is a deliberative (high-level, or heuristic) approach in which responses are reasoned about and in which there is typically some sort of symbolic representation of elements of a robot's environment. Separately, these two approaches are not each capable of providing the kinds of behaviors we see in relatively simple creatures.

As biological systems we are faced with this duality, yet both low- and high-level aspects work together. For example, we may reason about the perceived characteristics of a group of hills in the context of our science goals and decide which hill to ascend, but we don't similarly reason about which group of muscles to excite to start the climb.

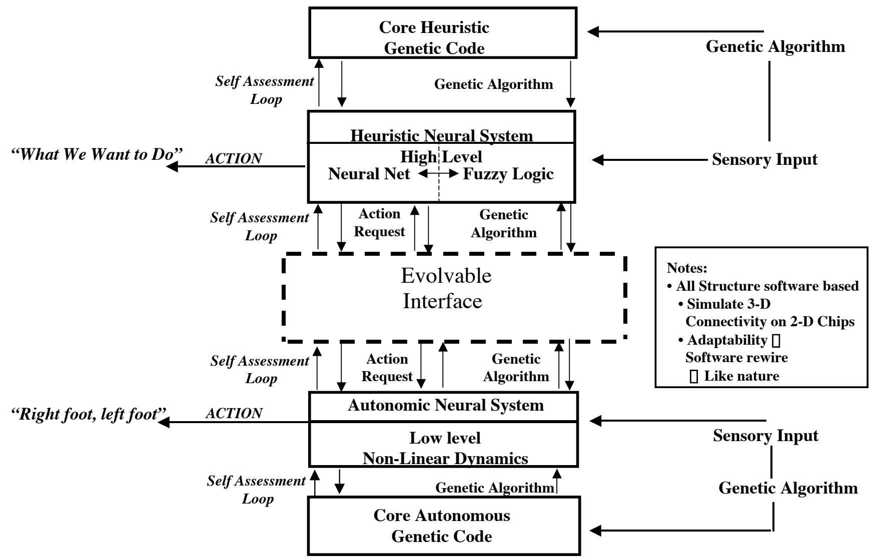

Figure 1. A schematic of the Neural Basis Function Architecture

In fact, in large part, we cannot pick and choose which muscles to use. The anatomy and function of our brain seems to translate our more symbolic thoughts and goals into a complicated series of signals distributed through our nervous system that drive our own varied behaviors. As we develop and learn, raw functions—muscle excitation, sight—are orchestrated into higher-level behaviors—walking, reading—that help us achieve our own goals. We have a built-in adaptability that allows our own control systems to adapt to the diversity of body forms and cultures in which we find ourselves.

Therefore, in contrast to many traditional approaches to Artificial Intelligence and the control of robots, we have proposed an architecture that features three elements: (1) low-level components, tightly coupled between robot and environment, (2) high-level components that focus on heuristics and abstractions (like mission goals), and (3) an Evolvable Neural Interface that mediates communications between these independent elements. Previously researchers have focused on the first two considered independently. At present, researchers are starting to consider syntheses of these two. Our approach recognizes that these two approaches are qualitatively different and each scales very poorly to the domain of the other: translating between these two domains is a demanding task. The ENI architecture provides an active communications medium between the low- and high-level components. It is evolvable because it adapts how it communicates signals both during a developmental phase and during operations. It is neural in the sense that the ENI has a multiply connected three-dimensional network topology of neuron-like nodes that communicate and possibly modify the signals that pass through them. As an interface, the ENI stands between the low- and high-level functional components. These three elements together, low-, high-level, and the ENI form an architectural function called a Neural Basis Function (NBF; Figure 1.).

Neural Basis Function Operational Characteristics

The NBF is a new architectural concept for robotic control. Most visible actions of the robot are the immediate result of low-level functions driving and protecting the hardware and reacting to input from the ENI and the systems environment. The higher-level functions reason about input they receive from the ENI and send commands back out through the ENI. Both low- and high-level components put information onto the ENI. The result of these interacting systems is purposeful behavior—purposeful in that the high-level components seek to drive the system towards meeting mission goals. In general, the low-level components simply do not operate on that abstract level. The ENI translates the relatively abstract symbols of the high-level into relatively simple numbers and commands that the low-level understands.

As described above, the ENI is a learning system. In the developmental phase, synthetic environments are created in which an NBF and its robot are rewarded for performing simple tasks. This reward acts as feedback to the degrees-of-freedom within the ENI. In this way, the symbolic constructs within the higher-level functions are mapped to lower-level behaviors. Variations in the environment or the robotic system or even in the detailed structure of the NBF can be used to expand the practice of the NBF/robot system. System degradation, fault, and failure of system components can be simulated and accounted for during the development of the system. Furthermore, transition from simulated systems to real systems involves the same procedure of adaptation. An iterative process is envisioned whereby computer simulation and deployment to hardware in real environments advances the capabilities and fidelity of both. However, the critical enabler in this is the built-in adaptability of the components of the NBF.

