

## AN ABSTRACT OF THE THESIS OF

Tyson Harold Harty for the degree of Master of Science in Human Performance presented on December 1, 2000. Title: The Application of Human Motor Control Principles to a Collective Robotic Arm.

Abstract approved: *Redacted for Privacy*

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Gene G. Korienek

Current robots are no match for biological organisms when adapting to real-world, dynamic environments. Collective control strategies, such as those used by synergistic biological systems composed of large numbers of identical parts like the human nervous system, provide a novel and alternative approach for the design of fault-tolerant, adaptable robotic systems that have traditionally relied on centralized control.

In this research, a robotic arm composed of multiple identical segments in a collective computational architecture was tested for its ability to produce adaptive pointing and reaching behavior. The movement rules for these robotic arm segments were based on the concepts of the “reflex arc” and the “action system” in the human nervous system.

Robotic arms of three to seven encapsulated segments were tested. These arms received no central directions and used no direct informational exchange. The arms were sensor-driven at their distal, or leading, outstretched ends to maximize pointing accuracy on a two-dimensional target plane. The remaining non-distal segments in the arms were moved in a sequential order using sensed locally-available movement information about neighboring segments.

Successful pointing and reaching behavior was observed in situations with and without movement obstacles. This led to the conclusion that because such behavior was not specified within each segment, the overall arm behavior emerged due to the interaction and coordination of all segments, rather than due to any single segment, centrally-controlled influence, or explicit inter-segmental method of communication.

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The Application of Human Motor Control Principles to a Collective Robotic Arm

by

Tyson Harold Harty

A THESIS

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Dean of Graduate School

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Tyson Harold Harty, Author

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And, of course, an extensive exercise in gratuity such as this would be scarcely complete without a nod to the following entities and circumstances for each contributing vital pieces at sometime or another to the thinking that culminated, however abstractly and verbosely, into this thesis and the puzzling lifeform behind it: Jane, Harold, and Lance Harty; the 1990-91 National High School Policy Debate Topic of "Space Exploration"; Kay Holekamp, "strong inference", Paula, and various members of the *Crocota crocuta* species; "Pelvis IV" by Georgia O'Keeffe; Doug O'Handley and the 1998 NASA Ames Astrobiology Academy; Karen, Russ, Krissy, Tosha, and Tia; my Georgia muses, Kelly, Mary Ellen, and Jehan; and the mountains and ocean of Oregon.

## TABLE OF CONTENTS

	<u>Page</u>
1. INTRODUCTION .....	1
2. METHODS .....	6
2.1 Apparatus .....	6
2.1.1 Puppet Robotic Arm .....	6
2.1.2 Target Grid.....	9
2.1.3 Movement Obstacle .....	10
2.2 Experimental Design.....	11
2.3 Procedures.....	12
3. RESULTS .....	15
3.1 Pointing.....	15
3.2 Number of Moves to Completion .....	15
3.3 Reaching .....	16
3.4 Number of Arm Segments .....	17
3.5 Obstacle.....	17
3.6 Control Rules .....	17
3.7 Summary of Results.....	19
4. DISCUSSION .....	21
4.1 Pointing.....	21
4.2 Number of Moves to Completion .....	23

## TABLE OF CONTENTS (Continued)

	<u>Page</u>
4.3 Reaching .....	23
4.4 Number of Arm Segments .....	23
4.5 Obstacle.....	24
4.6 Control Rules .....	25
5. CONCLUSIONS.....	27
REFERENCES .....	32
APPENDICES .....	34

## LIST OF FIGURES

<u>Figure</u>		<u>Page</u>
1	The conceptual model of Reed's (1982) action system in the nervous system.....	3
2	The conceptual model of Sherrington's (1910) reflex arc in the nervous system.....	3
3	Single segment of puppet robotic arm. ....	7
4	Photo of robotic arm attached to mounting plate in initial posture.....	7
5	Set of plastic collars on mating ends of puppet robotic segments as vernier locking mechanisms with 1° precision.....	8
6	Plastic collars shown locked in a specific angular position.....	8
7	The 50-cm radius circular target grid used to measure pointing accuracy for the robotic arm.....	10
8	Diagram of the experimental procedures used in this research .....	12
9	Photo detailing the placement of the obstacle, as shown aligned (by the dotted line) with the mounting plate and target grid.....	14
10	Example plot of pointing positions on target grid for a 3-segment robotic arm, showing searching behavior before focusing the distal segment on the target grid center. ....	21
11	Example plot of <i>Absolute Pointing Errors</i> after each segment move for a 3-segment robotic arm, demonstrating the successful coordinated point-to-target behavior with a collective computational architecture .....	22
12	Plot of final <i>Reaching Error Ratio</i> , demonstrating reaching-to-target behavior for a robotic arm with 4 segments, using a “Facilitative Chaining” strategy with no obstacle present .....	24



## LIST OF TABLES

<u>Table</u>		<u>Page</u>
1	Control rules for the “withdrawal reflex” strategy in the experiment which produced an <i>Absolute Pointing Error</i> of zero.....	16
2	Control rules for the “withdrawal reflex” strategy which produced a mean final <i>Reaching Error Ratio</i> of 0.48.....	18
3	Summary matrix of the results for the robotic arm experiments .....	19
4	Delimiting conditions for pointing behavior in a collective robotic arm .....	20
5	Delimiting conditions for reaching behavior in a collective robotic arm .....	20

## LIST OF APPENDICES

	<u>Page</u>
Appendix A: Literature Review: A Convergence of Robotic and Human Motor Control Approaches .....	35
1. INTRODUCTION .....	35
2. COMMON MODELING SYNTAX.....	37
3. HUMAN MOTOR CONTROL APPROACHES .....	39
3.1 Physiological Approach.....	39
3.2 Psychological Approach .....	41
3.3 Cybernetics Approach.....	42
3.4 Ecological Approach.....	44
3.5 Summary of Motor Control Approaches .....	47
4. ROBOTIC CONTROL PARADIGMS.....	49
4.1 Servomechanism Control.....	49
4.2 Central Control.....	50
4.3 Distributed Control .....	52
4.4 Collective Control.....	53
4.5 Summary of Robotic Control Paradigms.....	55
5. THE CONVERGENCE .....	57
6. IMPLICATIONS .....	60
REFERENCES .....	63
Appendix B: Complete List of Control Rules .....	67
Appendix C: Curriculum Vitae.....	78

## LIST OF APPENDIX FIGURES

<u>Figure</u>	<u>Page</u>
A-1 Definition of symbols used in the Data Flow Diagram modeling approach.....	37
A-2 Definition of symbols in the Structure Chart modeling approach. ....	38
A-3 A data flow diagram of Sherrington's (1910) reflex arc in the nervous system.....	39
A-4 A data flow model of the motor program and information processing approach to motor control. ....	41
A-5 A structure chart of the central approach of information processing.....	42
A-6 A structure chart of the hierarchical approach to human motor control (CTRL "#" = Controller "level in hierarchy"). ....	42
A-7 A data flow model of hierarchical cybernetics approach to human motor control.....	43
A-8 A data flow analysis of Reed's (1982) action system in the nervous system.....	45
A-9 A structure chart of the ecological approach to motor control (AS = "Action System").....	46
A-10 A data flow analysis of simple feedback .....	49
A-11 A structure chart of the central approach to robotic control .....	50
A-12 A data flow model of the central paradigm of robotic control .....	51
A-13 A structure chart of the distributed approach to robotic control (CTRL = Controller).....	52
A-14 A data flow model of the subsumption architecture, a decentralized approach to robotic control .....	53
A-15 A structure chart of the collective approach to robotic control .....	54

## LIST OF APPENDIX FIGURES (Continued)

<u>Figure</u>	<u>Page</u>
A-16 A data flow model of the collective approach to robotic control.....	55
B-1 Diagram for clarifying details of control rules in Tables B-6 to B-14.....	75

## LIST OF APPENDIX TABLES

<u>Table</u>	<u>Page</u>
A-1 The mapping of the convergence between human motor control approaches and robotic control paradigms.....	57
B-1 General distal segment control rules for all experiments .....	68
B-2 Distal segment control rules for “Facilitative Chaining”.....	69
B-3 Non-distal segment control rules for “Facilitative Chaining”.....	69
B-4 Distal segment control rules for “Inhibitive Chaining” .....	70
B-5 Non-distal segment control rules for “Inhibitive Chaining”.....	70
B-6 Distal segment control rules for “Withdrawal Reflex #1” .....	71
B-7 Distal segment control rules for “Withdrawal Reflex #2” .....	71
B-8 Non-distal segment control rules for “Withdrawal Reflex #2”.....	71
B-9 Distal segment control rules for “Withdrawal Reflex #3” .....	72
B-10 Non-distal segment control rules for “Withdrawal Reflex #3”.....	72
B-11 Distal Segment Control Rules for “Withdrawal Reflex #4a” .....	72
B-12 Non-Distal Segment Control Rules for “Withdrawal Reflex #4a” .....	73
B-13 Distal Segment Control Rules for “Withdrawal Reflex #4b” .....	73
B-14 Non-Distal Segment Control Rules for “Withdrawal Reflex #4b” .....	74
B-15 Control Rules for “Withdrawal Reflex 5” .....	74
B-16 Control Rules for “Withdrawal Reflex 6” .....	75

**LIST OF APPENDIX TABLES (Continued)**

<u>Table</u>	<u>Page</u>
B-17 A list of all experiments conducted in this research based on the combinations of the variables detailed in the text. ....	76

## DEDICATION

To  
the most amazing  
*Felis domesticus*  
I ever scratched  
behind the  
ears—

Tosha

## PREFACE

Although robotic and biological movement control theories have addressed similar issues and adopted parallel paradigms over the years, a discussion between the two disciplines has been lacking. My thesis research aimed to provide an experimental convergence for these two related disciplines by implementing a novel platform for testing new robotic control ideas with models from human motor control theory.

However, this research only scratched the surface of the powerful potential of using human motor control principles to design and control robots, and indeed, has opened up an extensive pathway for further exploration which I intend to pursue. To approach the desired qualities of biological movement in models of collective robots, this future research must implement the most current theories and concepts of human motor control that attempt to account for its complex and dynamic nature, some of which are highlighted in the literature review section of this thesis (Appendix A).

This thesis research with a puppet robotic arm will eventually lead to future studies with a real electromechanical arm that will hopefully realize the autonomous and adaptable attributes we associate with our own human arms. I also anticipate that the results gained from this line of research will widen the breadth of application for collective control principles to systems traditionally thought to require centralized control.

Tyson Harold Harty  
December 1, 2000  
Corvallis, Oregon USA  
Earth



# **The Application of Human Motor Control Principles to a Collective Robotic Arm**

## **1. INTRODUCTION**

Biological organisms are adaptive. Indeed, this distinguishing attribute sets biological organisms apart from existing artificial robotic organisms--the ability of biologicals to control and adapt their movements in ever-changing and unpredictable environments with high degrees of flexibility, autonomy, and complexity (Holland, 1992; McFarland, 1991). Even the most sophisticated robots used currently for planetary exploration have low adaptability in unpredictable environments (e.g. the surface of Mars) and are not capable of fully autonomous control (Bresina, Dorais, Golden, Smith, & Washington, 1998).

To explore this distinction, I investigated one of the underlying reasons for the successful adaptability of biological systems--their use of simple underlying control principles in a collective computational architecture, that is, one without centralized control. Biological organizations such as nervous systems and groups of interacting organisms (e.g., social insects, bird flocks, fish schools, etc.) use collective control strategies to produce their adaptive behaviors (Alt & Hoffmann, 1989; Holland, 1998; Kube & Zhang, 1993a, 1993b).

Such ubiquitous use of collective control in nature raises the question among roboticists and artificial life scientists: "How can the individual components of a complex system collectively generate group behaviors whose capabilities are greater than the sum of those individuals?" One answer to this question lies in the observation that biological systems exhibit "emergent behavior", because such systems are built from many interacting parts which together form group behaviors that can not be specified prior to their occurrence (Kelly, 1994). For instance in the human nervous system, emergence is observed in the phenomenon of "motor variability" or "peripheral indeterminacy", wherein the neural pathways by which the same task is performed are always different,

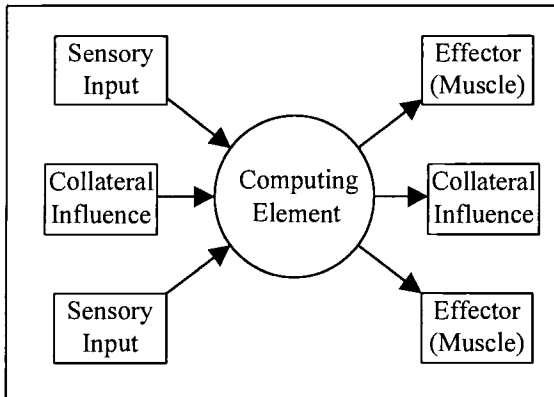
even though the outcomes of the particular task are almost exactly the same (Bernstein, 1967).

To investigate the possibility of biological-like emergence in a mechanical system, I implemented a collective control architecture in a robotic arm. As a control model for this robotic arm, I looked to the way the human nervous system controls the human arm in its amazing ability to produce precise yet adaptable movement solutions to pointing and reaching tasks. Unlike the human arm however, contemporary robotic and prosthetic counterparts come nowhere near exhibiting such human-like adaptive behavior in non-specified and unpredictable environments.

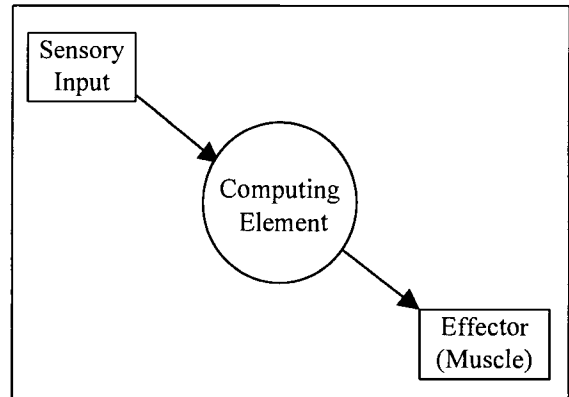
One current human motor control theory suggests that nervous systems use collections of simple neurophysiological units that synergistically interconnect to produce the extraordinarily diverse array of possible movements of everyday fine motor activities (Reed, 1996). Reed (1982) theorized a control architecture for the nervous system that is fully distributed across a collection of self-organizing, highly dissipative, elements called “action systems”. Individually, an “action system” is a dynamically allocated organization of 100 to 10,000 neurons that forms continuously in response to changes in neural activity and dissipates when its job is completed. In effect, an action system is a local computational unit of the nervous system, complete with sensory inputs, action outputs, and collateral influences to and from other action systems (Figure 1).

If Reed’s action system model sounds like a distributed control architecture with a local scope of control, it indeed is, implemented in the nervous system instead of computer hardware. With this similarity in mind, the action system concept provided an ideal biological analog from which to model a collective architecture to control the movement of a modular robotic arm. That is, each segment in the arm was designed as an action system containing its own independent perception, processing, and action components.

Furthermore, each robotic arm segment was also modeled after the reflex arc in the nervous system. Similar in concept to the action system, the reflex arc is a physiologically simpler three-to-ten neuron linkage of an afferent sensory neuron, a computational element, and an efferent neuron to effect muscle movement (Figure 2). Sherrington (1910) discovered the reflex arc as the most fundamental unit of control in



**Figure 1:** The conceptual model of Reed's (1982) action system in the nervous system.



**Figure 2:** The conceptual model of Sherrington's (1910) reflex arc in the nervous system.

the nervous system along with several basic principles about its control: facilitation, inhibition, and reflex chaining. In experiments with arm motion, he discovered that facilitation occurs when the movements of muscle groups complement each other, for example, when wrist flexion facilitates elbow extension during reaching for an object with the hand. If the biceps muscle (an elbow flexor) was shortening, then the triceps muscle (an elbow extensor) was lengthening, a phenomenon Sherrington termed reciprocal inhibition. In addition, he found that the nervous system coordinates movement via the interactions of multiple reflex arcs in sequential relationships between muscle groups called “reflex chaining”. A facilitative reflex chain, for example, can be observed as a particular activation sequence of muscle groups as during the so-called “righting reflex” when a mammal (e.g., dog, horse) rises from a lying posture to an upright posture (Roberts, 1967).

In controlling the robotic arm used in this research, the concept of reflex chaining was used as an overarching principle through which multiple arm segment movements could be coordinated without direct control. This allowed for overall arm behavior, if any, to emerge from the cooperation of individual segment movements. In addition, I used the specific strategies of “facilitative chaining” to guide a particular arm segment to maintain the movement vector of its adjacent segment, and “inhibitive chaining” to instruct the segment to oppose that vector. In addition, I used a biological analog of the nociceptor and crossed extensor reflexes (i.e. the reflexes which cause one to pull the arm

away if a hot object is touched) as a “withdrawal reflex” strategy (Latash, 1998). This “withdrawal reflex” strategy was triggered when a direction-switching movement of an adjacent arm segment was sensed and used by a given segment to initiate a “rule switching” behavior.

Since the control of the robotic arm involved a decision making process that resulted in a movement outcome, it was convenient to operationalize Sherrington’s (1947) reflex arc principles into control rules used by each segment to individually make movement decisions. The control rules were structured as conventional production rules (Schmuller, 1992), which incorporated transformations of the rotational magnitudes and directions that each segment sensed from its distally-adjacent segment in the arm by following the general form:

IF: Distally-adjacent segment direction is *[CW or CCW]* and rotation =  $[x^\circ]$ ,  
 THEN: Rotate *[transformed  $x^\circ$ ]* degrees in a *[transformed]* direction

(Note: CW = Clockwise and CCW = Counterclockwise)

For instance, Sherrington’s (1947) concept of “facilitative chaining” was structured in production rule format as:

IF: Distally-adjacent segment moves  $\theta^\circ$  CW (or CCW).  
 THEN: Rotate  $(\theta^\circ * 0.667)$  in the *same* direction,

Likewise, Sherrington’s (1947) concept of “inhibitive chaining” was structured in production rule format as:

IF: Distally-adjacent segment moves  $\theta^\circ$  CW (or CCW).  
 THEN: Rotate  $(\theta^\circ * 0.667)$  in the *opposite* direction.

