A Biologically Inspired Architecture of Machine Perception and Intelligent Control for Multi-Robot Coordination

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Abstract
Intelligent control, inspired by biological and AI (artificial intelligence) principles, has increased the understanding of controlling complex processes without precise mathematical model of the controlled process. Through customized applications, intelligent control has demonstrated that it is a step in the right direction. However, intelligent control has yet to provide a complete solution to the problem of integrated manufacturing systems via intelligent reconfiguration of the robotics systems. The aim of this paper is to present an intelligent control architecture and design methodology based on biological principles that govern self-organization of autonomous agents. Two key structural elements of the proposed control architecture have been tested individually on key pilot applications and shown promising results. The proposed intelligent control design is inspired by observed individual and collective biological behavior in colonies of living organisms that are capable of self-organization into groups of specialized individuals capable of collectively achieving a set of prescribed or emerging objectives. The nervous and brain system in the proposed control architecture is based on reinforcement learning principles and conditioning and modeled using adaptive neurocontrollers. Mathematical control theory (e.g. optimal control, adaptive control, and neurocontrol) is used to coordinate the interactions of multiple robotics agents.

I. Introduction

An *expectation gap* has developed between envisioned robotics systems and the currently realizable robotics systems. This expectation gap has arisen as a result of robotics falling short on their promise to provide inexpensive, efficient, and adaptable solutions to manufacturing problems. To use an eloquent analogy, robotics state-of-the-art today is what mainframe computers were to personal computers twenty years ago: *bulky, centralized, inflexible, and above all, expensive,* requiring specialized and costly personnel to install, operate, and maintain.

Given the analogy, the question arises: *Is it possible with today's technology to span the expectation gap* and accelerate the widespread use of robotics? Steps towards this direction are being taken by various research groups and partial results appear promising [1, 2, 3, 4]. Yet, no proposed architecture [5] seems to address all the issues involved in the development of a truly intelligent robotics system. The main obstacles that prevent the widespread use of robotics still remain; robots:

- cannot generalize to a variety of tasks (e.g., reprogrammability remains a challenging task that requires specialized expertise);
- cannot adapt to their environment or operate in the real world in an unfamiliar situation for which they have not explicitly programmed;
- exhibit poor error recovery and handling of new and unexpected environmental conditions;
- have difficulty with world models and frame grounding problem (See "elephants don't play chess," in [6]).

A recent report of the IEEE CSS Task Force on Intelligent Control has emphasized the complexity of the problem of intelligent control and enumerated its multiple facets [5]. However, it left the meaning and structure of intelligent control undetermined. In the same report, Albus, *On Intelligence and its Dimensions,* [5], provides a lengthy list of fragments of intelligence in different control processes. However, piecing these fragments together to design an intelligent control may prove to be a rather formidable task. By adopting a bottom-up approach for intelligent control allows the design to follow naturally in a dynamically evolving hierarchy.

Despite recent progress in adaptive control [Refs. 44-49], the stringent requirements of a precise modelization of the process dynamics (at least of the nominal plant) in terms of differential or partial differential equations, imposes a severe restriction in the ability of these extended conventional methods to address complex control systems, frequently encountered in manufacturing and robotics systems. Such complex systems may not even be describable by total or partial differential equations, making the use of model reference adaptive control applicable only in low level controllers. To address the design shortcomings and lack of adaptivity of conventional control in complex manufacturing and robotics systems, *intelligent control* has been used whereby intelligent implies a control capable of handling complex processes exhibiting some degree of intelligence.

Intelligent control, inspired by biological and AI (artificial intelligence) principles, has increased the understanding of controlling complex processes without precise mathematical model of the controlled process [12, 13, 14]. Through customized applications, intelligent control has demonstrated that it is a step in the right direction. However, intelligent control has yet to provide a complete solution to the problem of integrated manufacturing systems via intelligent reconfiguration of the robotics systems [5].

The proposed intelligent control design is inspired by observed individual and collective biological behavior in colonies of living organisms that are capable of self-organization into groups of specialized individuals capable of collectively achieving a set of prescribed or emerging objectives [15, 16, 17]. The nervous and brain system in the proposed control architecture is based on reinforcement learning principles and conditioning and modeled using adaptive neurocontrollers.

Mathematical control theory (e.g. optimal control, adaptive control, and neurocontrol) is used to coordinate the interactions of multiple robotics agents. Coordination and cooperation of multiple agents towards set objectives and specified tasks is accomplished through distributed control via inhibition and facilitation of actions and behaviors according to the fulfillment of set objectives. In this way, even conflicting tasks can be resolved and a robot colony can be self-organized to execute them and learn to resolve conflicts [20, 21]. The distributed control can be either an optimal controller, a neurocontroller, or a classical adaptive controller, depending on the knowledge of the process dynamics.

The proposed intelligent control design borrows principles from observed biological behaviors and blends them with mathematical control theory to achieve true adaptation and flexible coordination and cooperation. In the proposed research we will attempt to model the proposed intelligent control mathematically, analyses it, and experimentally validate its ability to control individual mobile robots and to coordinate multiple mobile robots cooperatively based on sets of prescribed objectives .