Because of its structure and adaptability, behaviors may be composed. This is the source of the term basis function in the name of the architecture. In analogy to basis functions of mathematical physics, behaviors implemented as NBF may be composed to construct other behaviors. The extension of software systems has been a central research problem of computer science since its inception. With NBFs the goal is to link low- and high-level components or complete NBFs to a pervasive ENI and then have the ENI and system adapt to the new components and tasks. For example, a robotic arm system may be implemented to grasp a rock, lower-level components would provide motor control, proximity sensing, and the like, while a higher-level component would perform path planning and rock selection, and the ENI would communicate signals between these components. To add the behavior of dropping or throwing a rock, many of the same components would be used, but their coordination by the ENI would have to be different. This difference could be driven by a higher-level expert rock-throwing system attached to the ENI along with a fast acting low-level signal driver to control the timing of the actuators. In essence, these two items would make up a "rock throwing" NBF to be added to the "rock grasping" NBF. Whether the robotic arm grasps or throws a rock is a higher-level decision to be made according to mission goals and communicated through the ENI that then enables or inhibits the appropriate behavior. During training, the ENI and other components of the NBF adapt their internal degrees of freedom to account for the specific robotic system and environment in which they are embedded.

Scalability, self-similarity, parallelism

The NBF architecture was designed to be scalable so that it could be used at multiple levels. Subsystems could feature their own set of NBFs controlling their own behaviors while providing an interface to other subsystems through the ENI. For a multi-level, multi-spacecraft mission like ANTS/PAM, the ENI exists throughout the entire swarm of spacecraft. Spacecraft with their individual subsystems all operate in parallel providing either greater capacity for performance or redundancy for reliability. NBFs at subsystem or even spacecraft levels can be seen as providing low-level autonomic functionality for the teams and swarms of spacecraft. A system that has this kind of scale-invariant symmetry, i.e. it looks the same at different levels of the system, is called self-similar. Through pre-mission training and adaptation during the mission itself, the internal degrees-of-freedom of the ENI adapt to better meet mission goals. Such an approach to system integration and test is a great departure from what has worked in the past for our relatively simple systems. A Synthetic Neural System based on NBFs limits the complexity visible by any particular controller and provides a single scale-invariant paradigm to help drive system organization and control.

Hubble Space Telescope Recovery: Uncontrolled Tumbling

An important example of an environment in which uncertainty and irregularity are problems is the case of rendezvous and capture of an uncooperative target. We have been looking into a problem motivated by HST recovery concepts. Spacecraft without attitude control and with internal degrees of freedom can shift momentum between those various degrees of freedom resulting in the spacecraft tumbling through space. External forcing such as drag and radiation pressure also affect the dynamics of the spacecraft. The predictability of this tumble depends on many factors, but in a worst case scenario the tumbling may be chaotic meaning that, like the weather, beyond some period of time, the attitude of the spacecraft becomes unpredictable. The problems posed by such a mode are that the system state is unpredictable and its dynamics complicated over time.

To explore NBF-based SNS architectures in this situation, we have developed a simulation wherein a chaotically tumbling target (HST) is approached and captured by a recovery vehicle (RV; Figure 2). The HST has six degrees of freedom associated with translational motion and attitude. Unlike the real HST, our model has four internal degrees of freedom that are coupled to the attitude's rotational velocity. The particular internal model we are using is not representative of the internal structure of the HST, but it provides a good general test case that features complicated behavior. Nothing fundamentally precludes using a higher fidelity model. Small dissipative forces couple the degrees of freedom and remove kinetic energy from the system while maintaining total system momenta. External driving stands in for drag and radiation pressure effects and adds energy and momentum to the system. There is a flow of energy between the external driving and the internal dissipation that shows up as complex dynamics of the HST model. In more advanced models, impulsive inputs such as from collisions with the RV or meteor and debris strikes could be included. The couplings and models are parameterized so that the nature of the dynamics can be controlled. These parameters, including initial positions and velocities, can be varied to exercise the NBF control software under a broad range of conditions. This variation can be automated and randomized to provide a wide range of learning and test opportunities and to start to provide a quantitative understanding of NBF and system characteristics. For most of our tests, we work with extreme cases in which HST behaviors are difficult to predict because these are stronger tests of our system architecture.