As the above control rule formats illustrate, I also coupled Sherrington’s reflex chaining concept with a two-thirds (0.667) relationship to provide a coordination among the segments in the collective robotic arm. The resulting attenuation of segment

movement in the chain of arm segments due to this relationship effectively balanced the effect of a segment's position in the arm. This two-thirds relationship has been observed for relative angular velocities between joints in simple human movements and theorized to be used more generally in human motor neural circuitry (De' Sperati & Stucchi, 1995).

Thus, a combination of Sherrington's reflex arc principles with Reed's action system model provided the design for the fundamental unit of control for each segment in the collective robotic arm used in this research. Fundamentally, each segment was a model of Sherrington's reflex arc, complete with sensory, computational, and effector units. Then as individual segments were linked into an arm, the complexity of the arm behavior increased, and Reed's action system model was more suited to the array of sensory inputs, collateral influences, and actions scoped within each segment. As a whole then, the multi-segmented robotic arm was a loosely coupled collection of action systems, in which deliberate isolation of the segments was done by using local scoping of sensing and action. Like the nervous system upon which it was based, this collective arrangement of robotic segments in an arm was designed to promote the *emergence* of adaptive behavior.

In summary, current robotic arms cannot perform successfully in unpredictable real-world situations where adaptability is key. I aimed to remedy this deficiency by designing a robotic arm with segments organized in a collective computational control architecture. Specifically, in this design a collective, multi-segmented robotic arm, the human motor control concepts of the action system (Reed, 1982) and the reflex arc (Sherrington, 1910, 1947) corresponded to each robotic segment, and the linkage of action systems (Reed, 1982) and the resulting reflex chain (Sherrington, 1910, 1947) corresponded to the overall multi-segmented robotic arm. As such, the *objectives* of this research were (1) to determine the usefulness of mapping a human motor control model into a robotic system, (2) to use a robotic system to demonstrate the usefulness of a particular model of human motor control, and (3) to evaluate the aspects of control of a collective robotic arm in the emergence of adaptive pointing and reaching behavior, independent of environmental obstacles.

## **2. METHODS**

This methods section details the apparatus, experimental design, and procedures that were used in this research to demonstrate the emergence of pointing and reaching behavior in a collective robotic arm.

### **2.1 Apparatus**

To decrease apparatus complexity, I chose to use a “puppet” robotic arm. This puppet was a linkage of individual identical segments with the ability to mechanically connect interchangeably with one another. The puppet segments did not contain real actuators, sensors, central processing units (CPUs), or power sources, yet were nonetheless a representative model of an electromechanical version of a robotic arm which would contain these components.

This puppet arm was attached to one side of 3-meter cubic room such that it was able to fully move in the 3D-space of the cube. On the wall opposite the arm, a target consisting of a 2D Cartesian grid was placed. Obstacles were placed with this data collection space to test for adaptability in pointing and reaching in the robotic arm. Together the robotic arm, target grid, and obstacles in a single room comprised the data collection space for all experiments.

#### **2.1.1 Puppet Robotic Arm**

All puppet robotic arm segments were identical molded hollow plastic modular units in the shape of a 90° arc of a torus with an outer diameter of 3.5-cm and a radius of 10-cm (Figure 3). The ends of each unit had corresponding male and female plug-and-socket fittings for attachment to other segments, allowing a segment of the robotic arm to freely rotate around the axes of the two other segments to which it could be connected. This arrangement provided two axes of rotation for each segment, one that could be

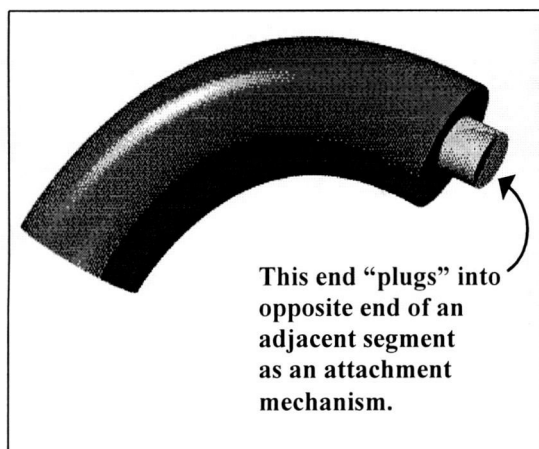


Figure 3: Single segment of puppet robotic arm.

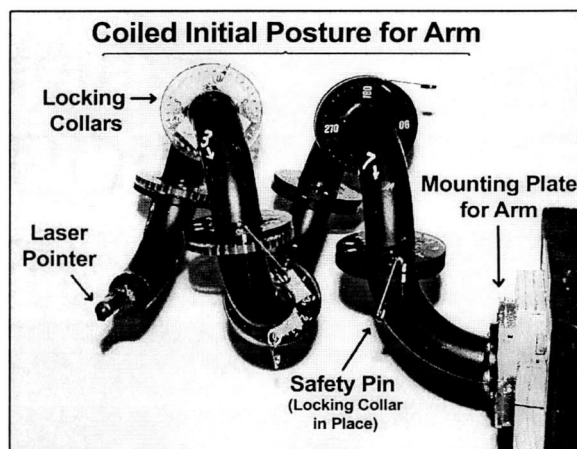


Figure 4: Photo of robotic arm attached to mounting plate in initial posture.

actively turned and another which was passively turned through its attachment to an adjacent segment.

Any number of these segments could be connected to form a chain of identical elbow joints, each having orthogonal orientations to each other, that then could be considered as a complete robotic arm of  $N$  segments. Since each segment could “actively” move in only one dimension with its single degree of freedom, an arm constructed of  $N$  segments had  $N$  degrees of freedom.

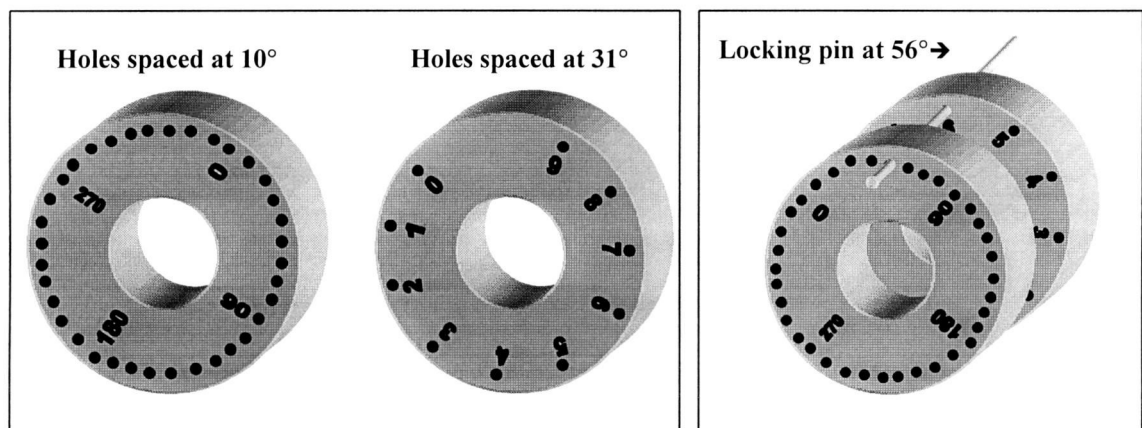
The proximal segment of the  $N$ -segment arm was connected to one face of the data collection space on a mounting plate that was positioned 110-cm above and perpendicular to the floor of the data collection space to provide ample movement space for the attached robotic arm (Figure 4). This mounting plate acted as a support system for the extended arm and included a fixed dummy-segment that did not rotate but provided a mating platform to which the proximal-most arm segment attached.

The overall  $N$ -segment arm was designed to be “sensor-driven” in its pointing behavior. The projection of a laser pointer mounted on the end of the distal, or leading, segment illuminated the pointing location of the distal segment on the target grid, allowing visual indication of pointing error for the human experimenter.

To provide an accurate and reliable position-locking mechanism for any two mating segments, two clear plastic collars (0.5-cm thick) with a 8-cm outer diameter and a 3.5-cm center hole were glued flush with the edges of both ends of each segment. One collar of each mating pair was drilled with thirty-six 1-mm holes evenly spaced at  $10^\circ$ -increments along a concentric circle 0.5-cm from the outer edge of the collar. The other collar of each mating pair was drilled with a series of ten 1-mm holes evenly spaced at  $31^\circ$ -increments along the arc from  $0^\circ$  to  $279^\circ$  on the concentric circle 0.5-cm from the outer edge of the collar (Figure 5). These collars were consistently aligned on each segment end and were clearly labeled at  $0^\circ$ ,  $90^\circ$ ,  $180^\circ$ , and  $270^\circ$  (on the 36-hole collars) and at  $0^\circ$ ,  $1^\circ$ ,  $2^\circ$ ,  $3^\circ$ ,  $4^\circ$ ,  $5^\circ$ ,  $6^\circ$ ,  $7^\circ$ ,  $8^\circ$ , and  $9^\circ$  (on the 10-hole collars) for easy identification by the human experimenter.

This particular arrangement of indexed holes worked as a vernier mechanism, allowing the collars to position their corresponding mating segments at relative positions to each other with a  $1^\circ$  angular resolution. Safety pins of matching diameter to the drilled collar holes were used as locking pins between appropriate holes on the two collars to hold the segments in place at a desired angular position (Figure 6).

The initial posture of the arm segments in every experiment was a fixed coiled



**Figure 5:** Set of plastic collars on mating ends of puppet robotic segments as vernier locking mechanisms with  $1^\circ$  precision.

**Figure 6:** Plastic collars shown locked in a specific angular position.



posture in which each segment was oriented at  $160^\circ$  to its proximally-adjacent neighbor, with one exception: the most proximal segment was oriented at  $70^\circ$  with the fixed dummy segment on the mounting plate. This was because the dummy segment offset the proximal segment at  $90^\circ$  counterclockwise relative to the other segments (Figure 4). This coiled initial posture was chosen as a logical position from which to initiate a behavior for a robotic arm, such as pointing and reaching toward an object.

Thus, this puppet provided an easy-to-implement physical system for quick iterative testing of a collective physical robotic arm architecture and collective control movement principles. As such, a human experimenter moved each segment according to a set of production rules simulated to be operating within each segment. The parameters of these control rules were determined by sensor values locally available to each segment that the human experimenter recorded in a spreadsheet on a computer in the testing room and used accordingly in carrying out segment movements.

While the use of a physical “puppet” robotic arm in this investigation may not have been as fast or precise as a computer simulation of a robotic arm, it proved useful for visualizing the internal dynamic properties and movement behavior of the overall arm. In addition, manipulation of the three-dimensional puppet was useful in the overall discovery process for new control rule building, an important tool that provided meaning to the otherwise abstract numbers that would be computed in a simulator.

### **2.1.2 Target Grid**

The target area to which the arm pointed was the center of a 50-cm radius circle drawn on 1-cm resolution graph paper and laminated to a 100-cm by 100-cm cardboard square. The exact target center was the origin of this 2D grid, which was divided into a  $\pm 50$ -cm Cartesian coordinate system in the X and Y directions. Concentric circles were drawn around the target origin at 5-cm intervals to aid the human experimenter in determining which set of coordinates was closest to the target (Figure 7).

The grid plane was mounted on the wall of the testing room opposite the mounting plate of the robotic arm, so that the target was in front of the arm. The target grid was positioned such that its center was on the same axis as the center of the puppet arm mounting plate and 140-cm from the front surface of the mounting plate. A tape measure (in mm) for measuring reaching distance of the arm was attached at the origin of the target grid by a freely-rotating bolt, enabling the experimenter to measure the linear distance from the target grid center to any location in the workspace.

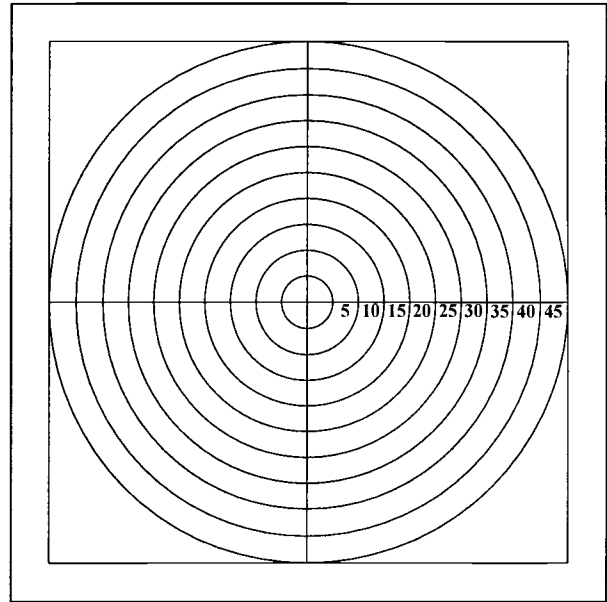


Figure 7: The 50-cm radius circular target grid used to measure pointing accuracy for the robotic arm.

### **2.1.3 Movement Obstacle**

A single obstacle was used to test for adaptability. This obstacle inhibited movement of the robotic arm by occupying the 3D-space between the arm and the target. The obstacle was a ¼-inch-thick stiff cardboard circle mounted through its center to a tripod that rested on the floor of the workspace, allowing the obstacle to be conveniently inserted into the solution path of the arm. The diameter of the obstacle was 33-cm, twice the diameter of the circular area enclosed by the full circular torus of four linked segments. This diameter of the obstacle was chosen based on the relative size of the segments and the overall arm.

## 2.2 Experimental Design

This research used a series of single-subject, single-trial, within-subject experiments to test a robotic "puppet" arm for its ability to produce coordinated pointing and reaching behavior with and without the presence of an obstacle. All movements of arm segments were performed in a synchronous order from the distal to proximal segment. As such, repeatability was not an issue in these experiments because the production rule control system was deterministic.

Fifty (50) experiments were conducted, based on the combination of the following three independent variables: (1) number of segments – 3,4,5,6, or 7; (2) obstacles – presence or absence; and (3) control rules – 8 unique sets (Appendix B). The 80 possible combinations of this 5 x 2 x 8 design were limited to 50 because some control rules sets were used only when obstacles were present. While these three independent variables were manipulated, the initial posture of the arm segments and location of the target grid were held constant in all experiments.

The eight different control rule sets used each contained separate production rules for the distal segment and the non-distal segment. This distinction was necessary since the distal segment used pointing error feedback from the target, while the non-distal segments used only locally-available sensed rotational movement magnitude and direction from their distally-adjacent neighboring segments.

For each experiment, three dependent measures were recorded after every discrete movement of a segment. Two dependent variables—*Absolute Pointing Error* and *Number of Moves to Completion*—measured pointing performance of the arm. A third dependent variable—*Reaching Error Ratio*—was used to examine emergent reaching behavior.

*Absolute Pointing Error* was defined as the distance from the pointing location of the distal segment (as determined by position of the laser point) to the target origin on the two-dimensional target plane. Due to the weight and loose fittings of the arm segments and their horizontal suspension within the workspace, gravity “settled” the arm into its final position after each movement and detracted from the precision of the projected

pointing accuracy on the target grid. For an arm of seven segments, this cumulative error in a fully extended posture was measured to be within  $\pm 5$ -cm.

The *Number of Moves to Completion* was defined as the number of discrete “distal-to-proximal” sequences necessary for the arm to point at the target.

*Absolute Reaching Error* was defined as the ratio of “the proximity of the arm to the target after each discrete segment move” to “the maximum arm reaching distance that could be attained by the particular number of segments in the arm”. This latter measure was determined at the start of each experiment.

## 2.3 Procedures

All 50 experiments used identical procedures and were conducted by a single trained experimenter to avoid human-introduced variability. All data was recorded in a spreadsheet, which allowed the experimenter to input various measured values during an experiment which were then automatically computed by the spreadsheet into the appropriate values for the performance measures of the arm. In addition, using formulas in the production rules and the movement parameters of adjacent segments, the spreadsheet computed the appropriate movements of each segment in the arm in a distal-to-proximal fashion. This computation was based on the application of the particular control rule used in each segment during an experiment. Figure 8 provides an overview of the experimental procedures.

All experiments began with the first pointing procedure of the distal segment from the fixed initial posture

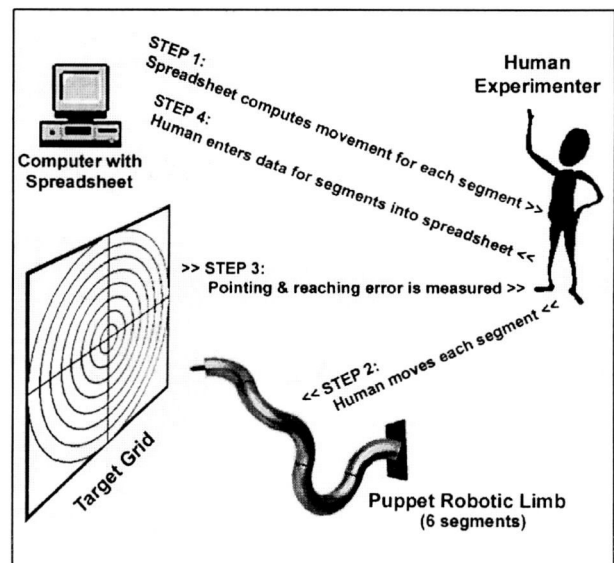


Figure 8: Diagram of the experimental procedures used in this research.

and ended when the distal segment was no longer able to make any movements to bring its pointing location any closer to the target. All segment movements were conducted in a synchronous, distal-to-proximal sequence.

In each experiment, the human experimenter rotated the distal segment in either a clockwise (CW) or counterclockwise (CCW) direction (relative to its neighboring segment) to minimize the absolute distance from its laser pointer to the target on the 2D-target grid plane. This movement procedure often involved determining which direction of rotation of the distal segment, CW or CCW, produced the “minimal magnitude of rotation” in order to most closely simulate the behavior of a real sensor responding to a flow of energy from some emitted target source. Although the movement direction and amplitude of the distal segment was situationally determined by the human experimenter, only the final movement magnitude and direction from initial posture to final posture of the distal segment was recorded to be used as sensory input by the next segment.

Next, the human experimenter moved each remaining non-distal segment sequentially in a distal-to-proximal fashion according to the control rules that transformed the movement of its distally-adjacent neighboring segment.