The proposed architecture is inspired by biological control concepts observed in the human and less complex vertebrate nervous systems [18]. Autonomous robots in the proposed architecture use distributed control algorithms to learn to coordinate their actions and cooperate in order to achieve prescribed tasks (objectives), which may very well be conflicting. Each autonomous mobile robot possesses its own nervous system and brain capable of learning and adapting to new environments through experience. The nervous and brain system of each autonomous unit is structured according to biological nervous systems observed in vertebrates, and in humans in particular as detailed below [18, 19].

The proposed *intelligent control architecture (ICA)* relates directly to flexible and intelligent manufacturing. Central element of the proposed control design is the ***robotics agent*** (defined in section C below). Robotics agents are assumed to be capable of performing a number of rudimentary tasks. Coordination of these rudimentary tasks through motivations leads to new and complex behaviors that can accomplish complex manufacturing objectives in a flexible manner. So long as any manufacturing objective is decomposable in behaviors attainable by the robotics agents in the colony (ies), no matter how complicated the objectives may be, they can, in principle, be executed by robotics agents through self-organization and behavioral coordination without the need of a central coordinator (programmer). Furthermore, due to self-organization and adaptation of behaviors according to the current availability of robotics agents in the colony(ies), the architecture provides an immediate solution to the error recovery problem and control reconfiguration.

II. Description of the proposed intelligent control architecture

The *central element* of the proposed control design is the ***robotics agent*** controlled by a self-organizing behavioral system inspired by biological and neurophysiological evidence and knowledge. Robotics agents are coordinated and cooperate through a *distributed multi-agent controller*, whose functions are described below.

An (robotics) agent is defined as a collection of effectors, sensors, and low level controllers, capable of producing action primitives.

An action primitive is defined as a simple action produced by coordination of reflexive actions by low level controllers in response to a simple command.

Reflexive action is a fixed, stereotyped, independent action executed by a low level controller.

A low level controller (LLC) is responsible of executing reflexive actions. It can be tuned adaptively to coordination (to other low level controllers) so as to execute action primitives in response to a simple command. An example of a LLC is a tunable (or adaptive) PID controller or a neurocontroller [22, 23].

The macro organization of the control structure of a robotics agent (*its nervous system)* is based upon the human nervous system, as shown in Fig. 1.

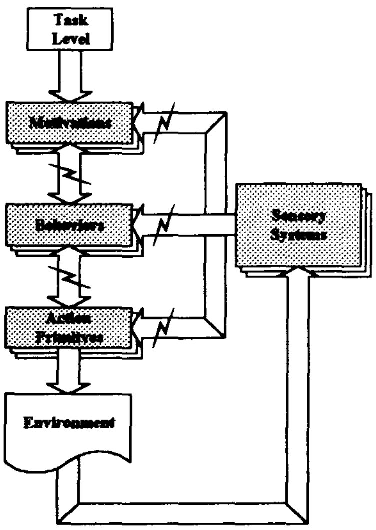

Fig. 1 Biology Inspired Architecture for Machine (robot) Perception and Intelligent Control

The *nervous system* in the proposed intelligent control architecture consists of the following four levels.

•The Task Level (central nervous system) where a given task is specified in a high level language or via symbolic representation.
•The Motivational Level (the motivational system and associated cortexes) where the task specification is compiled into a set of motivational rules which govern what the robot "wants." It includes building of appropriate associations for sensory input.
•The Behavioral Level (the peripheral nervous system and autonomous functions) provides the fundamental behaviors that can be combined in various ways to accomplish tasks; and
•The Action Primitive Level (the primary and higher order sensory and motor cortexes) combines the reflexes provided by the robotics agent to action primitives.

The control structure in the proposed intelligent control architecture is inspired by the decomposition of the required steps from a description of a task (objective) to its successful execution into Tasks, Motivations, Behaviors, and Coordination of actions and sensory inputs. The decomposition and the assumed interactions loops in the proposed architecture are included at a very high level in Fig. 1.

The proposed intelligent control structure is based on biologically supported evidence of unconditioned and conditioned stimuli and responses for sensory fusion and coordination of low level control actions [26, 27]. Translation of a set objective (task) into control actions is done through motivations and behaviors. It is assumed that conditioning may occur even at the behavior level, to allow the translation of high level behaviors into control commands in order to perform a given task.

A *behavior* is understood as the coordination of action primitives and sensory feedback by inhibition or facilitation of action primitives through conditioning [26, 27]. We distinguish two levels of behavior. A *low level* behavior that corresponds to direct coordination of action primitives and sensory feedback through conditioning. A *high level* behavior that corresponds to direct coordination of low level behaviors and sensory feedback through inhibition or facilitation. Both low level and high level behaviors use inhibition and facilitation. And both use some type of conditioned learning.

Motivations are understood as emerging desires that control behaviors through inhibition or facilitation [26,27]. Motivations may occur spontaneously and simultaneously, may be conflicting, or even non-causal. Interactions among motivations are, in general, weak and indirect (i.e. through sensory feedback).

