SENSORY MOTOR COORDINATION IN ROBONAUT

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ABSTRACT

As a participant of the year 2000 NASA Summer Faculty Fellowship Program, I worked with the engineers of the Dexterous Robotics Laboratory at NASA Johnson Space Center on the Robonaut project. The Robonaut is an articulated torso with two dexterous arms, left and right five-fingered hands, and a head with cameras mounted on an articulated neck. This advanced space robot, now driven only teleoperatively using VR gloves, sensors and helmets, is to be upgraded to a thinking system that can find, interact with and assist humans autonomously, allowing the Crew to work with Robonaut as a (junior) member of their team. Thus, the work performed this summer was toward the goal of enabling Robonaut to operate autonomously as an intelligent assistant to astronauts.

Our underlying hypothesis is that a robot can *develop* intelligence if it learns a set of basic behaviors (*i.e.*, reflexes – actions tightly coupled to sensing) and through experience learns how to sequence these to solve problems or to accomplish higher-level tasks. We describe our approach to the automatic acquisition of basic behaviors as *learning sensory-motor coordination* (SMC). Although research in the ontogenesis of animals (development from the time of conception) supports the approach of learning SMC as the foundation for intelligent, autonomous behavior, we do not know whether it will prove viable for the development of autonomy in robots. The first step in testing the hypothesis is to determine if SMC can be learned by the robot. To do this, we have taken advantage of Robonaut's teleoperated control system. When a person teleoperates Robonaut, the person's own SMC causes the robot to act purposefully. If the sensory signals that the robot detects during teleoperation are recorded over several repetitions of the same task, it should be possible through signal analysis to identify the sensory-motor couplings that accompany purposeful motion.

In this report, reasons for suspecting SMC as the basis for intelligent behavior will be reviewed. A robot control system for autonomous behavior that uses learned SMC will be proposed. Techniques for the extraction of salient parameters from sensory and motor data will be discussed. Experiments with Robonaut will be discussed and preliminary data presented.

INTRODUCTION

To interact naturally with people in a human-centered environment, a robot must be able to coordinate sensing with action. That is, it must have Sensory-Motor Coordination (SMC). It is possible to program a certain degree of SMC into a robot prior to its deployment. But it is impossible for a programmer to anticipate every physical contingency that may arise in a robot's interactions with people. This is due to the intrinsic complexity of a human-centered environment. Only animals (including people) have SMC that permits them to work effectively in a complex natural world. If SMC in animals were well understood – if the structures and functions of the systems that manifest it were known – then analogous systems could be implemented in robots.[1] SMC in animals is not completely understood, but research in it has recently advanced to the point where plausible mechanisms for it have been described. Evidence from studies in neurophysiology [1], ontogenesis [2,3], and cognitive science [4] suggests that to interact effectively and efficiently with its environment, an animal must learn through its own experiences the reciprocal causative relationships between sensing and action that foster its success or survival (cf. below). That is, SMC must be learned, or at least refined, through an animal's direct experience with acting in the world.

Schema theory [4] can be used to describe the functional aspects of an animal's behavior without exact specification of the biological systems that support it. Schemas exist at a frame of reference higher than that of the individual computational elements (neurons in the case of animals). A schema description of the behavior of an animal is inherently modular. It provides a framework for the description of behaviors in terms of the interactions of modules that control motion, process sensory information, create and recall memories, etc. In animals, the modules may more or less directly correspond to specific networks of neurons. But this separation of function from structure affords the possibility of realizing the behavior of an animal in a robot by substituting computers and electro-mechanical devices for neuron networks and bio-mechanical subsystems. Behavior-based robots (BBR) [5,6] are particularly amenable to this. BBRs act through the combination of *basic behaviors*, which are motor actions tightly coupled to sensory stimuli – both external to the robot and internal (*i.e.*, proprioceptic).

This report proposes a method for the learning of sensory-motor coordination through the teleoperation of a behavior-based robot. The goal of the work is to enable a robot to learn SMC by finding the correlations between sensory events and motor control events that co-occur during task execution. The robot is guided by a human operator through repeated trials of a specific task while recording all its incoming sensory data. The motor and sensory data gathered throughout the trials will be analyzed to find representative couplings between sensory stimuli and motor actions. If successful this will not

[1] Implementation is possible if the *functionality* of the biological systems can be reproduced in electro-mechanical systems. Schema theory suggests that it can. (cf. below).

only permit the robot to perform the task autonomously, but also (with an appropriate control system) enable the robot to adapt to variations in the task or in the environment.