At the beginning of experiments with obstacles, the circular obstacle was placed so that its center was aligned on the straight line between the axis of the mounting plate for the arm and the target origin, and so that the face of the obstacle was perpendicular to this line (Figure 9). The obstacle was placed at a distance of halfway between the “maximal reaching distance” and the “distance to target of the initial posture” of any particular arm. This “maximal reaching distance” was determined at the start of each experiment by manually extending all the segments until the maximum possible extension was reached and measuring the straight line distance from the tip of the laser pointer of the distal segment to the target origin. The placement of the obstacle in this manner effectively blocked a direct pointing trajectory of the distal segment and, as such, was designed so that the arm had to find an alternate pointing solution to the target.

When environmental obstacles were encountered, the distal segment was moved so that the laser pointer location did not fall onto the circular surface of one of the obstacles, even if such a point would be hypothetically closer to the target. In this condition, the obstacle simulated a “blockage” in the flux of energy from an emitted target source that a real sensor would detect. Non-distal segments, when encountering an obstacle, were moved according to what their specific rules dictated.

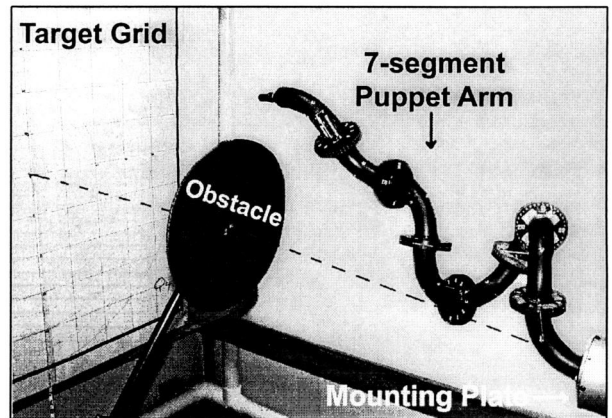


Figure 9: Photo detailing the placement of the obstacle, as shown aligned (by the dotted line) with the mounting plate and target grid.

Following each segment move, dependent measures were recorded. *Absolute Pointing Error* was measured by calculating the distance between the coordinate of the target (0, 0) on the 2D-grid and the (x, y) coordinate of the pointing location of the distal segment. In the case that the laser pointer location fell onto an obstacle following a move of a non-distal segment, then the condition “on the obstacle” was recorded rather than assigned a specific 2D-coordinate from the target grid.

*Reaching Error Ratio* was recorded after each segment move and was computed by the ratio,  $[(D3 - D2) - (D1 - D2)] / (D3 - D2)$ .  $D1$  (in mm) was measured as the straight-line distance from the tip of the laser pointer of the distal segment to the origin of the target grid.  $D2$  (in mm) was the “maximal arm reaching posture” and was determined at the start of each experiment by manually extending all the segments until the maximum possible extension was reached and measuring the straight line of the tip of the laser pointer of the distal segment to the target.  $D3$  (in mm) was the measurement from the tip of the laser pointer on the distal segment to the target when the arm was in initial posture for each experiment. The *Reaching Error Ratio* could range from -1 to 1, with 1 representing the closest reach possible (i.e. equivalent to the “maximal arm reaching posture” previously measured).

### **3. RESULTS**

Only 36 out of the 50 experiments conducted in this research were used in the data analyses, because based on the patterns of sensory input that the arm segments received, it became apparent that certain rules were not applicable in certain arm configurations. The experimental results were organized with respect to each dependent measure and independent variable as follows: (1) Pointing, (2) Number of Moves to Completion, (3) Reaching, (4) Number of Arm Segments, (5) Obstacles, and (6) Control Rules.

#### **3.1 Pointing**

Thirteen out of 36 experiments ended with a final pointing location on the 50-cm by 50-cm target grid. These experiments included arm configurations with a broad mix of facilitative chaining, inhibitive chaining, and withdrawal reflex control rules, as well as varying numbers of segments and both the presence and absence of an obstacle.

Seven of these 13 experiments had a final pointing location of 25-cm or less from the target. Two out of those 13 experiments ended with the distal segment pointed exactly on target, that is, with a final *Absolute Pointing Error* of zero. The first of these zero-error experiments was an arm with 4 segments without an obstacle present which used a simple “facilitative chaining” strategy. The second of these experiments was an arm with 3 segments with an obstacle present which used a simple “facilitative chaining” strategy coupled with a particular “withdrawal reflex” strategy that was employed when obstacles were encountered (Table 1).

#### **3.2 Number of Moves to Completion**

The *Number of Moves to Completion* of a final pointing solution (i.e. where the distal segment could point no closer to the target) ranged from 1 to 9 across the 36

Table 1: Control rules for the “withdrawal reflex” strategy in the experiment which produced an *Absolute Pointing Error* of zero.

Distal Segment Rule:

IF: Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,

THEN: Reverse direction and attempt to point as close as possible to the target.

Table 1: Control rules for the “withdrawal reflex” strategy in the experiment which produced an *Absolute Pointing Error* of zero.

Non-Distal Segment Rule:

IF: A reversal in movement direction by distally-adjacent segment is sensed,

THEN: Compute movement magnitude as  $[0.667 * (Y^\circ - X^\circ)]$ , where  $X^\circ$  = the magnitude of the distally-adjacent segment’s rotation before the reversal, and  $Y^\circ$  = its magnitude after the reversal. Compute movement direction as the *opposite of* as that of the distally-adjacent segment’s direction before the reversal.

experiments. The highest number of moves was 9, in an experiment with an arm of 3 segments with an obstacle present. This also was one of two experiments to have a final pointing error of zero, that is, exactly on the target grid center.

Three experiments used only one move to produce their final pointing solutions. These experiments used the “facilitative chaining” strategy with no “withdrawal reflex” rule, and had 3, 4, and 6 segments respectively, and obstacles present. However, their final pointing solutions were all off the target grid, that is, with final *Absolute Pointing Errors* of greater than 50-cm.

### 3.3 Reaching

Eight out of 36 experiments ended with final *Reaching Error Ratios* of 50% or greater, that is, they reached at least half the distance they could maximally reach to the



target. One of the experiments that produced a final *Absolute Pointing Error* of zero also produced the “closest final reach” with a final *Reaching Error Ratio* of 0.86, that is, the arm ended with its tip 86% of the distance to which it could maximally reach. This experiment used an arm with 4 segments and no obstacle present and a “facilitative chaining” strategy.

### 3.4 Number of Arm Segments

Based on means, experiments with 4 segments had the lowest final *Absolute Pointing Errors*, followed by 3, 7, 6, and 5 in that order, but the variances in each case were quite high. Similarly, experiments with 4 segments had the closest final *Reaching Error Ratios*, followed by 5, 6, 3, and 7 in that order, but again with high variances in each case. In terms of *Number of Moves to Completion*, there was no difference across levels of degrees of freedom, as all had a means, modes, and medians equal to three (Table 3).

### 3.5 Obstacle

Across all 36 experiments, the mean for final *Absolute Pointing Error* in experiments with no obstacles present (n=10) was 33-cm, compared to 46-cm for experiments with obstacles (n=23). Similarly, mean final *Reaching Error Ratio* in experiments with no obstacles present was 0.51, compared to 0.12 for experiments with obstacles. The *Number of Moves to Completion* was the same both for experiments with and without obstacle (mean = 3.0; median = 3).

### 3.6 Control Rules

Both basic control strategies of “inhibitive chaining” and “facilitative chaining” were similarly effective in final *Absolute Pointing Errors*, with 38-cm and 43-cm,

Table 2: Control rules for the “withdrawal reflex” strategy which produced a mean final *Reaching Error Ratio* of 0.48.

Distal Segment Rule:

IF: Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,

THEN: Rotate  $Y^\circ$  in the opposite direction, where  $Y = 20^\circ$ .

Non-Distal Segment Rule:

IF: A reversal in movement direction by distally-adjacent segment is sensed,

THEN: Compute movement magnitude as:  
 $[0.667 * (X^\circ + (0.20) * X^\circ)]$ , where  $X^\circ$  = the magnitude of the distally-adjacent segment’s rotation before the reversal. Compute movement direction as the *opposite of* that of the distally-adjacent segment’s direction before the reversal.

respectively. In terms of reaching, the facilitative chaining strategy was most successful, with a mean final *Reaching Error Ratio* of 0.58, or a 58% reach to the target. The inhibitive chaining strategy resulted in a mean final *Reaching Error Ratio* of 0.25. In terms of *Number of Moves to Completion*, both facilitative chaining and inhibitive chaining had means and medians equal to 3.

Two distinct “withdrawal reflex” rules were productive in accurate pointing and reaching. The “withdrawal reflex” rule presented in Table 1 was the most successful control strategy with regard to pointing with a mean final *Absolute Pointing Error* of 25-cm. The control rule set presented in Table 2 was the most successful “withdrawal reflex” strategy with regard to reaching with a mean final *Reaching Error Ratio* of 0.48.

Table 3: Summary matrix of the results for the robotic arm experiments.

		<u>Dependent Measures (Means)</u>		
		<i>Absolute Pointing Error [0-50-cm]</i>	<i>Reaching Error Ratio [-1 to 1]</i>	<i># of Moves to Completion</i>
<u>Independent Measures</u>	<u># of Segments</u>			
	3	38 ± 17	0.19 ± 0.48	4
	4	35 ± 23	0.41 ± 0.25	2
	5	50 ± 4	0.38 ± 0.22	3
	6	48 ± 3	0.24 ± 0.37	3
	7	41 ± 13	0.15 ± 0.42	3
	<u>Obstacles</u>			
	absence	33 ± 22	0.51 ± 0.31	3
	presence	46 ± 10	0.12 ± 0.35	3
	<u>Control Rules</u>			
	facilitative chaining	43 ± 21	0.58 ± 0.17	3
	inhibitive chaining	38 ± 15	0.25 ± 0.24	3
	withdrawal reflex (as in Table 1)	25 ± 35	0 ± 0.42	7
	withdrawal reflex (as in Table 2)	37 ± 4	0.48 ± 0.06	4

### 3.7 Summary of Results

Because the data collected in this research was based on a single-subject, single-trial design, neither inferential statistics nor statistical significance measures were used. Rather, since the underlying question of this research deals with the performance of the robotic arm, a summary of “meaningfulness” in terms of productive vs. non-productive combinations of independent variables is more useful than “significance”. A matrix of data summarizes the dependent measures for each of the independent variables (Table 3).

Since some delimitation from the original 50 experiments was used in evaluating pointing and reaching, matrices are provided in Tables 4 and 5 to summarize what delimiting conditions the experiments as a whole met.

In addition, across the 36 experiments for which data were collected, there were no meaningful correlations between pointing, reaching, and the numbers of moves required for a solution. Pearson product moment correlation coefficients computed for combinations of these three dependent measures, show at best, that they have a moderately low negative correlation (*Absolute Pointing Error* and *Reaching Error Ratio*,  $r = -0.26$ ; *Absolute Pointing Error* and *Number of Moves to Completion*,  $r = -0.33$ ; *Reaching Error Ratio* and *Number of Moves to Completion*,  $r = -0.16$ ).

Table 4: Delimiting conditions for pointing behavior in a collective robotic arm.

<u>Delimiting condition to be met by experiment</u>	<u># of Experiments which met condition</u>
Original number of experiments	50
Produced unique movement outcome of arm	36
Final pointing solution was on 50-cm by 50-cm target grid	13
Final <i>Absolute Pointing Error</i> was 25-cm or less	7
Final <i>Absolute Pointing Error</i> was zero (exactly on target)	2

Table 5: Delimiting conditions for reaching behavior in a collective robotic arm.

<u>Delimiting conditions to be met by experiment</u>	<u># of Experiments which met condition</u>
Original number of experiments	50
Produced unique movement outcome of arm	36
Final reaching posture was $\geq 50\%$ of closest possible reach	8
Final reaching posture was $\geq 75\%$ of closest possible reach	3
Final <i>Reaching Error Ratio</i> was 1.0 (exactly to target)	0

## 4. DISCUSSION

This discussion examines the results with respect to each dependent measure and independent variable as follows: (1) Pointing, (2) Number of Moves to Completion, (3) Reaching, (4) Number of Arm Segments, (5) Obstacles, and (6) Control Rules.

### 4.1 Pointing

All experiments that ended with pointing solutions on the target grid produced searching patterns in the segment-by-segment process of pointing-to-target behavior in the arm. These search patterns can be visualized by plotting successive points-to-the-target of the distal segment (Figure 10). These searching patterns did not show a

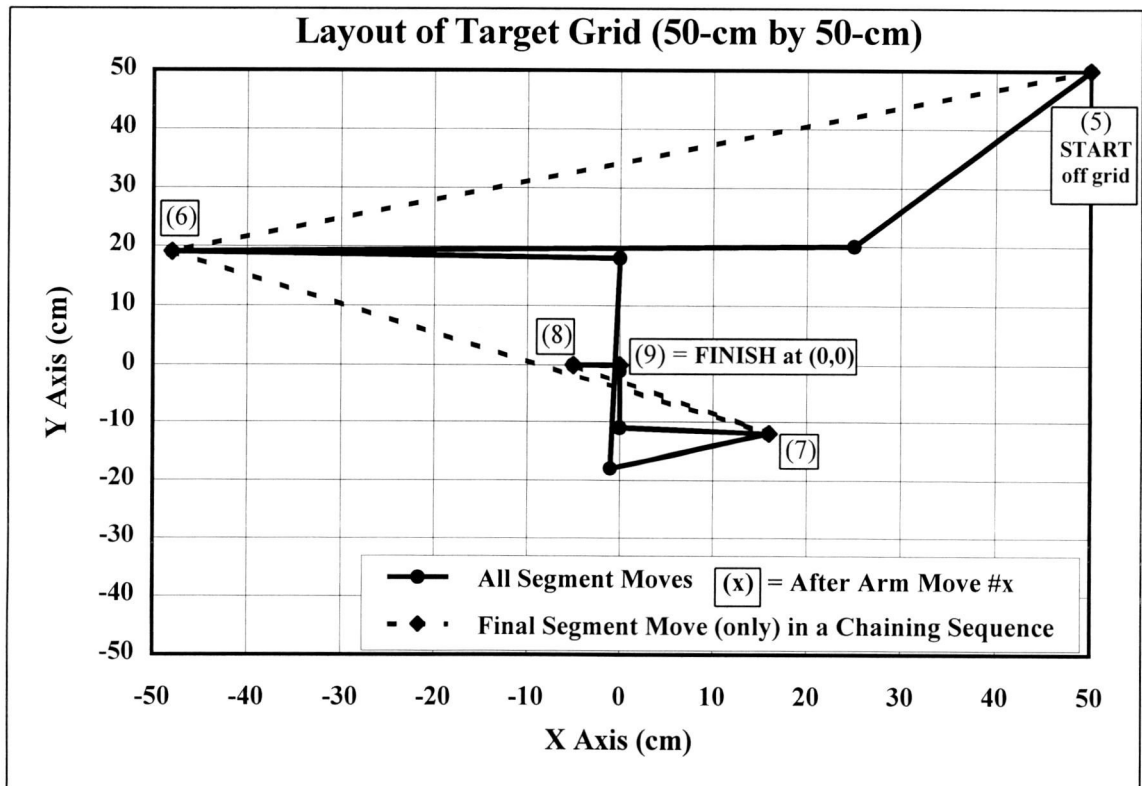
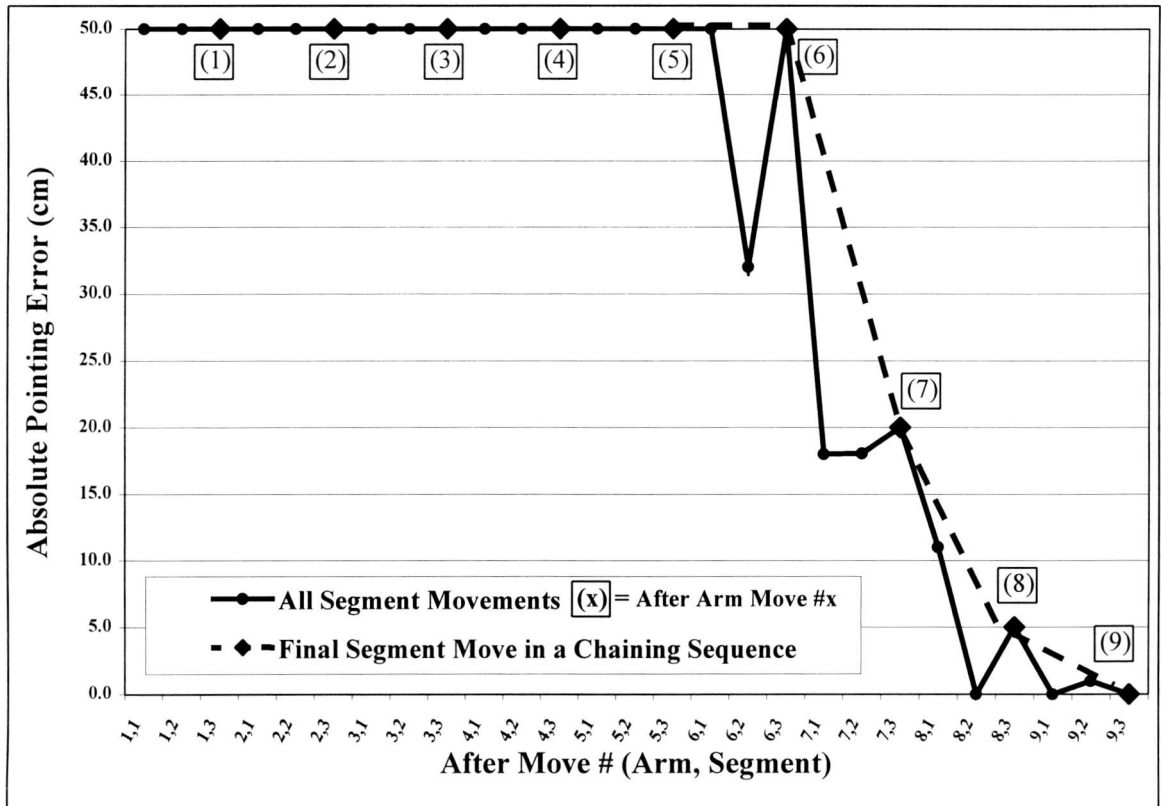


Figure 10: Example plot of pointing positions on target grid for a 3-segment robotic arm, showing searching behavior before focusing the distal segment on the target grid center.