Behaviors, on the other hand, occur deterministically and are always causal. Behaviors inhibit or facilitate other behaviors to interact with each other directly [26, 27].

In the generation and elimination of motivations and behaviors, and their interplay, it is necessary to define the motivational and behavioral levels.

Motivational level is the degree of influence each motivation has on each associated behavior(s).

Behavioral level is the degree of influence a behavior has on other behaviors and on action primitives.

Once a motivational level exceeds a threshold, a behavior is released. Thus, by adaptively controlling the motivational and behavioral level, allows the mapping between the motivation/sensory stimulus space and the released behavior to be modified by experience. Through this control mechanism, complex behaviors and actions may be produced from simple action primitives and low level behaviors in response to a stimulus or stimuli. A useful mathematical paradigm to describe the evolution and development of complex behaviors from simple primitive actions, is that of a σ-algebra. If the primitive behaviors are identified with structural atomic elements of the σ-algebra, the adaptive control generates complex behaviors that are members of this algebra. We can, then talk of the creation of a *"behavioral" algebra.* In this way, *the evolution of behaviors under the chosen adaptive mechanism can be analyzed mathematically.*

A major problem in designing intelligent control systems is the data fusion [28, 29]. Data fusion in the proposed architecture is a built-in function and is done automatically by associating unconditional stimuli (sensory input) to conditional stimuli (fused input signals) or directly to conditional responses. The collective sensory input creates a pattern of activity in the sensors, the Sensor Activity Pattern which is referred to as the conditioned stimuli. This conditioned stimuli then can be associated with an unconditioned stimulus response pair that is always active at the time this sensory pattern is perceived. Another possibility is the conditioned stimuli can be associated with a conditioned response that has shown positive results when executed in the presence of the current sensor activity pattern.

Hence, through conditioning, multisensory inputs can be fused together into a coherent stimulus (or stimuli), or be associated with a conditional response directly. The biology-based function of conditioning is, hence, used to eliminate the need for separate multisensory data fusion interface in the proposed architecture.

III. Supporting experimental evidence for the proposed architecture

a. Testing of the nervous system architecture

The behavior and action primitive levels of the proposed architecture have been tested in the autonomous locomotion of a six-legged mobile robot shown below, [22, 23]. See Braught and Thomopoulous in these proceedings for more details on the nervous system architecture.

Each leg of the robot is modeled as a rigid body with a single two degree of freedom joint where contact is made with the torso. Each leg of the robot contains two action primitives; move the leg to a specified horizontal position; and move the leg to a specified vertical position. The action primitives are implemented as modern controllers for DC servo motors with appropriate load torques. The reciprocal inhibition network responsible for the horizontal motion control of the legs is shown in Figure 2. The inhibition network responsible for the vertical motion control of the legs is shown in Fig. 3.

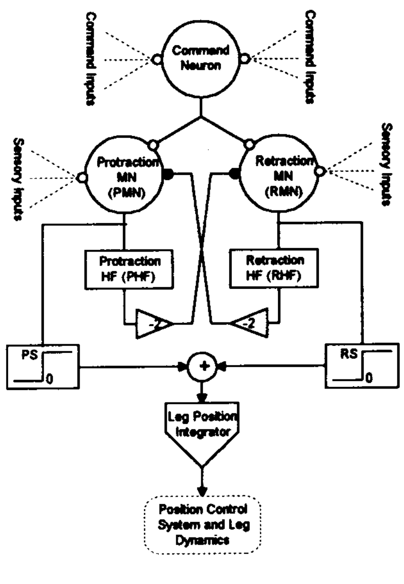

Fig. 2 Reciprocal Inhibition Network for Control of Horizontal Leg Motion.

A low level behavior is implemented for each leg which manipulates its action primitives to produce patterns of leg movement required for walking. The low level behavior is implemented as a neural circuit and is strongly based upon insect neruophysiology [55, 56, 57, 58]. A high level behavior is implemented to provide coordination of the legs into stable stepping patterns. The high level behavior is also implemented based upon information about the neural organization of insect nervous systems. [59, 60] The motivational level has not been implemented in the hexapod because of the single mindedess of its goal, namely learning stable stepping patterns for walking.

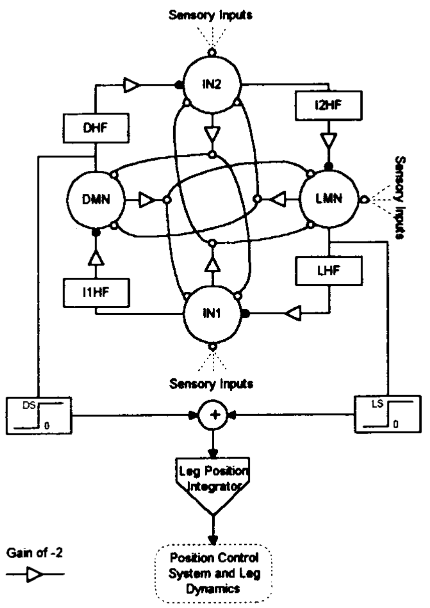

Fig. 3 Inhibition Network for Control of Vertical Leg Motion.