The RV is represented by a six degree of freedom, translation and attitude, along with an internal system of rotation wheels for attitude control. Currently, relative position and attitude information is provided, by fiat, to a low-level control system that governs the RV's translation and attitude. A network of synthetic neurons based on Tilden's work with nonlinear oscillators provides this low-

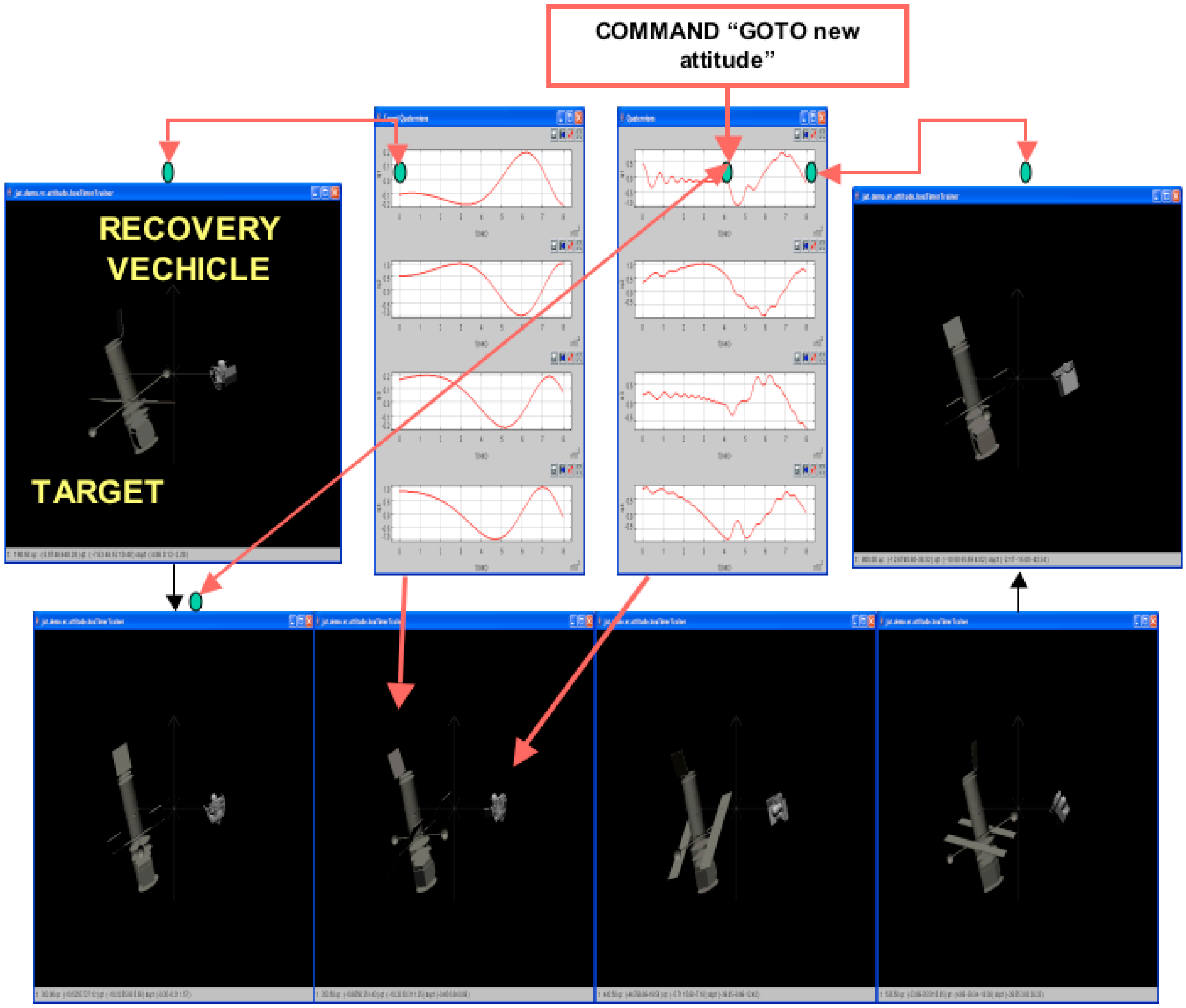

Figure 2. Simulation snapshots showing a Recovery Vehicle (RV) responding to a high-level command to change its attitude relative to a tumbling target. In these sequences, the RV attitude is controlled by a low-level six-neuron nervous net operating four reaction wheels: no particular optimization or other controls were applied. Graphs are of the spacecraft attitudes in quaternions.

level control. This network is designed to accept input from an ENI that communicates information from sensors and higher-level heuristic controllers. Currently, the ENI is a more traditional artificial neural net, but one that is trained using an Extended Kalman Filter to more efficiently navigate its training space (Lary et al. 2004a; Lary et al. 2004b).