**Figure 11:** Example plot of *Absolute Pointing Errors* after each segment move for a 3-segment robotic arm, demonstrating the successful coordinated point-to-target behavior with a collective computational architecture.

progression of smoothly decreasing target distance that is a hallmark of human reaching behavior, but rather, moved in a choppy fashion due to the  $90^\circ$  relationship between robotic segments. However, if the pointing locations following each complete distal-to-proximal movement chaining sequence were examined separately from other segment moves, the target locations did follow a smoothly decreasing trend (i.e. the “dotted line” in Figure 10).

In addition, the irregularity of the searching pattern was evident in the decreasing progression of *Absolute Pointing Errors* from the initial posture to the final pointing solution of the arm (Figure 11). If the *Absolute Pointing Errors* following each complete distal-to-proximal movement sequence were examined separately from other segment moves, the *Absolute Pointing Errors* followed a smoothly decreasing trend (Figure 11).

## 4.2 Number of Moves to Completion

In these experiments, it was determined that a pointing solution for the robotic arm had occurred when the distal segment was no longer making any movements to deviate its position from the point closest to the target that it could achieve. As a result, no further movements propagated proximally down the arm to other segments and all segments movements halted. However, since varying numbers of moves (1 to 9) were used in the experiments, no conclusion about *Numbers of Moves to Completion* can be drawn. The lack of any correlation between *Numbers of Moves to Completion* and pointing or reaching behavior, suggests that the robotic arm can use any number of moves to achieve target solutions, depending on the particular environmental situation at hand.

## 4.3 Reaching

The distance-to-target measure for reaching in these experiments was effective in demonstrating that preliminary reaching behavior could be produced over successive distal-to-proximal movements in the collective control architecture of the robotic segments (Figure 12). If the reaching locations following each complete distal-to-proximal movement chaining sequence were examined separately from other segment moves, the reaching positions did follow a smooth decreasing trend (i.e. the “dotted line” in Figure 12).

## 4.4 Number of Arm Segments

It is difficult to make a conclusive statement about the effect of varying numbers of segments on pointing and reaching, due to the broad distribution of successful pointing and reaching examples across all levels of degrees of freedom in the experiments. In general, greater degrees of freedom will produce higher redundancy of movement

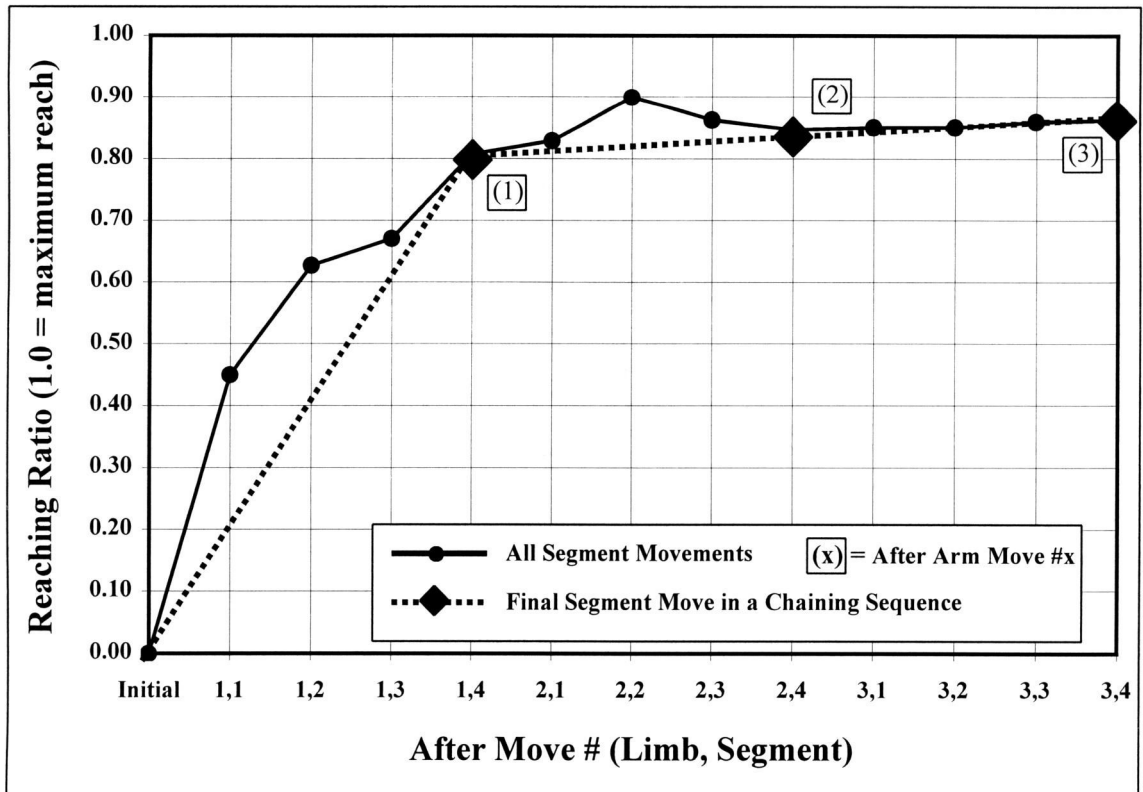


Figure 12: Plot of final *Reaching Error Ratio*, demonstrating reaching-to-target behavior for a robotic arm with 4 segments, using a “Facilitative Chaining” strategy with no obstacle present.

solutions in a robotic arm, but the experiments conducted in this research did not test for this redundancy. It may be that the particular setup of obstacle in these experiments did not provide enough variability and complexity in the environment for redundancy to come into play. In addition, the control rules used may not have provided enough variability in behavior for redundant degrees of freedom to matter. These are factors to be explored in future research.

## 4.5 Obstacle

While the obstacle did not prevent the target from being successfully pointed at in some experiments, overall those experiments without obstacle fared better than those



experiments with obstacles in terms of pointing and reaching performance measures. Although, control rules in experiments with obstacles were less productive as a whole than in experiments without obstacles, the fact these control rules were able to generate new movement solutions and adapt in some degree to the obstacle shows preliminary promise for the use of human motor control rules in a collective architecture to produce adaptive behavior.

In addition, although target location could have been used as another measure of adaptability in addition to obstacles, it would not have been generalizable since the performance on different targets would have been specific to the particular mechanical orientation of this particular puppet robotic model and the relationship between varying degrees of freedom and initial posture. As such, the use of obstacles in this type of data collection proved more likely to provide conclusions about the emergence of adaptation that is more generalizable beyond this particular mechanical setup.

## **4.6 Control Rules**

The variety of control rules investigated in these experiments provided an initial glimpse into the possibilities of controlling robotic arms with biologically-inspired strategies. Some control rules were not applicable in certain arm configurations, since they produced the exact same results at particular “branching points” in sensory patterns as did other control rules. In these situations, the particular rules were, in effect, dead end rules that did not receive the appropriate pattern of sensory stimuli to activate.

The “Facilitative Chaining” strategy worked well to promote distal segment orientation via the successive movement of non-distal segments, when no obstacles were present. However, in the presence of obstacles, facilitative chaining did not promote adaptation, since the movement of non-distal segments “facilitated” further movement “into” the obstacle once the distal segment had encountered it. Thus, though facilitative chaining can point successfully without obstacles, it is evident that additional control rules are needed to promote adaptation to obstacles.

In contrast, the “Inhibitive Chaining” strategy did not drive the arm further into an already-encumbered situation, but tended to back the arm out of such situations. This behavior was very similar to what the “Withdrawal Reflex” strategies produced, since they both incorporated an inhibitive type of direction-reversing behavior. As such, both the “Inhibitive Chaining” and “Withdrawal Reflex” rules enabled the arm as a whole additional non-obstacle-encumbered working space than did the “Facilitative Chaining” rule when an obstacle was encountered by one of the segments.

In fact, the “Withdrawal Reflex” rules (i.e. ones that did not use pure “Facilitative Chaining” or “Inhibitive Chaining” strategies) all used a facilitative chaining rule as their fundamental behavior-generating strategy, but employed a “rule switching” tactic when obstacles were encountered. This rule switching procedure used a certain pattern of perceived sensory information to choose a different subset of the control rule. In effect, this rule switching behavior enabled the arm segments to adapt to obstacles by “sensing” barriers to movement and responding by reversing direction. Neighboring segments were able to sense this non-explicit form of communication as the “withdrawal reflex” pattern of reversal movement of their neighboring segment, and make appropriate adaptive “rule switching” decisions to control their own movement.

## 5. CONCLUSIONS

This research implemented a collective computational control architecture among the segments of a robotic arm in an attempt to produce emergent pointing and reaching behavior. To simplify implementation, a non-actuated, puppet robotic arm was used in conjunction with a set of control rules to guide a human experimenter in moving the arm segments. Though not all possible obstacle placements, target locations, and initial postures for this robotic arm model were investigated, the ones used were a representative subset from which I was able to draw a number of conclusions, demonstrating the usefulness of mapping human motor control concepts into a robotic system:

1. It is possible to extract, operationalize, and implement human motor control strategies in a non-biological, mechanical system such as a robotic arm.

Specifically, this research demonstrated that the Sherringtonian (1910; 1947) concepts of facilitation, inhibition, and reflex chaining in the human nervous system could be extracted out of the world of biological variability (and out of the influence of possible confounding variables therein), operationalized, and tested as control rules to guide the movement of individual segments collectively arranged in a non-actuated, puppet robotic arm.

In addition, the computational architecture of our robotic arm was based on the action system concept of Reed (1982, 1996), an explanation of the human nervous system as an emergent organization of collective groupings of neurons which locally control muscular actions. The successful implementation of the action system concept in this multi-segmented robotic arm provides experimental verification that an action system can coordinate movement across multiple joints.

2. Simple rules used to control the local movements of individuals in a collective computational architecture can produce coordinated group behavior.

The scope of control of each segment in the robotic arm was such that it could only sense its own interaction with the environment and only control its own actions. Each segment had no shared representation of the overall movement goal of the arm as a whole, and was in effect, informationally isolated from all other segments. As such, each segment acted as a single purpose machine that encapsulated a specific adjustment to environmental change. It was from this direct relationship between the individual segment and the environment that the group behaviors of pointing and reaching in the arm emerged.

3. A form of “emergent group behavior” was observed among the collective arrangement of arm segments in the robotic arm.

The “group behaviors” of pointing and reaching in these experiments were the sum of the collective movements of all segments in the robotic arm. However, this group behavior was not specified within each segment, yet the arm as a whole was able to produce coordinated pointing and reaching behaviors. This lack of task specification from a global perspective suggests that pointing and reaching *emerged from the individual contributions* of each segment.

Specifically, the control rules that guided the movements of the individual segments used only locally-scoped sensory information to direct only local action. There was nothing in the control rules of the segments that would dictate the pointing and reaching behavior of the arm as a whole. Rather, it was the use of environmental feedback in the form of pointing error, coupled with distal leadership in the arm limiting the order of movement execution, that provided a goal for the arm's behavior.

However, although the distal segment of the arm used pointing error feedback to minimize its distance to the target, it alone could not achieve (with its single degree of freedom of movement) an accurate pointing solution in most cases. Only through the cooperation of the other segments' movements in the arm could the distal segment's own limited interaction with the environment in the form of target error feedback be used to guide the arm to a successful pointing solution. Thus, the control solution of the arm was

not embedded in a single segment, but rather was completed by the interactions of every segment with its locally-sensed environment.

Additionally, in terms of reaching behavior, no specific reaching feedback information was made available to any of the segments, and no specific parameters were incorporated into the control rules for reaching as there were for pointing. Yet, reaching behavior was observed for the arm as a whole. Nevertheless, it is worth noting that humans can point at an object without necessarily reaching to that object and vice versa. As such, it is not surprising that a robotic arm controlled by human motor control strategies can as well.

However, can this robotic arm's behavior truly be called "emergent" in the same sense that biological behavior is observed to be "emergent"? I ask this question because the robotic arm was composed of collection of interacting deterministic processes that moved in a synchronous fashion, rather than built as multiple non-linear processes moving asynchronously. In biological systems, emergence occurs because of the high degree of non-determinism in its pieces and their interactions (Kelly, 1994; Holland, 1998). Perhaps then, this robotic arm lies somewhere in the middle of the spectrum of behavior between "specified" and "emergent". To achieve true biological-like "emergence", this robot arm will have to be implemented in a way that allows group behavior to emerge from an interaction of multiple non-linearly moving segments.

4. Redundant degrees of freedom in a robotic arm, if controllable, can only serve to increase the level of adaptability through more effective interaction with the environment.

The limiting factor to the reaching ability of this robotic arm was the actual mechanically-constrained length of the arm segments, an effect similar to the reaching constraint of the human arm. However, the important point to make is that an implemented robotic arm like a human arm analog should not be limited in its movement ability, so that it can effectively be redundant its in movements, thereby able to search its movement space for target solutions using as few or as many moves as necessary. The

existence proof of this increased adaptability through redundant degrees of freedom is the nervous system's ability to control the human arm.

5. Control principles that afford broader search patterns to a robotic arm produce more adaptive solutions for pointing and reaching behavior.

Specifically, control principles that instill the arm with a greater degree of “animacy”, or continuous movement, tend to promote adaptation. Close observation of biological organisms reveals a high degree of animate behavior, much of which seems somewhat non-directed. Indeed, biological organisms are almost constantly active and exhibit much more behavior than is “necessary” to accomplish the intent of the organism (Reed, 1996).

This notion of “necessary” and “unnecessary” behavior is significant in that much of the “unnecessary” behavior has to do with being in contact with the environment, staying current, and being able to adapt to environmental variance and take advantage of affordances. This constant exploration of the environment used by biological systems is the necessary animation that energizes the search for productive behavior solutions (Reed, 1996). The implication is that, like biological organisms, artificial ones (e.g. robots) need to be animate above and beyond the level necessary to complete their desired behavior (Korienek, Harty, and Bautista, 2000).

6. The interaction of the robotic arm with obstacles can actually increase its adaptiveness by providing affordances for further movement in situations that would normally be impeded by the obstacle.

Specifically, control rules, such as the “withdrawal reflex” rules used in this research, can be designed to take advantage of these affordances to increase the likelihood of successful target pointing. Thus, rules that use certain patterns of sensory inputs to trigger a “withdrawal reflex” and further evoke behavior from a segment can actually promote animacy. For instance, the “withdrawal reflex” elicited a crude “backing-up” procedure in the arm segments that proved to be a way to constantly adjust

arm position to work around obstacles. This behavior in a robotic arm is similar to what one observes in a mobile robot exhibiting an emergent “wall-following” behavior while traveling on a two-dimensional surface (Jones, Flynn, and Seiger, 1999; Mataric, 1993).

In sum, this research provided preliminary evidence that pointing and reaching movements of the complexity and accuracy that is expected from human and robotic arms may be possible without explicit programming of that movement. Future research in this area of collective control architectures for robotics has the potential to produce a fully electromechanical autonomous, adaptive robotic arm. This type of robotic arm has applications in a variety of remote and hazardous environments and as a new type of prosthetic arm. The style of flexible, adaptable control exhibited by such a robot would contrast with the algorithm-based, precise, and highly repeatable control that is seen in conventional robots (Moravec, 1999). These two styles of control produce a tradeoff in operation and behavior, demonstrating that robots with biologically-inspired control systems could fill application niches in which conventional robots are limited, especially those in which unpredictable, dynamic conditions are the mainstay.

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**APPENDICES**

## **Appendix A: Literature Review**

### **“A Convergence of Robotic and Human Motor Control Approaches”**

#### **1. INTRODUCTION**

“To understand motion is to understand nature.”

- Leonardo da Vinci  
(1452-1519)

The manner in which humans and other animals control their movements has long fascinated scientists and philosophers. In the past fifty years, there has been an especially accelerated quest to create artificial organisms and autonomous robots to mimic the behavior of living organisms to aid in this understanding. Through such endeavors, researchers have gradually gained a fuller comprehension of the control mechanisms that millions of years of evolution have incorporated into biological life, and ultimately, human beings. But while many human motor control theories have been experimentally tested and many robotic control models constructed, a full comprehension of how humans control their movement or how robots can exhibit human-like behavior has yet to be attained.

It is interesting to note that the evolution of control paradigms used to design and build robots over the past century has paralleled the progression of theories used to explain human motor control. The spectrum of each has progressed from an initial top-down approach, using a centralized single controller to a contemporary bottom-up approach, using fully distributed multiple controllers. Due to this parallelism in thought, it is apparent that mutual benefit to both fields could be accomplished by adopting a collaborative biorobotic approach to the study of the human nervous system and using the knowledge gained thereby to refine perspectives of how the nervous system is controlled. Furthermore, if robots are used as testbeds for motor control theories to answer specific research questions, biologically-inspired robots can be more easily designed from the

aspects of biomechanics and neural control thus revealed. It would seem that both areas of study would benefit greatly from such a convergence of knowledge.

However, while robotic and human movement control theories have addressed similar issues and adopted parallel paradigms over the years, a discussion between the two disciplines has been lacking. While there has been much recent interest in so-called “biomorphic” and “biomimetic” robotics, these research efforts have focused primarily on incorporating the successful morphologies of biological organisms into robotic systems rather than their underlying control strategies (Beer, Chiel, Quinn, & Ritzmann, 1998).

As such, the first objective of this literature review is to examine the evolution of thought in human motor control and robotic control, form comparisons, and document a convergence of these two related disciplines so that both may mutually benefit. The second objective is to put forward two standardized common representations—data flow analysis and structure charting—so that a quantifiable comparison can be made.

This will be accomplished by first presenting a modeling syntax to facilitate comparisons, a sort of common tongue, followed by an overview of the main control themes in motor and robotic control. Next, four human motor control approaches and four robotic control paradigms will be presented and summarized in terms of (1) computational architecture, (2) scope of control, and (3) representation of information. The final section of this review will be a discussion of the points of convergence of these areas of study.

## 2. COMMON MODELLING SYNTAX

In any discussion that spans multiple disciplines, it is important to manage the differences in representation and vocabulary. For the symbolic modeling approaches to be used in this literature review, Data Flow Diagrams (DFD) and Structure Charts (SC) were chosen for their generality and simplicity (Yourdon & Constantine, 1974). There are applications in this review where DFDs and SCs fit better than in others, but the tradeoff is an occasional translation error compared to the benefits of comparison.