Conditioning methods of adaptation have been shown to be effective in both the low level and high level behaviors of the hexapod robot. Within the low level behavior conditioning is used to modify the duration of the retraction and protraction phases of a leg. [30, 31, 32] Effectively the low level behavior adjusts its internal dynamics thus learning to emulate leg motions dictated by a set of biologically consistent reflexes (compare Figures 4 and 5). The adaptation in the low level behavior is sufficient to allow a static organization for the coordinating behavior.

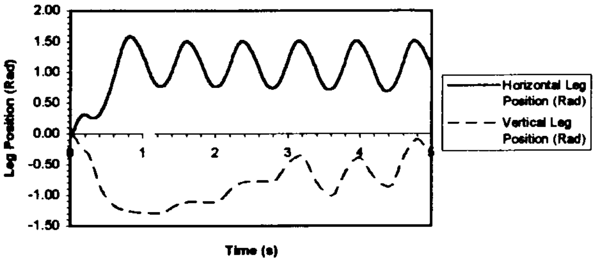

Fig. 4 Uncoordinated Leg Movements prior to Conditioning

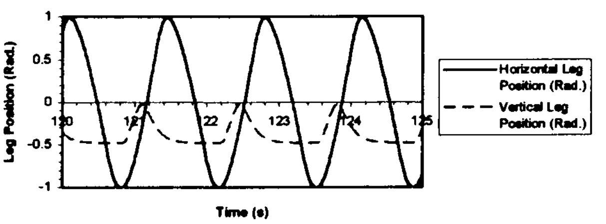

Fig. 5 Fully Coordinated Leg Movements after Conditioning

b. Multi-agent coordination achieved via mathematical control theory

The use of motivations to accomplish distributed multi-agent coordination has been successfully tested in a robot colony executing two conflicting objectives simultaneously. Successful coordination of autonomous robotics agents around set objectives has been demonstrated in a difficult control problem [24, 25]. The control problem involves a colony of robots which reside on a 2-D platform that is free to rotate about a pivot point at its center of mass. The control task is two fold: first, the robots must balance the platform; and second, the robots attempt to reduce the area spanned by the colony.

The specified task is decomposed by hand into the following behaviors. Each robot is assumed to have the necessary low-level behaviors and action primitives required for walking in any direction. Each robot is then given two high-level behaviors, a leader behavior and a follower behavior, which manipulate the low-level walking behaviors to produce the desired action. A leader behavior causes the robot to move so that the center of mass of the robot colony moves in the direction necessary to balance the platform. A follower behavior causes a robot to search out and track the nearest leader robot. Both the leader and follower behaviors have been designed using optimal control theory and can be considered equivalent to fixing motivations, behaviors and interconnections that are required across wide ranges of applications and environments (see below).

Within the defined system the purpose of the motivational system becomes the selection of either the leader or follower behaviors such that both facets of the task are accomplished. Because the two behaviors are mutually exclusive one motivational state, a leader motivation, is sufficient to accomplish the task. The leader motivation level is proportional to a measure of the stability of the platform (i.e. how well it is balanced). Each robot contains and updates via its sensors its own leader motivation. The probability that an individual robot releases its leader behavior is directly proportional to the leader motivational level. Therefore, the more unstable the platform the more likely that a robot will express its leader behavior and conversely for the follower behavior.

Comparing Figures 6 and 7 show that the proposed distributed control is capable of accomplishing the goal of stabilizing the platform even in the presence of severe (90%) atrophy of the robot colony. The bumps in figures 6 and 7 are caused by individuals changing from leaders to followers and thus destabilizing the system.

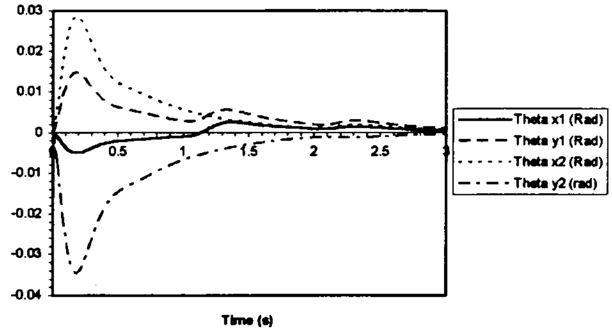

Fig. 6 Typical Platform Angle Trajectories using Optimal Control and Full Colony Strength

Figure 8 illustrates that the control also reduces the area of the colony to its minimum size by enabling the platform to be balanced with only one robot exhibiting the leader behavior. Hence, the use of the motivational level of the proposed architecture appears to be capable of producing self-organizing distributed multi-agent control systems capable of achieving even conflicting goals simultaneously.