The RV and the HST target are implemented as objects in the Java programming language and are built using the Java Astrodynamics Toolkit (JAT 2005). JAT is also being used for GSFC's Formation Flying Testbed, which is a high-TRL test facility for conducting flight control experiments. Therefore there exists a rapid pathway to advance our NBF architectural concepts. We have ported JAT and supporting software to GSFC's Beowulf cluster supercomputers so that (1) we may run many test and training cases in parallel, and (2) we may test NBF components such as higher-level heuristics or lower-level signal processing that can take advantage of multi-processor parallelism. The latter of these two ties into our work with high performance computing and the Space Technology 8 flight project in which high performance, high reliability Beowulf-style cluster computer technology to be deployed onboard a spacecraft (Cheung et al. 2004). Once the basic structure of the NBF has been implemented, we plan to genetically adapt the system to a broad range of HST recovery scenarios.

In addition to the basic structure we plan to examine the composability of NBFs by adding lower- and higher-level control components that will then be put through the training and evolution regime mentioned above. These include a three-dimensional LIDAR/structured-light-based vision system for low-level ranging and attitude determination (e.g. Le Moigne and Waxman, 1988) and a higher-level prediction and navigation component that uses a neural net and physics-based heuristics to plan and execute a recovery trajectory.

Conclusion

Preliminary training of an ENI has shown that high-level commands along with relevant sensor information about the RV and the HST target can be translated into low-level actuator input that suffices to control the attitude of the RV. Preliminary work has also shown that the neural net of the ENI can also be used to predict the behavior of the system, in this case, the HST target, which means that it can provide real-time feedback that the low-level system can use to adjust its behavior. This is an important capability, because we are seeing the beginnings of a robust and computationally efficient autonomous system that can catch a chaotically tumbling target. The NBF would be a software package trained and developed on the ground and uploaded to a conventionally developed system.

Acknowledgements

This work has been supported by NASA/GSFC's Internal Research and Development program and NASA/GSFC's Director's Discretionary Fund. Support has also been provided by NASA's Revolutionary Aerospace Systems Concepts program (2003) with continuing collaboration with NASA/LaRC and the Space Architect's Office. Support was also provided by NASA Contracts NNG04EE43D, NAS5-99189, and NAS5-00220. Elements of this note are from Rilee et al., 2005 and involve NASA Goddard Space Flight Center Provisional Patent applications 14657, 14762, 14763, 14764, 14848, 14849, 14850, 14858, and 14859.

References

The ANTS and NBF/SNS project website is at http://ants.gsfc.nasa.gov/ [cited 17 January 2005].

Cheung, C., S. Curtis, P. Yeh, M. Rilee, P. Clark and W. Truszkowski, Intelligent Systems in the Evolvable ANTS Architecture, AIAA-2004-6302, AIAA 1st Intelligent Systems Technical Conference, Chicago, Illinois, Sep. 20-22, 2004.

Curtis, S. A., J. Mica, J. Nuth, G. Marr, M. Rilee, and M. Bhat, ANTS (Autonomous Nano-Technology Swarm): An Artificial Intelligence Approach to Asteroid Belt Resource Exploration, International Astron. Federation, 51st Congress, October, 2000.

Curtis, S., M. Rilee, W. Truszkowski, C. Cheung, and P. Clark, Neural Basis Function Control of Super Micro Autonomous Reconfigurable Technology (SMART) Nanosystems, AIAA-2004-6304, AIAA 1st Intelligent Systems Technical Conference, Chicago, Illinois, Sep. 20-22, 2004.

JAT: The Java Astrodynamics Toolkit project website is http://jat.sourceforge.net/ [cited 17 January 2005].

Lary, D., Müller, M. and Mussa, H. , Using neural networks to describe tracer correlations Atmospheric Chemistry and Physics, Vol. 4, pp 143-146, 31-1-2004 [2004a]

Lary, D. and Mussa, H. , Using an extended Kalman filter learning algorithm for feed-forward neural networks to describe tracer correlations, Atmospheric Chemistry and Physics Discussions, Vol. 4, pp 3653-3667, 30-6-2004 [2004b].

Le Moigne, J., A.M. Waxman, "Structured Light Patterns for Robot Mobility," IEEE Journal of Robotics and Automation, Vol. RA-4, No. 5, 1988. [for example]

Rilee, M., S. Curtis, C. Cheung and J. Dorband, Evolving a Self-organizing Neuromechanical System for Self-healing Aerospace Structures, AIAA-2004-6703, CANEUS 2004 Conference on Micro-Nano-Technologies, Monterey, California, Nov. 1-5, 2004

Rilee, M.L., S.A. Curtis, J.E. Dorband, D.E. Lary, H.Y. Mussa, C.Y. Cheung, Thriving in the irregular and the unknown: system control for space exploration, AIAA-2005-2710, 1st Space Exploration Conference, Orlando, FL, January, 2005.