The Data Flow Diagram (DFD) provides a methodology to describe any system that processes information in such a way that, in spite of differences in physical structure, similar general principles emerge. The DFD methodology is a top-down one and relies heavily on the use of functional decomposition to identify the key activities of a system and their interrelationships. This methodology entails confronting problems of mechanisms, processes, and problems of how a system works, at a level of detail which the behavioral sciences has traditionally glossed over.

The central concept of the DFD is a diagramming technique that produces descriptions of systems using a graphical language for representing the data structures in the system, their interrelationships, and their relationship to the system functions. By using common symbols, DFD graphs may be combined or modified more easily than models of disparate graphical symbols (Figure A-1). There are four modeling constructs used in this methodology: (1) flow of data (represented by an arrow), (2) transformation of data (represented by a labeled circle), and (3) storage of data

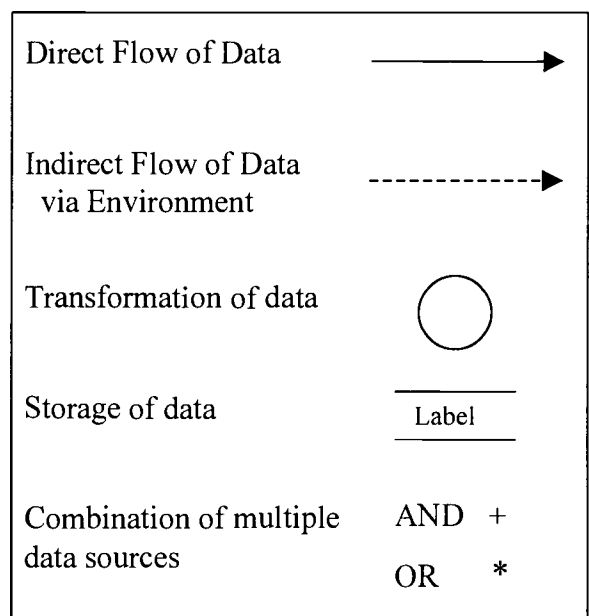


Figure A-1: Definition of symbols used in the Data Flow Diagram modeling approach.

(represented by two parallel lines and a label between them). When two or more lines are entering or exiting a given process, storage, or bound, the relationship of these lines to each other must be defined by an operator symbol. The number of symbols in a diagram is determined by the breadth and depth of analysis that is required for the purpose of that particular model.

In the DFD, a given process is first graphically represented in its most global

syntax and then recursively decomposed until an appropriate level of representation is achieved. Building a DFD model consists of proposing a very abstract solution and then successively refining, or decomposing, it until it is entirely expressed in the chosen level of representation. An alternative to this top-down approach is the bottom-up strategy. In the bottom-up strategy the model is built from the lowest or most detailed level and sequentially built layer upon layer up to the most abstract or highest level of representation of the model

While the flow and transformation of data through a system is one view of the system, another that is particularly useful and complementary to the DFD approach is Structure Charting. The symbols associated with structure charting represent the organization of a computational architecture and are used to illustrate computational elements, separation of computation, and flow of control through a larger system (Figure A-2). Boxes connected by solid lines indicate the transfer of control and a passing of information between computational pieces in an overall system, with arrows indicating direction of control. In contrast, dotted lines without arrows designate connections where information is not directly shared between computational units, but rather where the environment in which the system is contained is used as an intermediate step in communication.

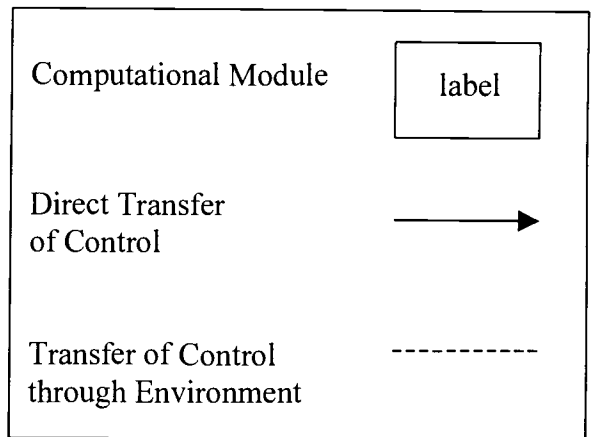


Figure A-2: Definition of symbols in the Structure Chart modeling approach.

### 3. HUMAN MOTOR CONTROL APPROACHES

Over the past 100 years, this issue of movement control has been investigated experimentally using approaches based in (1) physiology (Sherrington, 1910, 1947), (2) psychology (Keele, 1968; Adams, 1971), (3) cybernetics (Bernstein, 1967), and (4) ecological psychology (Gibson, 1966; Reed, 1982, 1996).

#### 3.1 Physiological Approach

In his influential manuscript, “The Integrative Action of the Nervous System,” Sherrington (1947) presented an analysis of biological movement in terms of underlying neural processes which he established by systematic and extensive behavioral experimentation with mammalian reflex actions. Sherrington (1910, 1947) postulated that the reflex arc was the elementary unit of action in the production of coordinated behavior and that such coordination involved a successive combination, or chaining, of reflexes.

In Sherrington’s (1947) definition of a reflex arc, several elements are necessarily involved: an initiator, a conductor, and an effector (Figure A-3). In the nervous system, the initiator is the sensory neuron (or neurons) which initiates action in the arc; the conductor consists of the axons and synapses involved in the conduction of nervous impulses, and the effector is the muscle that produces the action. The computation, or transformation of information, in the reflex arc takes place in the synaptic interconnections of the interneurons of the spinal cord through spatial and temporal

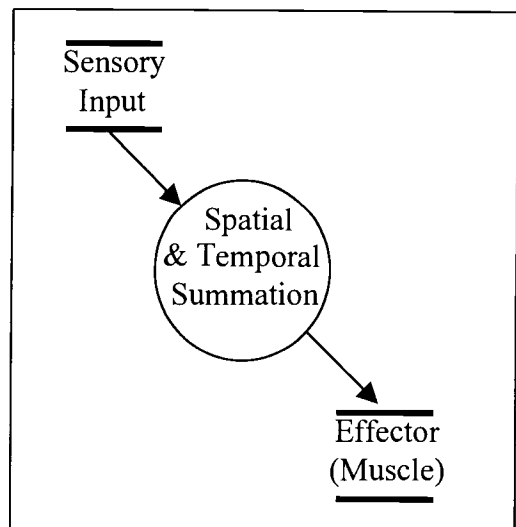


Figure A-3: A data flow diagram of Sherrington’s (1910) reflex arc in the nervous system.

summation of excitatory post synaptic potentials and inhibitory post synaptic potentials on the cell membrane of post synaptic neurons (Roberts, 1967).

In addition, Sherrington (1947) devised several general concepts on nervous system action based on his observations of reflex arcs. These concepts describe the coordinated movement of muscle groups in the body due to their innervation:

<u>Concept</u>	<u>Definition</u>
Facilitation	Muscle A moves to facilitate muscle B movement
Inhibition	Muscle A moves to inhibit muscle B movement
Irradiation	Muscle A movement influences muscle B movement
Recruitment	Muscle A movement initiates muscle B movement
Reciprocal Inhibition	Muscle A moves in cooperation with muscle B
Reflex Chaining	Muscle A moves in coordination with muscle B

Taken together, these six Sherringtonian concepts provide a particular explanation of mammalian motor control, in which the interactions of a group of hierarchically and serially arranged components (e.g. bones, muscles, and nerves) can be explained by a simple generic set of elements. Indeed, Sherrington's physiological work laid the groundwork for an understanding of movement control, later built upon by more sophisticated research inquiries by many experimentalists and theorists (Adams, 1971; Bernstein, 1967; Easton, 1978; Green, 1972, 1982; Keele, 1968; Kelso, 1995).

Individually, there is no computational structure of a reflex arc due its simplicity, so no structure chart is presented. Yet, multiple reflex arcs combine to form a distributed network throughout the peripheral nervous system. These reflex arcs do not need to look "up" to determine what the central nervous system might be contributing to the control of action. As such, Sherrington was thinking in terms of a loosely distributed computational architecture. In terms of representation of information, the state of a given reflex arc is maintained as an integrated potential on the cell membrane of a single motor neuron, although additional state can be represented in associated neurons. However in terms of control, the scope of any single motor neuron is primarily local.



### 3.2 Psychological Approach

The classic psychological approach to human motor control views the nervous system as an information processor, or a metaphorical computer ( Craik, 1948; Weiner, 1948). When the senses identify a stimuli, the brain selects a response by accessing a program to create the response, and then outputs action-based instructions to the muscles (Figure A-4). Intermediate representations of this process are stored in memory. This process relies on the computational power of a central processor whose work is divided into stages of processing.

The number of stages in the information processing approach and the specification of what a given stage accomplishes are experimental issues that have been addressed over the years and are still being considered. Adams (1971), for instance, developed a closed-loop theory of motor control in which feedback from a movement is compared to some correct stored internal reference. Keele (1968) proposed that movement is constructed via “motor programs,” detailed instructions for every movement determined through the processing of information in the central nervous system. The “motor program” concept has been extended to “central pattern generators” (CPG) to include pre-programmed rhythmic movements such as locomotion, chewing, and breathing (Grillner, 1975). CPGs are hypothetical neural structures that explicitly generate rhythmic neural activity that then is transformed to rhythmic muscle activity and rhythmic movements (Latash, 1998).

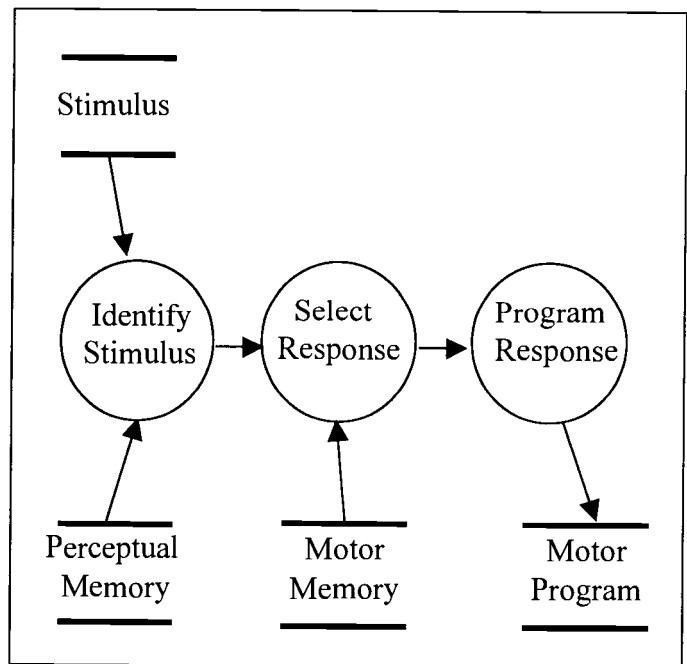


Figure A-4: A data flow model of the motor program and information processing approach to motor control.

In terms of computational architecture, the information processing approach uses centralized control, wherein the brain processes all sensory information the nervous system receives and then sends out signals in the form of programs to the muscles (Figure A-5). Thus, the scope of

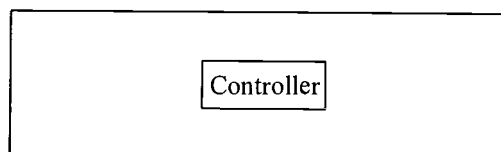


Figure A-5: A structure chart of the central approach of information processing.

control of the brain in this nervous system model is the entire body, and this capability implies an enormous processing and storage capacity to account for the immense variety of movements in everyday activity. Likewise, the information processing approach implies that the internal representation of information necessary to make decisions and movements must be constantly updated through the sensory system.

### 3.3 Cybernetics Approach

Cybernetic theorists, in their comparative study of control in animals and machines, have approached the issue of human motor control from a hierarchical viewpoint, where the direction of control is from the top of the hierarchy to the bottom (Figure A-6). In this way, the nervous system is viewed as containing a number of interdependent processing levels, in which higher “neural circuits” control the flow of activity in lower “neural circuits” (Gallistel, 1980). Bernstein (1967) provided evidence for a more distributed, hierarchical control architecture in the nervous system where intents and other high-level control issues are controlled by the brain, but further details of action are added at the lower peripheral levels of

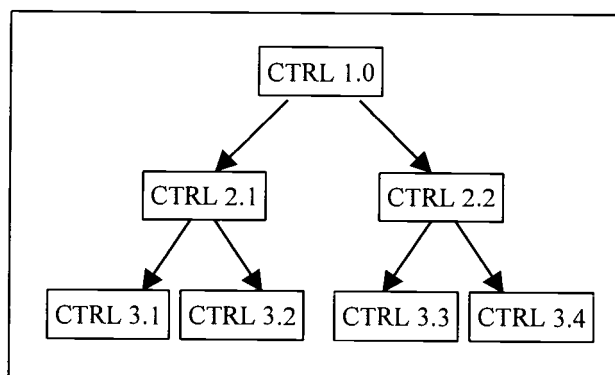


Figure A-6: A structure chart of the hierarchical approach to human motor control. (CTRL “#” = Controller “level in hierarchy”)

individual neurons and muscles (Figure A-7).

One of Bernstein's (1967) primary observations was the low likelihood that the large number of degrees of freedom in the human musculoskeletal system could be continuously controlled by a single central controller. The term "degrees of freedom" refers to the number of possible movements of a mechanical system, based on the number of elements and the ways they are constrained. Rather, the key to successful control of the large number of degrees of freedom in the nervous system appears to be its capability to selectively limit degrees of freedom to produce behaviors (Bernstein, 1967). Greene (1982) further explained that multiple degrees of freedom do not complicate the control of movement but rather exist within the nervous system so that a small selection of multiple degrees of freedom can be used in "simply conceived and executed recipes of movement."

Other theorists have explained this ability to selectively limit degrees of freedom by the existence of functional groupings of neurons called "coordinative structures" (Easton, 1978) or "neuromotor synergies" (Lee, 1984). Such functional groupings can be controlled as if they contained fewer degrees of freedom, thus reducing the number of control decisions necessary. Coordinative structures might exist as neurons which group together to perform certain tasks and then dissipate when the task is completed (Kugler, et al., 1980; Nashner, 1982). Furthermore, the concept of the coordinative structure suggests that a reusability of neurons is used in the nervous system as opposed to a permanent allocation or "hard-wiring" of neurons. This would explain Bernstein's (1967) concept of "peripheral indeterminacy" in the nervous system, in which a variety of

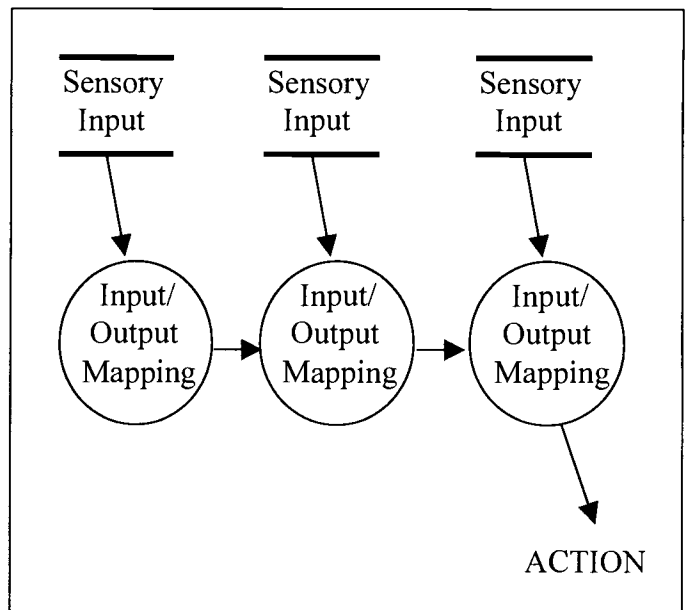


Figure A-7: A data flow model of hierarchical cybernetics approach to human motor control.

underlying neural pathways can differentially interact to produce the same movement outcome.

Thus, the cyberneticists used a hierarchically-organized distributed computational architecture to explain the control of the nervous system. In this model, individual “synergies” represent the state of information relative to their activity. Scope of control is local, although it is modulated by descending signals from higher levels in the hierarchy.

### **3.4 Ecological Approach**

The ecological approach to motor control is driven by the work of James Gibson (1966), who proposed that the “world” of an organism is not reconstructed from information that has been abstracted from the environment and transformed by some information processing method of the nervous system, nor does it rely on complex interpretations of neural signals through stored representations or memories of past experience. Rather, the environment of an organism is made up of the dynamic information that an organism perceives through the active tuning of its sense organs. Gibson (1966) termed this active perception of the environment by an organism “direct perception.” An organism does not need to store environmental information in a world model because through its constant animacy, or continuous behavior, in the environment that information is sensed and directly coupled to its further action.

Expanding on this ecological perspective, Reed (1982, 1996) proposed that organisms are composed of multiple interacting “action systems,” which in the nervous system are localized computational units that enable organisms to regulate their behavior according to the flow of information that they actively pick up from their environment. Reed (1982) suggested that such action systems cannot be examined as the independent contributions of separate afferent inputs and efferent outputs of the nervous system. Rather, movement is continuously under a mixed control where efferent “motor output” and afferent “sensory feedback” interact and where the functionally independent roles of

sensory and motor information do not exist. Thus, movements are seldom simply reactive, but rather are adaptive and functionally specific (Reed, 1982).

In Reed's (1982) action system model, the loop of control of the nervous system is complete when the organism interacts with its environment in a relationship without distinct boundaries (Reed, 1996). The environment itself contains the information an organism needs to complete its control computation. This information is directly perceived by the organism as it uses constant behavior, or animacy, to update it. Thus, at the level of an individual organism, Reed's action system model suggests that action is regulated with respect to "affordances," or relationships between the organism and the environment (Reed, 1982).

Stated another way, the role of the environment in describing movement cannot be underestimated. For instance, the path of a beetle walking across a forest floor might be quite complex, but does not necessarily reflect the complexity of the beetle, but rather may be due to the complexity of the environment in which the beetle is walking (Resnick, 1994). If the environment is solid ground, it affords walking behavior, but if the environment is water, then it affords swimming behavior. In other words, behavior must be regulated by the environment, and cannot occur without it (Reed, 1996).

While early hierarchical theories had proposed the existence of functional groupings—"coordinative structures" (Easton, 1978; Turvey, 1987) and "neuromotor synergies" (Lee, 1984)—Reed's (1982, 1996) more comprehensive "action system" expanded this idea into a heterarchically-arranged model. Heterarchical systems are those with no implied direction of control, but where control can flow from top to bottom, bottom to top, or laterally (Stelmach & Diggles, 1982).