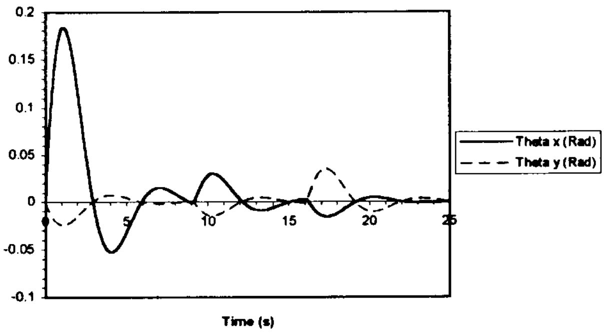

Fig. 7 Platform Angle Trajectories using Optimal Control and 90% Atrophy of Colony

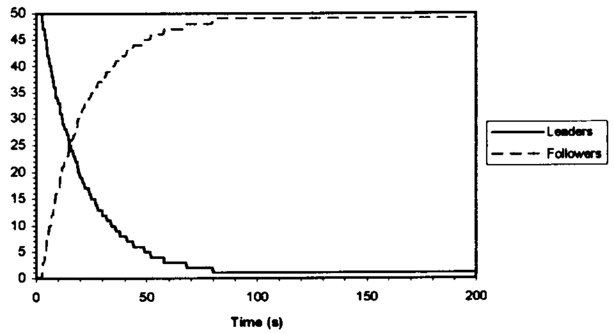

Fig. 8 Typical Numbers of Leaders-vs-Followers using Optimal Control

IV. Advantages of proposed intelligent control architecture

The main advantages of the proposed architecture are:
1. allows self-organization of the autonomous units and learning according to biological evidence;
2. allows multi-agent coordination through distributed control via inhibition and facilitation even when set objectives are conflicting. Conflict-resolution is thus achieved automatically.
3. creates specializations among robotics agents in a colony. Specialization facilitates the execution of complicated tasks.
4. accomplishes multi-sensor data fusion in a straight-forward manner through conditioning. It does not require then the development of separate and complex data fusion algorithms.
5. has built-in failure recovery functions that allow the robotics agents to adapt to unknown operational environments or recover from errors without external intervention. Hence, from this point of view, the proposed control architecture is robust as well.

The difference between the proposed intelligent control design and other intelligent control design approaches lies in the:
• definition of the structural robotics elements;
• use of biologically inspired adaptive neurocontrollers that are used to produce elementary responses (actions) from action primitives (reflexive actions);
• motivation/behavior high level organization;
• use of mathematical distributed control for the coordination of the robotics agents and their actions; and
• built-in ability to fuse multisensory signals without the need for an explicit algorithms to achieve fusion, an advantage of the proposed architecture not present in other intelligent control designs (more details are elaborated in the description of the legged locomotion paradigm).

V. Issues related to the proposed architecture

The nervous system approach to behaviors and the motivational approach to distributed multi-agent coordination have been shown to be effective. In this proposal we intend to merge more completely the nervous system and motivational system approaches. The largest part of the proposal involves the acquisition and refinement of new behaviors via the use of GA and NN techniques. The resulting compound architecture will be tested with respect to its ability to generate effective emergent behaviors and to coordinate multiple robotics agents in the accomplishment of set objectives.

The issues that need to be addressed in the proposal architecture include:

- Self-organization
- Distributed Control
- Stability
- Efficiency
- Fault tolerance
- Error recovery - Malfunctioning

addressing these issues requires the:
• *Investigation* of acquisition of new behaviors and new motivations in the proposed control architecture
• *Tuning* of motivations and behaviors to execute a prescribed task. Investigate emergent behavior and the segregation into specialist robots which due to their proficiency in a give task become predisposed to executing that task as opposed to others with which it has less experience.
• *Derivation* of existence conditions that will guarantee that given a (manufacturing or otherwise) task and a set of robotics agents supplied by the described nervous system, the task can be decomposed into motivations and behaviors that will allow the robotics colony to execute it.

The conditions must be readily obtainable without requiring that the control problem be solved first. This is functionally equivalent to the controllability and observability issues of modern control theory. And shown in the robot colony coordination paradigm via optimal control, perhaps some of the same reasoning that led to the modern controllability and observability theorems can be used to develop these conditions for the case of distributed control.

• *Derivation* of reachability conditions that will determine, given a task and a set of robotics agents that are capable of carrying out cooperatively once properly coordinated, whether the proposed controller-coordinator is capable of inducing the necessary coordination in the colony that will allow the required cooperation among agents in order to execute the task successfully.

• *Development* of a *behavioral algebra* that will allow the description and the analysis of the proposed intelligent control architecture in a rigorous and precise mathematical fashion. The field of complexity theory and chaos along with cellular automata and decision theory (Bayesian and non-Bayesian) are expected to have a significant role in the development of this algebra.

• *Demonstration* of the validity of the proposed intelligent control architecture experimentally through an experimental application/demonstration that involves a number of mobile robotics manipulators and walking robots attempting to perform a coordinated task while stabilizing themselves on a pivoting platform in space. The distinction between mobile and walking robots is done purposely, to indicate possibly different locomotion modes in the colony.