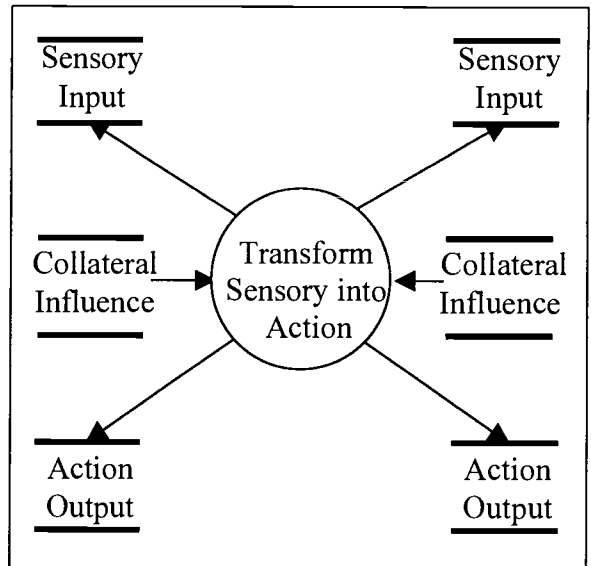


Figure A-8: A data flow analysis of Reed's (1982) action system in the nervous system.

Specifically, action systems are self-organizing, highly dissipative, collective elements that comprise the fully distributed control architecture for the nervous system (Reed, 1982, 1996). They are dynamically allocated organizations of 100 to 10,000 neurons that comprise a local computational unit complete with sensory inputs, action outputs, and collateral influences to and from other action systems (Figure A-8). Action systems form in response to changes in neural activity and dissipate when their job is completed. At its most basic level, the action system uses Sherrington's (1910) reflex arc, the simple three-to-ten neuron linkage of a sensory neuron, a computational element, and an efferent neuron to effect muscle movement.

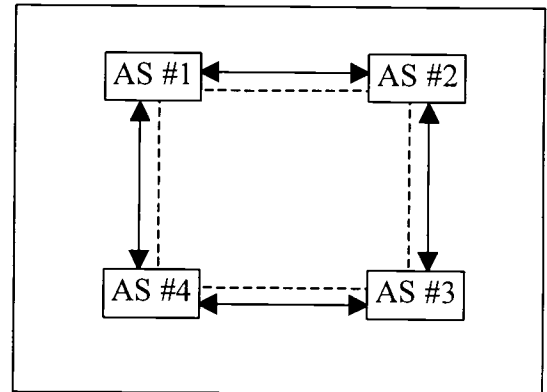


Figure A-9: A structure chart of the ecological approach to motor control.  
(AS = "Action System")

Thus, the ecological approach has progressed toward an explanation of the nervous system as directly coupled to the environment through perception and action. Physiologically, the nervous system is a more collective computational architecture with local scooping of both sensory and action information within each member of the collective, which, is the action system. Action systems can share information directly, if they are "hard-wired" in neuronal circuits, or they can use the environment as an indirect communication medium (Figure A-9). From the ecological perspective, the maintenance of state and representation of information is not very important, as that information is constantly available in the environment. Actually, Reed (1996) surmised that maintenance of state would force a control system to be consistently operating on old and somewhat inappropriate information.

### 3.5 Summary of Motor Control Approaches

The theoretical approaches to how the human nervous system controls movement has progressed in the 20<sup>th</sup> century from using a singular centralized controller to using multiple distributed controllers tightly coupled to their interaction with the environment. The simple physiological approach based on early neurophysiological observations (Sherrington, 1910) began by suggesting that simple movements are controlled by the coordination of simple open-loop sensory-computation-action systems called reflex arcs.

The view of the brain as a computer suggests extensive internal representation and processing of sensory information that produces action output by motor programs (Adams, 1971; Keele, 1968). These information processing explanations relied on a number of discrete steps which occurred in the nervous system before movement could be generated. As the central controller, the brain would select, start, and stop movement similar to the way in which a contemporary desktop computer executes a large program.

The cybernetics approach to explaining human motor control distributes control away from a central location with a hierarchy of functional neuron groupings throughout the nervous system. Bernstein's (1967) notion of this distribution system focused on the large number of degrees of freedom in the nervous system, distinct points at which decisions about movement were made. Other theorists have suggested that this localized control is carried out by transient groupings of neurons called "synergies" or "coordinative structures" (Easton, 1978; Lee, 1984).

The ecological explanation of motor control extended the notion of localized control even further in a heterarchical arrangement with no implied direction of control. Rather, control of behavior can only be achieved through an organism's constant animate interaction with its environment, such that active perception occurs to complete the nervous system's computation of control. As such, the behavior of an organism occurs due to the affordances, or context-specific relationships, formed between itself and its environment.

Thus, the problem of human motor control, once thought immensely complex for a central cerebral controller, has been partially simplified by distributing control to multiple controllers.



## 4. ROBOTIC CONTROL PARADIGMS

The last 50 years of robotics research and development have resulted in primarily four different control paradigms, progressing in similar fashion as did theories of human motor control. These paradigms are represented simply as: (1) servomechanism control, (2) central control, (3) distributed control, and (4) collective control.

### 4.1 Servomechanism Control

Servomechanism control uses simple feedback in which a controller of a system changes its command signals based on their outcomes which are “fed back” into, or sensed by, the controller (Figure A-10) (Latash, 1998). For example, biological organisms use feedback to maintain a variety of homeostatic activities such as body temperature and blood pressure. Likewise, feedback-based control provides the basis of many simple control devices that humans have engineered, such as the thermostat.

In robotic systems, feedback has been used to control position via the maintenance of stability and accuracy within some prescribed limit for a task (Jones, Flynn, and Seiger, 1999). Another good example is Braitenberg’s (1984) work with conceptual robotic vehicles in which he used a variety of simple feedback circuits in the design of a wide of variety of behaviors. These vehicles were thought experiment models for psychological concepts that demonstrated how behavioral complexity can arise from such simple control loops as the servomechanism.

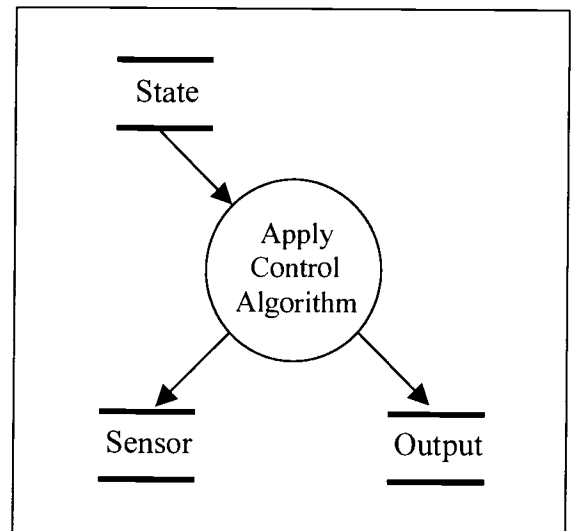


Figure A-10: A data flow analysis of simple feedback.

The servomechanism has no computational structure due to its simplicity, and hence no structure chart is presented. Yet when linked together in a larger system, the servomechanism relies on the overall central computational architecture in which information about each servomechanism is represented as a variable to which sensor information is compared. Scope of control is local and usually limited to the specific action of the servomechanism.

## 4.2 Central Control

Robotics technology since the middle of the 20<sup>th</sup> century has paralleled the development of centralized computer systems, and thus robotics designers have traditionally used central control strategies as the solutions of choice (Brooks & Flynn, 1993; Moravec, 1981, 1999) (Figure A-11). The primary advantages of such a strategy are optimality, reliability, and reproducibility of specified movement tasks. With these goals in mind, centrally-controlled robots are programmed to work precisely within a defined environment for a specific set of tasks or goals.

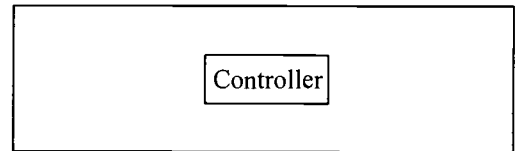


Figure A-11: A structure chart of the central approach to robotic control.

Centrally controlled robots rely heavily on the use of models of their environments to plan a series of actions to achieve movement goals (Jones, Flynn, and Seiger, 1999). These abstract models are used as maps to represent the world of the robot and to direct the translation of environmental information from the robot's sensors to its behavioral actions (Figure A-12).

This defined world model of the centrally-designed robot constrains the specific types of physical architectures that can optimally be used to perform specified behaviors, as the high level of goal modeling and representation ultimately determines the flexibility of the robot in responding to changing conditions (Jones, Flynn, and Seiger, 1999). For

example, a given behavioral solution is functional only until the goal is met or the path is obstructed by some condition not anticipated and encoded into the original global map or controller. When such obstacles prevent goal achievement, the internal map must be updated using information gathered from the failed attempt in order for a new path must be resolved. As

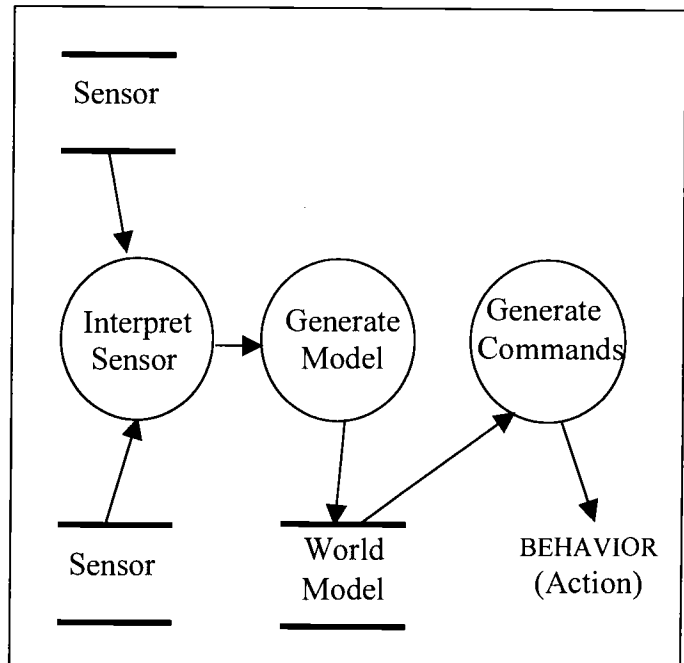


Figure A-12: A data flow model of the central paradigm of robotic control.

such, centralized control has proven to be expensive in terms of computational resources due to the requirements of explicit searching, mapping, and recognition of environmental and robotic characteristics for problem solving (Brooks, 1991; Dudek et al., 1996).

Furthermore, the limits of environmental sensors (including the capability of a visual recognition system) and the flexibility of the central computing software limit the accuracy of any mapped information. Complete functioning of the robot can be compromised by total or even partial loss of a necessary sensor. For example, a mobile robot or a robotic arm that is operating in a changing environment (e.g. not specified in the world model) or using ambiguous information from damaged sensors could be stranded by control software that cannot resolve a unique solution path. Defining and programming all the possible alternative movement solutions the robot might need is clearly not feasible due to the dynamic, ever changing, nature of real-world environments and the tradeoffs of computer hardware necessary to process and store all required information and solutions.

In sum, these planning architectures are, by definition, centrally organized computational architectures. The core of its control is its own internal representation of

the information in the world, which can be updated neither easily nor quickly due to real-time computational constraints. In most cases, all or a large part of the local world is represented in memory for use in planning and controlling with the scope of the plan global to the system.

### 4.3 Distributed Control

An alternative robotic control architecture that has developed over the past two decades is decentralized control in the form of parallel or distributed-processing architectures. In this type of robotic system, control is not centered in one centralized processing unit (CPU), but rather is encapsulated within each of the actual elements being controlled (Figure A-13). These elements are separate individual robots or processors, but they are linked by data sharing protocols. This decentralization of distributed control can also be implemented as a hierarchical system, where control is subdivided into tasks in a top-down control pattern.

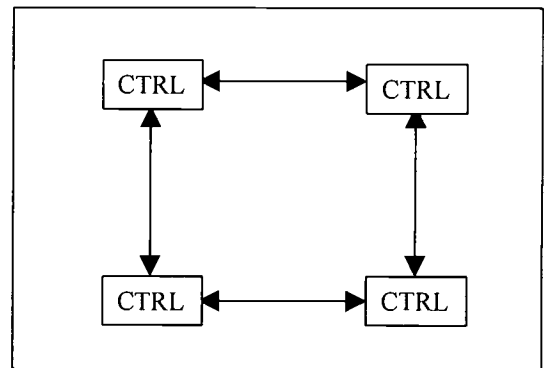


Figure A-13: A structure chart of the distributed approach to robotic control.  
(CTRL = Controller)

A commonly used decentralized model is the subsumption architecture initially described by Brooks (1986) and represents a significant change from the model-driven approach used by central control architectures. In the subsumption architecture, sensors are mapped onto actions without intermediate abstractions, and the actions of the robot arise from the interactions among low-level behaviors. Using a real-time, sensor-prioritized arbitration scenario, the dominant behavior for a given sensed pattern is selected, which should be the appropriate behavior for the present condition (Figure A-14). As such, by being grounded in the sensed world, the subsumption architecture is

parallel and does not rely on a singular data structure or world model to make control decisions.

In terms of computational architecture, the distributed paradigm places control in each of its separate elements rather than a more central location. The scope of control in a distributed system is local and usually limited to the specific action of the individual element, though since information is represented both globally as well as within each distributed element, control can be shared across separate individuals.

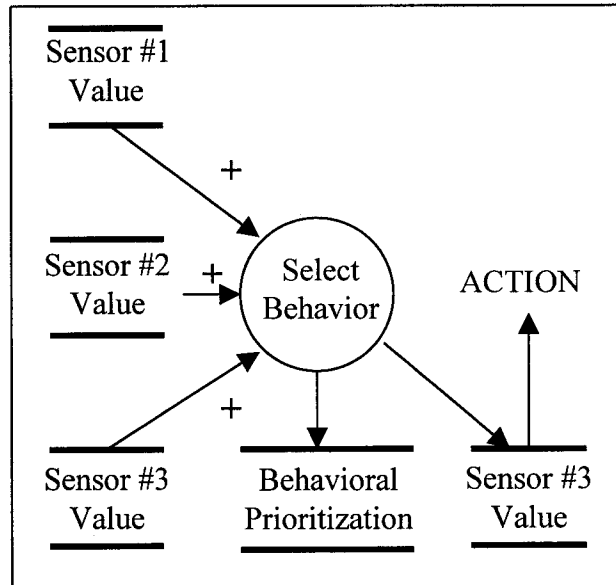


Figure A-14: A data flow model of the subsumption architecture, a decentralized approach to robotic control.

#### 4.4 Collective Control

To take the distributed style of control one step further, one could infer from existing biological models that a model of pure collective behavior as opposed to a prioritized behavior selection method might produce more adaptive behavior in response to environmental perturbations. In the subsumption architecture proposed by Brooks (1991), control was an issue in the selection of an appropriate behavior for a given sensory pattern. However, the weakness of this architecture in terms of adaptability to environmental complexity lies in its inability to create or select a behavior that it was not previously programmed to produce (McFarland, 1991).

Collectives are those systems that use only localized sensing, communication, and action between members of the group, allowing each member to act without knowledge of the group state. In this way, complex behaviors arise from an interaction rather than a simple summation of the individual robot behaviors. In robotics, these members of a

collective are often termed “agents,” and are structured thus in “agent-based computational architectures” (Figure A-15).

A hallmark of biological collectives is computational economy in the regulation of complex behaviors (Alt & Hoffmann, 1991; Dudek et al., 1996). However, this unique advantage in a collective robotic system created from identical autonomous members has only recently been noted and studied (Beer et al., 1998; Dudek et al., 1996; Holland, 1998; Moravec, 1999). For example, a set of independent, mobile robots were designed to compete and cooperate in herding behaviors involving box pushing (Kube & Zhang, 1993a, b). These types of behaviors emerged from membership interactions that were not directly predicted from the sum of each member’s actions.

Other collective robotic systems have been developed to mimic insect societies and consist of multiple identical mobile robots (Drogoul et al. 1998; Kube and Zhang 1993a,b; Mataric 1993). Typically, these robot members depend on local sensory information, performing stimulus-response tasks with little processing, operating without reference to a global map. They may have rudimentary communication with other members of the group (Fukuda & Ueyama, 1993, 1994) or may be completely isolated.

Mataric (1993) used bottom-up experimentation to design control systems for a collection of mobile robots engaged in a single task. In this approach, the model of autonomous “agents” was used to encapsulate all aspects of a given mobile robot. With the mobile robots all being very similar (if not identical), the emergent behavior (i.e. following, aggregation, and flocking) came from the interaction of the robots with each other and their environment (Figure A-16). It is this notion of control computation completed by interaction with the environment that is another hallmark of collective control.

The main goal, then, of current collective robotics research has been to develop control theories or laws governing multi-agent systems such as multiple mobile robots.

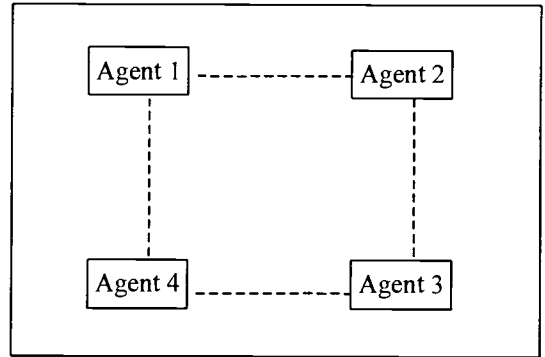


Figure A-15: A structure chart of the collective approach to robotic control.

The question is asked: if one agent can be controlled to perform a task, how can multiple agents be controlled to perform tasks collectively (Dudek et al., 1996)?

This type of collective computational architecture is on the opposite extreme of the control spectrum from a central architecture, since control is completely distributed and information is isolated among elements of the collective. Scoping of control follows a “think locally, act locally” tenet

(Kelly, 1994). In the collective control paradigm, the representation of information is not important, as that information is constantly available through the active sensing done by collective members of their local environment.