VI. Summary and Conclusion

A working model for a biology-inspired control architecture has been developed. Biological / Psychological information [12, 18, 19, 26, 27]; Neural Networks and associated learning techniques such as *Heuristic Adaptive Critic* [33, 34, 35]; Genetic Algorithms and other evolutionary strategies [36, 37, 38, 39, 40]; and methods derived from mathematical control theory [25] have been used to develop the architecture

Biological and psychological information supplies a solid basis for our belief in the proposed approach. Analysis of biological and psychological data provides a means of significantly reducing the space that must be searched for the final solution. The reduction in search space is accomplished by fixing motivations, behaviors and interconnections that are required across wide ranges of applications and environments. This technique was shown to be highly effective in increasing the learning rate in the hexapod nervous system architecture discussed above [22, 23]. It is the structure dictated by this biological and psychological information that dictates the base configuration from which autonomous agents can be develop.

Biological and psychological information is also suitable for providing guidance in developing methods of acquisition for new behavior and motivational connections within the architecture. Populations of differing connections between sensory input, motivations, behaviors and action primitives can be generated using genetic algorithms. Effectively the genetic algorithm performs the creation of a neural network. It is then the ability of the neural network to adapt to its environment and to accomplish the prescribed tasks which determines the genetic fitness of the individual. [50, 51]. The adaptation of the neural network will be implemented via reinforcement and conditioned learning techniques which may either strengthen or weaken the connections originally specified by the GA.

Because the neural network generated by the genetic algorithm is subject to learning over time its overall fitness and thus the fitness of the individual may not be determined in a conventional manner using simple fitness functions. Rather, the function used to rate the genetic fitness of each individual must be a time discounted function of the degree to which that individuals motivations are satisfied [34, 35, 36]. This method of determining fitness contains an interesting effect related to multi-agent cooperation. Because individual motivations are tied to sensory information, an individual may perform an action that may not directly lead to the satisfaction of the individual motivation alone, but may satisfy the of combined individuals motivation. Thus the genetic fitness of both individuals is perceived as greater than it would have been in the presence of only one of the individuals, thereby inherently promoting multi-agent cooperation.

The development of a mathematical theory for the analysis and prediction of the behavior of the proposed intelligent control architecture, or some constrained form of it under assumptions, is envisioned to emerge from mathematical concepts related to complexity theory and chaos, decision theory (Bayesian and Evidential Theory [43]) and finite state machine approximations (Cellular Automata).

Complexity theory and chaos and cellular automata (CA) can provide strong guidance in the development of mathematical formailzations of the proposed architecture and its operation. A particularly interesting direction being explored is the description of the system in terms of a CA where our action primitives describe the actions the automaton may make and the specified tasks to be accomplished are the gross behaviors of the automaton. The task then becomes determining the set of rules for the automaton using the action primitives that will provide the desired gross behavior. In the light of this description it is hoped that complexity theory, chaos, and cellular automata research will first lead to the discovery of existence conditions for the automaton's rules [52, 53]. These conditions are thought to be similar to controllability and observabiliy of mathematical control systems theory.

BIBLIOGRAPHY

[1] Simon, D., Espiau, B., Castillo, E., Kapellos, K., "Computer-Aided Design of a Generic Robot Controller Handling Reactivity and Real-Time Control Issues", IEEE Transactions on Control Systems Technology, V. 1 No. 4, pp. 213-229, 1993.

[2] Anderson, T., Donath, M., "Animal Behavior as a Paradigm for Developing Robot Autonomy", Robotics and Autonomous Systems, V. 6, pp. 145-168, 1990.

[3] Verschure, P., Krose, B., Pfeifer, R., "Distributed Adaptive Control: The Self-Organization of Structured Behavior", Robotics and Autonomous Systems, V. 9, pp. 181-196, 1992.

[4] Dorigo, M., Schnepf, U., "Genetics-Based Machine Learning and Behavior-Based Robotics: A New Synthesis.", IEEE Transactions on Systems, Man, and Cybernetics, V. 23, No. 1, 1993.

[5] CSS Task Force Technical Report on Intelligent Control, IEEE Control Systems Society, Final Report, December 1993, preprint, Jan. 1994, email list AICS discussion group, to appear in IEEE Control Magazine, June 1994.

[5a] P. Antsaklis, Intelligent Control, Technical Report of Task Force on Intellignet Control, IEEE Control Systems Society, December 1993.

[5b] J. S. Albus, "On Intelligence and its Dimensions," in Intelligent Control, Technical Report of Task Force on Intelligent Control, IEEE Control Systems Society, December 1993.

[6] Brooks, Rodney, "Elephants Don't Play Chess", Robotics and Autonomous Systems, V6, pp. 3-15, 1990.

[12] Altman, J., Kien, J., "New Models for Motor Control", Neural Computation, V. 1, pp. 173-183, 1989.

[13] Beer, R., Hillel, C., Sterling, L., "A Biological Perspective on Autonomous Agent Design", Robotics and Autonomous Systems, V. 6, pp. 169-186, 1990.

[14] Ayers, J., Crisman, J., "Biologically-based Control of Omnidirectional Leg Coordination", Proceedings of the 1992 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 574-581, 1992.

[15] Wilson, E., "The Insect Societies, (Belknap Press of Harbard University Press, Cambridge, MA), 1971.