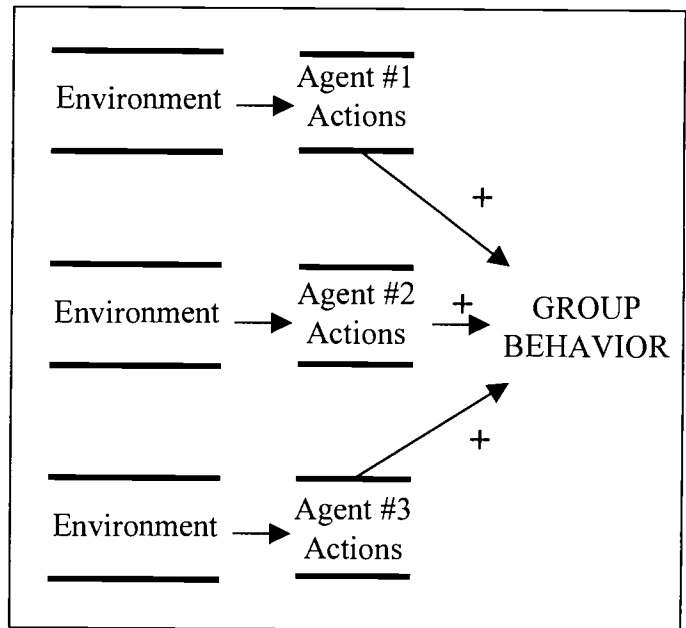


Figure A-16: A data flow model of the collective approach to robotic control.

## 4.5 Summary of Robotic Control Paradigms

In summary, the history of robotic control has progressed similar to the theoretical line of thought to explain the way the human nervous system controls movement. Initially, robots were no more than combinations of feedback systems. Gradually, industrial robots expanded with prodigious use of the centrally-directed approach used in computers. These machines are amazing in their precision and repeatability, but have no means of adapting to changing environments. Any behavior not specifically programmed was considered an error.

Only recently in the latter half of the 20<sup>th</sup> century has an effort been made to reduce the computational overhead inherent in central architectures by distributing control throughout a system. Initially, this was done hierarchically with a number of “smaller” controllers spread throughout a system all taking commands from a central overseer and adding local control capability where needed. Next, this hierarchy flattened to a more heterarchical model where no control direction was implied but global knowledge of information was shared throughout all the computational entities in the system.

Presently, the innovative robotic control paradigm is moving toward a fully collective control model in which behavior emerges from interactions between multiple distributed computational agents rather than through explicit sharing of control information and global knowledge. It is at this emerging point of robotic control that potential benefits can be reaped by a convergence with the paralleling theories of motor control.



## 5. THE CONVERGENCE

This literature review has discussed the evolution of four primary theoretical approaches to explain human motor control and the four dominant paradigms for controlling robots. The following criteria have been used as points of discussion of the convergence between these two realms of control: (1) computational architectures, (2) scope of control, and (3) representation of information. Based on the parallels that have been revealed in the discussions in this review, a mapping can be made between human motor control approaches and robotic control paradigms (Table A-1).

Specifically, the reflex arc (Figure A-3) of the nervous system and the servomechanism (Figure A-10) of robotic control systems are similar in their simple sensor-computation-action arrangement and their building-block quality. That is, they are used by both the nervous system and robot designers as fundamental units from which to build more complex control architectures.

The motor programming / information processing explanation (Figure A-4) of motor control is akin to the central control paradigm (Figure A-12) used in traditional robotic designs. Both are based on the notion that control structure should be overarching and pervasive to every part of a system. As such, all inputs and outputs lead

Table A-1: The mapping of the convergence between human motor control approaches and robotic control paradigms.

<u>Human Motor Control Approach</u>		<u>Robotic Control Paradigm</u>
Physiological	←→	Servomechanism
Psychological	←→	Central
Cybernetics	←→	Distributed
Ecological	←→	Collective

to and from a central “computer” which models the world, constructs plans, and directs action.

Cybernetics approaches, in attempting to draw parallels between the biological and mechanical realms, are inclined toward distributing control throughout a system. In human motor control theory, this approach has viewed the nervous system primarily as a top-down hierarchical system with the brain as the chief controller on top, followed by the spinal cord interneurons, and ultimately ending with more local control at the level of the peripheral neurons and muscles (Figure A-7). Similarly, subsumption architectures (Figure A-14) and other distributed robotic control architectures have incorporated a chief controller for behavior prioritization and higher-level decisions, but allowed some local control of action to occur at actuators distributed throughout the robot.

Lastly, the ecological approach to motor control and the collective robotic paradigm (Figure A-16) have approached the interaction of an organism or robot with its environment as a way to shed light on the control problem. Realizing that the complexity of the real world makes centralized information processing a near-impossible task, they have turned to a collective explanation that uses localized control distributed throughout parts of the system based on specific interactions with local environments. As a comparison, Reed’s (1982) action system model (Figure A-8) of control in the nervous system sounds very much like a distributed control architecture with local control, and that is because it indeed is, implemented in the “wetware” of the nervous system rather than the “hardware” of computer electronics.

Thus, it should become evident from the progression of the motor control and robotic bodies of research in the last century that a transition is occurring from central control approaches and behavior specification to collective control approaches and behavioral emergence. Indeed, this transition in both disciplines reflects the larger trend in humanity’s scientific endeavors over the centuries. Traditionally, science has relied on a reductionistic paradigm to understand nature through decomposition of systems into parts. While this approach might work with simple systems, humans have begun to realize only in the latter half of the 20<sup>th</sup> century that complex systems are synergistically organized. That is, there is no way a full understanding of a complex system can be

discovered by a fractional examination of its parts, because the behavior is an emergent property of the *interactions* of those parts upon assembly (Kelly, 1994).

While the human motor control and robotic disciplines have focused on the same problem of how to control systems with large number of degrees of freedom, their approaches, techniques, and domain knowledge have been different. By designing robotic control systems from scratch, the engineer knows everything about how they are built and, presumably, how they work. On the other hand, the investigator of human motor control is more like a detective attempting to understand the previously unknown by creating explanatory scenarios from incomplete facts.

Yet despite these differences, both disciplines have converged on distributed control systems as their contemporary explanation or implementation method. This perspective is well in line with the study of complex systems in general, which has made it more and more evident that biological systems employ a method of computationally-isolated local controllers that use simple rules to produce complex, adaptive behavior (Kauffman, 1992; Kelly, 1994).

Indeed, study of the nervous system, one of the most complex systems in nature, has led to contemporary thinking, influenced by the ecological approach to motor control, that suggests that nervous systems use a collection of simple neurophysiological units that are synergistically interconnected to produce the extraordinarily diverse array of possible movements of everyday fine motor activities (Korienek, 1992; Reed, 1996; Korienek, Harty, & Bautista, 2000). By modeling the nervous system in this collective capacity and operationalizing the fundamental control aspects, robot designers can begin to build robots that produce the same degree of behavioral complexity as that produced by biological nervous systems.

Thus, to fully understand how movement is controlled in biological organisms and how movement can be controlled in robots, emergence must be examined and tested as the controlling influence in collective architectures. Through innovative robotic approaches to the study of motor control, which ultimately benefit both the robotics and the motor control disciplines, it is hoped that this understanding can be achieved.

## 6. IMPLICATIONS

The benefit to robotics and motor control researchers by understanding and expanding upon the convergence of their two bodies of knowledge is invaluable. Not only can better robots be built based on a more comprehensive understanding of their biological counterparts, but also motor control experimenters can begin to use robotic models as testing platforms that circumvent the problems of variability in biological models by distilling to the critical issues of control.

In the field of robotics, one ultimate goal is to create artificial organisms that exhibit, and even surpass, the behavioral capabilities of naturally-evolved biological organisms. While robot designers have always used biological inspirations, the approach to carefully examine the underlying control systems of organisms rather than just their morphologies is an emerging trend.

As such, the current capability profile and prevailing conception of robots is still skewed as “repeatable and precise machines in controlled environments”. Only recently have new generations of robots using more distributed control architectures shown some preliminary degree of autonomous and adaptive characteristics. To proceed a step further than the typical distributed architecture, the key to full autonomy and adaptability appears to lie ultimately with collective control based on human motor control models and the notion of emergence as opposed to specification of behaviors.

However, the ways in which emergence arises from simple rules implemented by a large number of interacting parts is not easily determined, and it is on this fundamental problem that the research efforts of roboticists and motor control researchers alike should be focused. Specifically, to promote research in this direction, designing for emergence of behavior should be the rule-of-thumb approach in robotics rather than designing for specification. This can be done by building in redundancy of behavioral capability rather than specified pre-programmed responses. Instead of storing information in the robot, sensory awareness of the robot should be increased to allow it access to information already embedded in the environment. This way the robot can use affordances, or context-specific relationships with the environment, to create its behavior.

The behavioral mechanism of a robot should be one of regulating, or continuously modulating, its behavior in resonance with encountered environmental perturbations. A robot, like biological organisms, needs no representation of the environment, because it is maintaining continuous sensory contact with the environment. In this sense, the conventional “perception as stimuli” and “action as response” relationships do not hold. Rather, there can be a continuous “perception-action” linkage between the robot and the environment in an ongoing regulatory process that is the robot’s behavior (Korienek, Harty, & Bautista, 2000).

But perhaps the single most important breakthrough that motor control research has to offer the future of robotic control is the role of the environment as understood by ecological psychologists. It has already been discovered that there is a consistent interaction of biological organisms with their environment known as animacy (Gibson, 1966; Reed, 1982, 1996). The implication is that a robot should be designed to exhibit animacy in order to successfully use the affordances in its environment. Without animacy there cannot be meaningful interaction with the environment, since the biological-like autonomous, adaptive behavior of a robot, like an animate organism, is modulated by the characteristics of the environment.

In addition, roboticists and motor control research should address the following questions: How much informational sharing is necessary between segments? How can increased sensor awareness be used to build more adaptable “intelligent” control systems? How can higher-level behavioral “intents” be managed in a collective architecture? To answer these questions and others, members of both disciplines must be willing to explore and implement the most current principles of human motor control that attempt to account for its complex and dynamic nature (Easton, 1972, 1974; Greene, 1972, 1982; Reed, 1982, 1988; Turvey, 1977, 1990).

In closing, it is hoped that the exploration and successful implementation of biologically-inspired collective architectures as control systems for robots can ultimately achieve the following characteristics (3 Sigma Robotics, 2000; Dudek et al., 1996; Kube & Zhang, 1993a, 1993b; RIKEN, 1992):

- (1) Fault-tolerant and fail-safe operation in hazardous and remote environments
- (2) Fully autonomous operation with no human intervention required
- (3) Ability to adapt to changing environments and task requirements
- (4) Life-like behavioral complexity which emerges from the interactions of multiple, simple elements
- (5) Lower overall costs from the simplification of the individual elements

Furthermore, it is anticipated that the results gained from a convergence of human motor control research with robotic control technology using collective control ideas will widen the breadth of applications for robots that previously were limited due to the traditional centralized control paradigm.

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## Appendix B: Complete List of Control Rules

This appendix contains the control rules, listed in production rule format, for all experiments conducted in this thesis research. The following list indicates which table describes which experiment. Table B-17 is a summary of the experimental layout for this research.

<u>Table Number</u>	<u>Rule Set</u>
B-1	General Distal Segment Control Rules for all Experiments
B-2	Facilitative Chaining – Distal Segment
B-3	Facilitative Chaining – Non-Distal Segments
B-4	Inhibitive Chaining – Distal Segment
B-5	Inhibitive Chaining – Non-Distal Segments
B-6	Withdrawal Reflex 1 – Distal Segment
B-7	Withdrawal Reflex 2 – Distal Segment
B-8	Withdrawal Reflex 2 – Non-Distal Segments
B-9	Withdrawal Reflex 3 – Distal Segment
B-10	Withdrawal Reflex 3 – Non-Distal Segments
B-11	Withdrawal Reflex 4a – Distal Segment
B-12	Withdrawal Reflex 4a – Non-Distal Segments
B-13	Withdrawal Reflex 4b – Distal Segment
B-14	Withdrawal Reflex 4b – Non-Distal Segments
B-15	Withdrawal Reflex 5
B-16	Withdrawal Reflex 6
B-17	Summary Table of all Experiments

Table B-1: General distal segment control rules for all experiments

(Note: CW = Clockwise, and CCW = Counterclockwise)

Distal Segment Rule #1

IF: Laser point location is “on target,”  
 THEN: Do not rotate in any direction.

Distal Segment Rule #2

IF: Laser point location is not “on target,”  
 AND IF: Laser point location is on the 2D target plane,  
 AND IF: Pointing error to the target can be decreased via rotation,  
 THEN: Rotate CW or CCW (which ever requires the smaller rotational magnitude) until the laser pointer location is as close as possible to the target.

Distal Segment Rule #3

IF: Laser point location is not “on target,”  
 AND IF: Laser point location is not on the 2D target plane,  
 AND IF: Laser point location is on a hypothetical infinite extension of the target plane,  
 THEN: Rotate CW or CCW until the laser pointing location is as close as possible to the target as subjectively determined on the hypothetical infinite extension of the target plane.

Distal Segment Rule #4

IF: Laser point location is not “on target,”  
 AND IF: Laser point location is not on the 2D target plane,  
 AND IF: Pointing direction is pointing either parallel to or away from the hypothetical infinite extension of the target plane,  
 THEN: Rotate CW or CCW (whichever produces the smallest magnitude of rotation) until the laser pointer is pointing at the hypothetical infinite extension of the line which is perpendicular to the hypothetical infinite extension of the positive direction of y-axis on the target grid.

(Table 1 is continued on next page)

Table B-1 (cont'd): General distal segment control rules for all experimentsDistal Segment Rule #5

- IF: The location of the laser pointer falls on the surface of the obstacle,  
 THEN: Continue rotation (even though the closest point to the target is “through” the obstacle) so that the location of the laser pointer is NOT on the surface of the obstacle, but at the point closest to the target which is off the obstacle.

Table B-2: Distal segment control rules for “Facilitative Chaining”Distal Segment Rule #6

- IF: Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,  
 THEN: Stop rotation at the obstacle.

Table B-3: Non-distal segment control rules for “Facilitative Chaining”Non-Distal Segment Rule #1a

- IF: Distally-adjacent segment moves  $\theta^\circ$  CW.  
 THEN: Rotate ( $\theta^\circ * 0.667$ ) CW.

Non-Distal Segment Rule #1b

- IF: Distally-adjacent segment moves  $\theta^\circ$  CCW.  
 THEN: Rotate ( $\theta^\circ * 0.667$ ) CCW.

Non-Distal Segment Rule #2

- IF: Continued movement during a normal CW or CCW rotation is inhibited by an obstacle or another segment,  
 THEN: Stop my rotation at that point.

Table B-4: Distal segment control rules for “Inhibitive Chaining”

Distal Segment Rule #6

IF: Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,  
 THEN: Stop rotation at the obstacle.

Table B-5: Non-distal segment control rules for “Inhibitive Chaining”

Non-Distal Segment Rule #3a

IF: Distally-adjacent segment moves  $\theta^\circ$  CW.  
 THEN: Rotate ( $\theta^\circ * 0.667$ ) CCW.

Non-Distal Segment Rule #3b

IF: Distally-adjacent segment moves  $\theta^\circ$  CCW.  
 THEN: Rotate ( $\theta^\circ * 0.667$ ) CW.

Non-Distal Segment Rule #4

IF: Continued movement during a normal CW or CCW rotation is inhibited by an obstacle or another segment,  
 THEN: Stop my rotation at that point.

Table B-6: Distal segment control rules for “Withdrawal Reflex #1”

Distal Segment Rule #7 (see Figure B-1)

- IF: Initial movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment (i.e. this is the case where the distal segment begins its movement already against an obstacle),
- THEN: Reverse direction and attempt to point as close as possible to the target.

Table B-7: Distal segment control rules for “Withdrawal Reflex #2”

Distal Segment Rule #8 (see Figure B-1)

- IF: Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,
- THEN: Reverse direction and attempt to point as close as possible to the target.

Table B-8: Non-distal segment control rules for “Withdrawal Reflex #2”

Non-Distal Segment Rule #5 (see Figure B-1)

- IF: A reversal in movement direction by distally-adjacent segment is sensed,
- THEN: Compute movement magnitude as  $[0.667 * (Y^\circ - X^\circ)]$ , where  $X^\circ$  = the magnitude of the distally-adjacent segment’s rotation before the reversal, and  $Y^\circ$  = its magnitude after the reversal. Compute movement direction as the *same* as that of the distally-adjacent segment’s direction before the reversal.

Table B- 9: Distal segment control rules for “Withdrawal Reflex #3”

Distal Segment Rule #8 (see Figure B-1)

- IF: Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,
- THEN: Reverse direction and attempt to point as close as possible to the target.

Table B-10: Non-distal segment control rules for “Withdrawal Reflex #3”

Non-Distal Segment Rule #6 (see Figure B-1)

- IF: A reversal in movement direction by distally-adjacent segment is sensed,
- THEN: Compute movement magnitude as  $[0.667 * (Y^\circ - X^\circ)]$ , where  $X^\circ$  = the magnitude of the distally-adjacent segment’s rotation before the reversal, and  $Y^\circ$  = its magnitude after the reversal. Compute movement direction as the *opposite of* as that of the distally-adjacent segment’s direction before the reversal.

Table B- 11: Distal segment control rules for “Withdrawal Reflex #4a”

Distal Segment Rule #9 (see Figure B-1)

- IF: Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,
- THEN: Rotate  $Y^\circ$  in the opposite direction, where  $Y = 20^\circ$ .



Table B-12: Non-Distal Segment Control Rules for “Withdrawal Reflex #4a”

Non-Distal Segment Rule #7 (see Figure B-1)

- IF: A reversal in movement direction by distally-adjacent segment is sensed,
- THEN: Compute movement magnitude as:  
 $[0.667 * (X^\circ + (0.20) * X^\circ)]$ , where  $X^\circ$  = the magnitude of the distally-adjacent segment’s rotation before the reversal. Compute movement direction as the *opposite of* that of the distally-adjacent segment’s direction before the reversal.

Table B-13: Distal Segment Control Rules for “Withdrawal Reflex #4b”

Distal Segment Rule #9 (see Figure B-1)

- IF: Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,
- THEN: Rotate  $Y^\circ$  in the opposite direction, where  $Y = 20^\circ$ .