[16] Seeley, T., "The Honey Bee Colony as a Superorganism", American Scientist, V. 77, 1989, pp. 546-553.

[17] Franks, N., "Army Ants: A Collective Intellignece", American Scientist, V. 77, 1989, pp. 139-145.

[18] Kandel, E., Schwartz, J., Jessell, T., "Principles of Neural Science, Third Edition", (Appelton & Lange, Norwalk, Connecticut), 1991

[19] "Feedback and Motor Control in Invertibrates and Vertibrates", Eds. Barnes, W., Gladden, M., (Croom Helm, London), 1985.

[20] *From Animals to Animals*, Proceedings of the First International COnference on Simulation of Adaptive Behavior, Editors J.-A. Meyer and S. W. Wilson, MIT Press, Boston, 1991.

[21] Brooks, R., "A Robot that Walks; Emergent Behaviors from a Carefully Evolved Network", Neural Computation, V. 1, 1989, pp. 253-262.

[22] G. Braught and S. C. A. Thomopoulos, "A Neural Architecture for learning Hexapod Locomotion based upon Insect Neurophysiology," IMACS '94, April 12-14, 1994, Lille, France.

[23] G. Braught and S. C. A. Thomopoulos, "A Neural Architecture for Learning Horizontal and Vertical Leg Coordination based upon Insect Neurophysiology," CDC '94, submitted.

[24] S. C. A. Thomopoulos and G. Braught, "Biology Inspired Control Architecture for Multipurpose Robotics," Symposium on Intelligent Control, submitted.

[25] G. Braught and S. C. A. Thomopoulos, "Application of Optimal Control Theory to the Distributed Control of an Artificial SUperorganism," Technical Report, Decisiona nd Control Systems Lab., Dept. of Electr. Engr., Penn State Univ., April 1994.

[26] "Motivational and Control Systems Analysis", Ed. McFarland, D., (Academic Press, London, 1974).

[27] "Neural Mechanism of Goal-Directed Behavior and Learning", Eds. Thompson, R., Hicks, L., Shvyrkov, V. (Academic Press, NY, 1980).

[28] S. C. A. Thomopoulos, "Sensor Integration and Data Fusion," Invited paper in special issue on Sensor Integration and Data Fusion for Robotic Systems, Journal of Robotic Systems, Vol. 7, No. 3, 1990, pp. 337-372.

[29] S. C. A. Thomopoulos, "Decision and Evidence Fusion in Sensor Integration," Advances in Control and Dynamic Systems, Ed. C. T. Leondes, Vol. 49, Part 5 of 5, pp. 339-412, Academic Press, Nov. 1991.

[30] Muller-Wilm, U., "A Neuron-like Network with the Ability to Learn Coordinated Movement Patterns", Biological Cybernetics, V. 68, 1993, pp. 519-526.

[31] Taga, G., Yamaguchi, Y., Shimizu, H., "Self-Organized Control of Bipedal Locomotion by Neural Oscillators in Unpredicable Environment", Biological Cypernetics, V. 65, 1991, pp. 147-159.

[32] Berns, K., Dillmann, R., Zachmann, U., "Reinforcement-Learning for the Control of an Autonomous Mobile Robot", Proceedings of the 1992 IEEE/RSJ International Conference on Intelligent Robots and Systems, Raleigh, NC, July 7-10, 1992.

[33] Barto, A. G., Sutton, R. S. & Watkins, C. J. C. H., "Learning and Sequential Decision Making," in *Learning and Computational Neuroscience,* M. Gabriel and J. W. Moore (Eds), MIT Press, 1991.

[34] Sutton, R. S., "Reinforcement Learning Architectures for Animats, Proc. of 1st Intl. Conf. on Simulation of Adaptive Behavior: *From Animals to Animats*, J.-A. Meyer and S. W. Wilson (Eds.), MIT Press, 1991, pp. 288-296.

[35] Jin, L.J., "Self-Improving Reactive Agents: Case Studies of Reinforcement Learning Frameworks," Proc. of 1st Intl. Conf. on Simulation of Adaptive Behavior:

From Animals to Animats, J.-A. Meyer and S. W. Wilson (Eds.), MIT Press, 1991, pp. 297-305.
[36] Todd, P. M. and Miller G. F., "Exploring Adaptive Agency II: Simulating the Evolutioin of Associative Learning," Proc. of 1st Intl. Conf. on Simulation of Adaptive Behavior: *From Animals to Animats*, J.-A. Meyer and S. W. Wilson (Eds.), MIT Press, 1991, pp. 306-315.
[37] Koza, J. R., "Evolution and Co-Evolution of Computer Programs to Control Independently-Acting Agents," Proc. of 1st Intl. Conf. on Simulation of Adaptive Behavior: *From Animals to Animats*, J.-A. Meyer and S. W. Wilson (Eds.), MIT Press, 1991, pp. 366-375.
[38] S. C. A. Thomopoulos, "Sensor Integration and Data Fusion," Invited paper in special issue on Sensor Integration and Data Fusion for Robotic Systems, Journal of Robotic Systems, Vol. 7, No. 3, 1990, pp. 337-372.
[39] S. C. A. Thomopoulos, D. K. Bougoulias and C.-D. Wann, "**Dignet:** An Unsupervised Clustering Algorithm for Centralized and Distributed Pattern Recognition, Classification, and Hypothesis Testing," IEEE Transactions on Aerospace and Electronic Systems, AES-30, No. 4, Oct. 1994, in press.
[40] I. N. M. Papadakis and S. C. A. Thomopoulos, "Binary Hypothesis Testing with Structured Adaptive Networks," IEEE Transactions on Automatic Control, to appear in Nov. 1994 issue.
[41] Patrikar, A., Provence, J., "Control of Dynamic Systems Using Fuzzy Logic and Neural Networks," International Journal of Intelligent Systems, Vol. 8, pp. 727-748, 1993.
[42] Ishibuchi, H., Fujioka, R., Tanaka, H., "Neural Networks that Learn from Fuzzy If-Then Rules," IEEE Transactions on Fuzzy Systems, Vol. 1, No. 2, pp. 85 - 97.
[43] S. C. A. Thomopoulos, "Sensor Integration and Data Fusion," SPIE Proceedings on Advances in Intelligent Robotics Systems, Sensor Fusion II: Human and Machine Strategies, Vol. 1198, pp. 178-191.
[44] S. C. A. Thomopoulos and I. N. M. Papadakis, "On the Existence of Solutions in Adaptive Control," Conference on Decision and Control, CDC '90, Dec. 3-5, 1990, Honolulu, Hawaii.
[45] Sun, J., "A Modified Model Reference Adaptive Control Scheme for Improved Performance," Proc. Of the American Control COnference, Vol. 1, pp 150-155, Boston, MA, June 1991.
[46] Datta, A., and Ioannou, P. A., "Performance Improvemetn Versus Robust Stability in Model Reference Adaptive Control," Proc. of the COnference on Decision and Control, Vol. 1, pp. 748753, Brighton, England, Dec. 1992.
[47] I. N. M. Papadakis and S. C. A. Thomopoulos, "Improved Performance MRAC of Linear and Nonlinear Systems," American Control Conference, ACC '93, San Fransisco, June 2-4, 1993.
[48] M. Papadakis and S. C. A. Thomopoulos, "Improved Performance Model Reference Adaptive Control of Linear and Nonlinear Systems," International Journal of Adaptive Control and Signal Processing, J. Wiley Publisher, 1994, in press.
[49] M. Papadakis and S. C. A. Thomopoulos, "Improved Performance Model Reference Adaptive Control with Parameter Mismatch Compensation," IEEE Transactions on Automatic Control,, Nov. 1994.
[50] Harvey, I., "The Artificial Evolution of Behavior," Proc. of 1st Intl. Conf. on Simulation of Adaptive Behavior: From Animals to Animats, J. A. Meyer and S. W. Wilson (Eds.), MIT Press, 1991, pp. 400-408.
[51] Paredis, J., "The Evolution of Behavior: Some Experiments," Proc. of 1st Intl. Conf. on Simulation of Adaptive Behavior: From Animals to Animats, J. A. Meyer and S. W. Wilson (Eds.), MIT Press, 1991, pp. 419-425.
[52] Kiss, G., "Autonomous Agents, AI and Chaos Theory," Proc. of 1st Intl. Conf. on Simulation of Adaptive Behavior: From Animals to Animats, J. A. Meyer and S. W. Wilson (Eds.), MIT Press, 1991, pp. 518-524.
[53] Jefferson, D., Collins., R. et. al. "The Genesys System: Evolution as a Theme in Artificial Life," Proceeding of Second Conference on Artificial Life, Langton, G. Farmer, D. (Eds.), Addison-Wesley, 1990.
[54] Steels, L. "The Artifical Life Roots of Artifical Intelligence," Artifical Life, Vol. 1, No. 1/2, 1994, pp. 75-119.
[55] U. Bassler, "The walking- (and searching-) Pattern Generator of Stick Insects, a Modular System Composed of Reflex Chains and Endogenous Oscillators", Biological Cybernetics, Vol. 64, 1991, pp. 429-436.
[56] A. Selverston, "Are Central Pattern Generators Understandable?," The Behavioral and Brain Sciences, Vol. 3, 1980, pp. 535-571.
[57] U. Bassler, "On the Definition of Central Pattern Generator and its Sensory Control", Biological Cybernetics, Vol. 54, 1986, pp. 65-69.
[58] F. Delecomyn, "Neural Basis of Rythmic Behavior in Animals," Science, Vol. 210, Oct. 31, 1980, pp. 492-498.
[59] Cruse, H. "A Quantitative Model of Walking Incorporating Central and Peripheral Influences: II. The Connections Between the Different Legs", Biological Cybernetics, Vol. 37, 1980, pp. 137-144.
[60] Dean, J. "A Model of Leg Coordination in the Stick Insect, Carausis Morosus: II. Description of the Kinematic Model and Simulation of Normal Step Patterns", Biological Cybernetics, Vol. 64, 1991, pp. 403-411.