Table B-14: Non-Distal Segment Control Rules for “Withdrawal Reflex #4b”

<u>Non-Distal Segment Rule #7</u> (see Figure B-1)	
IF:	A reversal in movement direction by distally-adjacent segment is sensed,
THEN:	Compute movement magnitude as: $[0.667 * (X^\circ + (0.20) * X^\circ)]$ , where $X^\circ$ = the magnitude of the distally-adjacent segment’s rotation before the reversal. Compute movement direction as the <i>opposite of</i> that of the distally-adjacent segment’s direction before the reversal.
<u>Non-Distal Segment Rule #8</u> (see Figure B-1)	
IF:	Continued movement during a normal CW or CCW rotation of attempting to point as close as possible to the target is inhibited by an obstacle or another segment,
THEN:	Rotate $Y^\circ$ in the opposite direction, where $Y = 20^\circ$ .

Table B-15: Control Rules for “Withdrawal Reflex 5”

<u>Distal Segment Rules</u>
Same as: “Withdrawal Reflex #1” (Table B-6) “Withdrawal Reflex #2 for distal segment” (Table B-7)
<u>Non-Distal Segment Rules</u>
Same as: “Withdrawal Reflex #4b for non-distal segments” (Table B-14)

Table B-16: Control Rules for “Withdrawal Reflex 6”

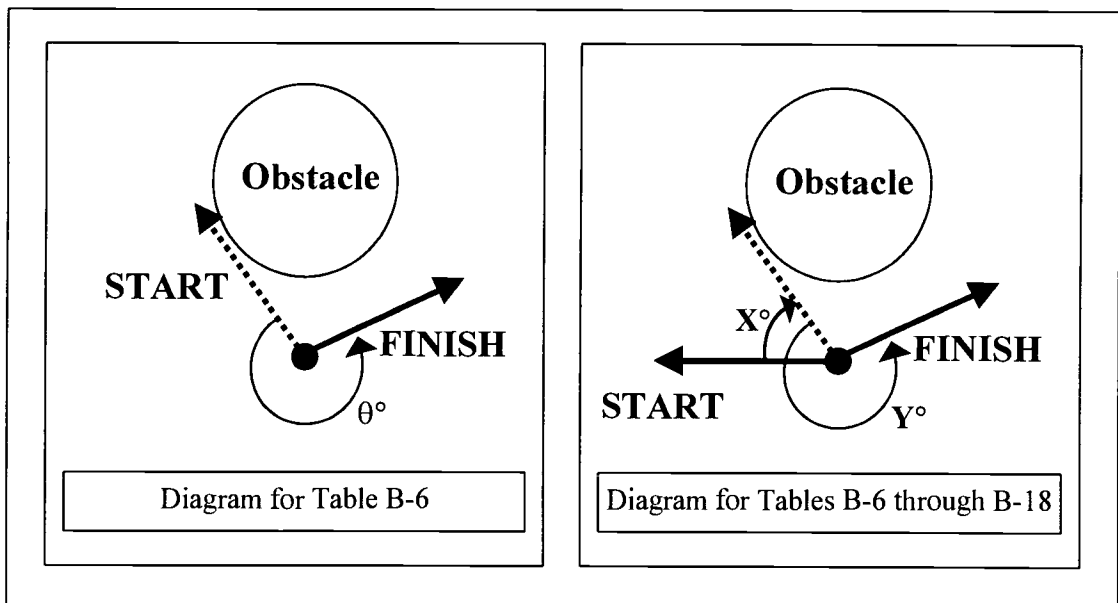
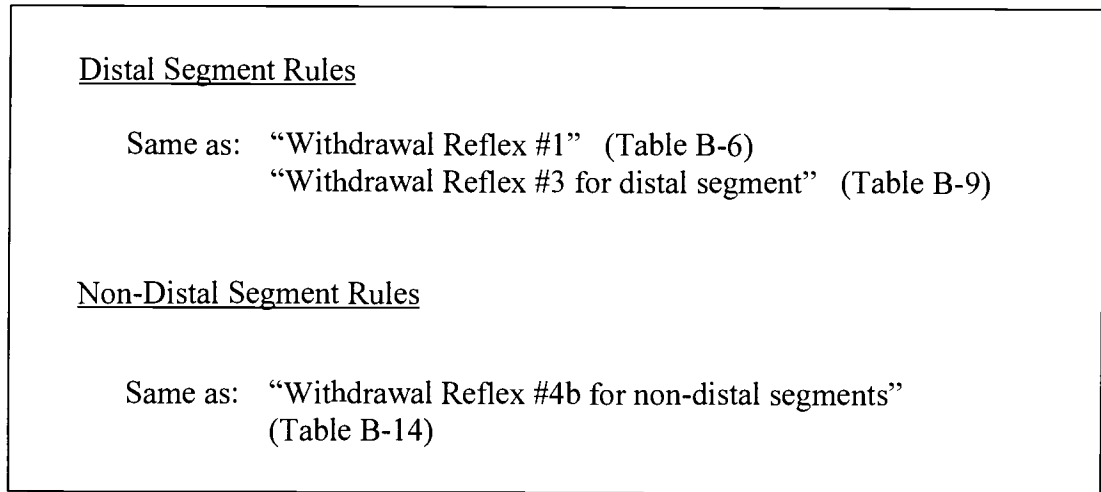


Figure B-1: Diagram for clarifying details of control rules in Tables B-6 to B-14.

**Table B-17:** A list of all experiments conducted in this research based on the combinations of the variables detailed in the text.

<u>Experiment #</u>	<u>Control Rule Set</u>	<u>Number of Segments</u>	<u>Obstacle Present?</u>	<u>Was Exp Unique?</u>	<u>If "NO", same as Exp#</u>	<u>Used in Data Analysis?</u>
1	FC	3	NO	YES		YES
2	FC	4	NO	YES		YES
3	FC	5	NO	YES		YES
4	FC	6	NO	YES		YES
5	FC	7	NO	YES		YES
6	FC	3	YES	YES		YES
7	FC	4	YES	YES		YES
8	FC	5	YES	YES		YES
9	FC	6	YES	YES		YES
10	FC	7	YES	YES		YES
11	IC	3	NO	YES		YES
12	IC	4	NO	YES		YES
13	IC	5	NO	YES		YES
14	IC	6	NO	YES		YES
15	IC	7	NO	YES		YES
16	IC	3	YES	YES		YES
17	IC	4	YES	YES		YES
18	IC	5	YES	NO	13	NO
19	IC	6	YES	YES		YES
20	IC	7	YES	YES		YES
21	FC-nd + WR-1 + WR-2	3	YES	YES		YES
22	FC-nd + WR-1 + WR-2	4	YES	YES		YES
23	FC-nd + WR-1 + WR-2	5	YES	NO	8	NO
24	FC-nd + WR-1 + WR-2	6	YES	YES		YES
25	FC-nd + WR-1 + WR-2	7	YES	YES		YES
26	FC-nd + WR-1 + WR-3	3	YES	YES		YES
27	FC-nd + WR-1 + WR-3	4	YES	NO	22	NO
28	FC-nd + WR-1 + WR-3	5	YES	NO	18	NO
29	FC-nd + WR-1 + WR-3	6	YES	NO	24	NO
30	FC-nd + WR-1 + WR-3	7	YES	YES		YES
31	FC-nd + WR-1 + WR-4a	3	YES	YES		YES
32	FC-nd + WR-1 + WR-4a	4	YES	NO	22	NO
33	FC-nd + WR-1 + WR-4a	5	YES	NO	8	NO
34	FC-nd + WR-1 + WR-4a	6	YES	NO	24	NO
35	FC-nd + WR-1 + WR-4a	7	YES	YES		YES

(Table continued on next page)

**Table B-17 (cont'd):** A list of all experiments conducted in this research based on the combinations of the variables detailed in the text.

<u>Experiment #</u>	<u>Control Rule Set</u>	<u>Number of Segments</u>	<u>Obstacle Present?</u>	<u>Was Exp Unique?</u>	<u>If "NO", same as Exp#</u>	<u>Used in Data Analysis?</u>
36	FC-nd + WR-1 + WR-4b	3	YES	YES		YES
37	FC-nd + WR-1 + WR-4b	4	YES	YES		YES
38	FC-nd + WR-1 + WR-4b	5	YES	YES		YES
39	FC-nd + WR-1 + WR-4b	6	YES	YES		YES
40	FC-nd + WR-1 + WR-4b	7	YES	YES		YES
41	FC-nd + WR-5	3	YES	YES		YES
42	FC-nd + WR-5	4	YES	YES		YES
43	FC-nd + WR-5	5	YES	YES		YES
44	FC-nd + WR-5	6	YES	YES		YES
45	FC-nd + WR-5	7	YES	NO	40	NO
46	FC-nd + WR-6	3	YES	NO	26	NO
47	FC-nd + WR-6	4	YES	NO	42	NO
48	FC-nd + WR-6	5	YES	NO	43	NO
49	FC-nd + WR-6	6	YES	NO	44	NO
50	FC-nd + WR-6	7	YES	NO	40	NO

<b><u>KEY to Abbreviations:</u></b>	
<u>Control Rule:</u>	<u>See the following Tables for details</u>
FC = Facilitative Chaining (Distal and Non-Distal)	B-2, B-3
FC-nd = Facilitative Chaining (Non-Distal rules only)	B-3
IC = Inhibitive Chaining	B-4, B-5
WR-1 = Withdrawal Reflex #1	B-6
WR-2 = Withdrawal Reflex #2	B-7, B-8
WR-3 = Withdrawal Reflex #3	B-9, B-10
WR-4a = Withdrawal Reflex #4a	B-11, B-12
WR-4b = Withdrawal Reflex #4b	B-13, B-14
WR-5 = WR-1 (distal) + WR-2 (distal) + WR-4b (non-distal)	B-6, B-7, B-14
WR-6 = WR-1 (distal) + WR-3 (distal) + WR-4b (non-distal)	B-6, B-9, B-14

## Appendix C: Curriculum Vitae

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### **EDUCATION**

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2000	<b>MS</b>	<b><i>Biological Robotics</i></b> - Oregon State University (GPA 3.9/4.0) <i>Thesis: The Application of Human Motor Control Strategies to a Collective Robotic Arm.</i>
1995	<b>BS</b>	<b><i>Zoology</i></b> - Michigan State Univ (GPA 3.8/4.0 with high honors) <i>(Emphasis in Animal Behavior, Ecology, and Evolutionary Biology)</i>

### **PROFESSIONAL and RESEARCH EXPERIENCE**

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2000 - present	<b>Research Scientist, 3 Sigma Robotics, Corvallis, OR</b> ( <a href="http://www.3sigmarobotics.com/">http://www.3sigmarobotics.com/</a> ) Founding member of this innovative research and advanced development company that conceptualizes next-generation intelligent robotic systems which yield creative solutions to real world problems for a wide range of application domains in the aerospace, energy, communication, toy, & medical industries.
Summers 1998-99	<b>Research Biologist (GS-7), Gravitational Research Branch, Life Sciences Division, NASA Ames Research Center, Moffett Field, California</b> Part of research team (PI: Robert B. Welch, Ph.D.) which designed and built a preflight adaptation trainer for astronauts which simulates both the visual and the bodily sensations of walking in the .38-g conditions of Mars via a lower body positive pressure device coupled with a treadmill and a computer-generated virtual Mars valley.
1998 - 2000	<b>NSF Graduate Research Fellow, Biological Control Lab, Oregon State Univ., Corvallis, OR</b> Investigated the principles of emergent control structures in human motor control and used to design biologically inspired robotic limbs. Part of this effort involves the software simulation and prototype design of a robotic limb modeled as a collection of agents whose emergent behavior results in pointing, reaching, and grasping behavior.
Summer 1998	<b>NASA Astrobiology Academy Fellow, Ames Research Center, Moffett Field, CA.</b> I was a member of this 10-week summer institute of higher learning whose goal is to guide future leaders of the U.S. Space Program through interaction with scientists, engineers, and leaders in government, academia, and private sectors; participation in multidisciplinary research; and visiting key space research & industrial facilities.
1997-1998	<b>Veterinary Research Technician, Mich St Univ Veterinary Hospital, East Lansing,</b>

- 1995-1996 **Wildlife Biologist**, Spotted Hyena Project, Masai Mara National Reserve, *Kenya* and Dept. of Zoology, Michigan State University (Funded by National Science Foundation & Packard Foundation)  
 Research Manager for a study of free-living spotted hyenas (*Crocuta crocuta*) for K.E. Holekamp, Ph.D. Observed, recorded, & analyzed data for studies of rank inheritance, natal dispersal, behavioral endocrinology, and immunocompetence. Performed darting; immobilization; tagging; handling; measuring; necropsy; radio telemetry by vehicle, foot & hot-air balloon. Collected blood, tissue, DNA, and fecal samples for analysis. Maintained service of vehicles, field camp, & lab equipment. Cooperated with local government and wildlife officials. Supervised camp attendants; budgeted accounts of grant-related purchases. [Full-time for 12 months]
- Winter 1993/94 **Field Videographer & Design Assistant**, Virgin Islands National Park, *St. John & St. Croix, U.S. Virgin Is.* & Communication Technology Lab, Mich. St. Univ., *E. Lansing, MI*  
 Member of a design and video production team on location for an interactive educational CD-ROM computer program about ecology and natural history of the U.S. Virgin Islands, based a Michigan State University Overseas Study course, "Natural Science in the Virgin Islands", taught by Dr. L.C. Besaw.
- Summer 1993 **Biological Research Assistant**, School for Field Studies, *Beverly, MA*  
 Study (with D.M. Bruns-Stockrahm, Ph.D.) of population ecology and communication system of free-living Gunnison's prairie dogs (*Cynomys gunnisoni*) and established protocol for studying warning bark behavior.
- Spring 1993 **Research Assistant**, Fruit & Tree Nut Research Lab, U.S. Dept. of Agriculture, *Byron, GA*  
 Performed laboratory growth-chamber studies (with B.W. Woods and W.L. Tedders) on long-term project manipulating photoperiod effects on sexual cycles of pecan tree aphids as a potential means of biological control.
- Summer 1992 **Research Assistant**, Georgia Dept. of Natural Resources & Valdosta St. Univ, *Valdosta, GA*  
 Conducted population survey and management strategy for the endangered gopher tortoise in south Georgia.

## ACADEMIC AWARDS and HONORS

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- 1999 **National Science Foundation Graduate Research Fellowship.**  
 Title: "*Applying the Principles of Biological Control to Robotics and Prostheses*"
- 1999 **National Defense Science & Engineering Graduate Fellowship** (declined)  
 U.S. Dept of Defense
- 1993 **Alumni Distinguished Scholarship** (4-year full-tuition award), Michigan State Univ,
- 1993 **United States Presidential Scholar**, U.S. Department of Education, *Washington, DC*
- 1993 **National Science Scholar**, U.S. Department of Education, *Washington, DC*

## PUBLICATIONS and PRESENTATIONS

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- Korienek, G.G., Harty, T.H., & Bautista, A.B. (2000). Sensory Interactions with the Environment: Insights and Concepts from Ecological Psychology. Submitted to: *Artificial Life (Special Issue on "Evolution of Sensors in Nature, Hardware, and Simulation")*.
- Korienek, G. G., Bautista, A. B., Harty, T.H., & Leddon, C. (2000). The use of biologically-inspired rules to control a collective robotic arm. *Distributed Autonomous Robotic Systems 4*. Berlin: Springer-Verlag.
- Korienek, G.G., Harty, T.H., Leddon, C., & Bautista, A.B. (2000). Emergent Behavior of a Robotic Limb: An Example of a Biologically Inspired Collective Control Architecture. NASA Workshop on Biomimetic Robotics, August 14 - 16, 2000. NASA Jet Propulsion Laboratory, California Institute of Technology.

- Harty, T.H.** (2000). "To Rake and Plunger! Ballad of the Viking Handymen." *Prism: Oregon State University Student Literary-Arts Magazine* Vol. XXV, No. 2 (Spring 2000). Ed: S. Albers.
- Korienek, G. G., Bautista, A. B., **Harty, T.H.**, & Leddon, C. (2000). An investigation into the biological regulation of a robotic limb. To be submitted to: *Journal of Adaptive Behavior*.
- Harty, T.H.** (2000). "A Code of Medical Ethics for the New Millennium." *Reflections: Newsletter of the Program for Ethics, Science, and the Environment* Vol 7(1). Oregon State University.
- Korienek, G.G., **Harty, T.H.**, Leddon, C., & Bautista, A.B. (February 2000). *Emergent Behavior of a Robotic Limb: And Example of a Biologically Inspired Collective Control Architecture*. Poster presented at: Space & Robotics 2000, Albuquerque, NM.
- Welch, R.B., Korienek, G.G., Schwandt, D., Leddon, C., **Harty, T.H.**, & Vanyo, C. (February 2000). *Adapting to Simulated Altered Gravity*. Poster presented at: Space & Robotics 2000, Albuquerque, NM.
- Korienek, G.G., Leddon, C, & **Harty, T.H.** (2000). "*Mars Pants*": *A Lower Body Pressure Differential Approach to Locomoting in Simulated Altered Gravity*. Poster at: Space & Robotics 2000, Albuquerque.
- Harty, T.H.** (April 1999). *The Application of a Biologically Inspired Collective Control Architecture to a Robotic Limb*. Graduate Student Conference 1999, Oregon State University, Corvallis, OR.
- Harty, T.H.** (August 1998). *Adapting to Simulated Altered Gravity*. Presented to: Astrobiology Academy, NASA Ames Research Center, Moffett Field, CA.
- Welch, R.B., Korienek, G. G., Aratow, M., Schwandt, D., **Harty, T.H.** , Bhatia, N.L., Whalen, R., & Boda, W. (July 1998). *Adapting to Simulated Altered Gravity*. Poster presented at: Life Sciences Division, NASA Ames Research Center, Moffett Field, CA.
- Aho, M.D., D.M. Bruns-Stockrahm, S.L. Adolf, B.L. Steffan, **T.H. Harty**, & Workman, T.M. (1994). Warning barks and alarm behaviors of Gunnison's prairie dogs (*Cynomys gunnisoni*) in Colorado. *Proceedings of the North Dakota Acad. of Sci.* 48:70.
- Harty, T.H.** (1994). From the Serengeti to the Canadian Rockies. *HConnection: A Newsletter of the Michigan State University Honors College*. Vol 3(2/Nov1994):3 & 6.