SENSORY-MOTOR COORDINATION

Sensory-Motor Coordination underlies the physical behavior of an animal in response to its environment. More than a response, SMC is a feedback loop that changes both the animal and the environment. An animal's motions are caused by muscle contractions. These contractions are elicited by electrochemical signals that are generated by circuits of motor neurons. When the animal moves, it causes a relative shift in the environment. As the environment shifts, energy patterns sweep across the animal's sensory organs. Sensory organs are transducers that, in effect, transform external, spatio-temporally dynamic energy fields into electrochemical signals carried by circuits of sensory neurons internal to the animal. These sensory signals (more or less directly) modulate the signals in the original motor circuits. Learning occurs in the mapping from sensory response signal to motor control signal. Thus, an animal senses the environment and acts. The action changes the environment relative to the animal, which senses those changes and acts accordingly.

SMC is likewise needed by a sensory-guided robot. The basic behaviors of a BBR are independent units of SMC. They include what are commonly called reflex actions. When a basic behavior is enabled[2] and the stimuli associated with it occur, the action is performed -- without resort to modeling or deliberation. Basic behaviors are canonical in the sense that all actions exhibited by the robot are generated through the cooperation and competition of basic behaviors operating concurrently or in sequence. At any given point in time, some of the basic behaviors will be enabled and others suppressed depending on the task and environmental context of the robot. Since a BBR exhibits any and all its behaviors through the combination and sequencing of basic behaviors, a BBR is wholly dependent on, and to a large extent defined by, sensory motor coordination.

Sensory-motor coordination is fundamental for another compelling reason. It forms a foundation for higher level learning and perception. In particular, the categorization of sensory stimuli can be accomplished through SMC [7]. A mobile agent can learn the sensory patterns that correspond to an obstacle by associating stimuli with its motor responses, as when a characteristic stimulus pattern routinely accompanies the sudden inability to move. Similarly, as Pfeifer has demonstrated, an agent can learn to distinguish between objects that it can manipulate and those which it cannot [8]. If the internal sensation of a need (a drive or a goal) having been satisfied accompanies a set of actions performed in the presence of specific stimuli, that stimuli can be recognized as

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[2] A BBR typically has a suite of basic behaviors, not all of which are operational at the same time. Depending on the task and environmental contexts, various basic behaviors will be enabled or disabled. If a behavior is enabled – made operational – it will remain quiescent until its triggering sensory stimuli are present.

being beneficial to the agent (*e.g.*, an energy source -- food). Recent experiments by Pfeifer and others have demonstrated that such SMC events can be used to learn classifications of objects and events in the environment more easily and more accurately than can traditional machine sensing strategies such as model-based vision [9,10].

SCHEMA THEORY

Since the behavior of animals is mediated by their nervous systems, the understanding of their behavior from first principles requires an understanding of nervous systems. Neuroscience has provided a structural description that includes neurons (individuals and networks) and layers, columns, and modules in the brain [11]. But the *function* of these structures is not completely understood and it is function more than structure that determines behavior. Functional analysis is complicated by the fact that many of the neuronal structures participate in different functions. With certain exceptions there are no discernible one-to-one mappings of low-level structure to high-level function [4].

Arbib *et al.* employ schema theory "as a framework for the rigorous analysis of [animal] behavior that requires no prior commitment to hypotheses on the location of each *schema* (unit of functional analysis) but can be linked to a structural analysis as and when it becomes appropriate." [4] (p. 33). Thus schemas are descriptions of functions that are performed by networks of neurons and the muscles and appendages that they control. Schema theory enables the top-down analysis of a complex behavior by providing a structure for logically dissembling it, that is it facilitates the analytical decomposition of a complex behavior into sets of simpler behaviors. On the other hand, schemas also enable the bottom-up analysis of sets co-occurring behaviors. The collective behavior of a set of simple schemas can be deduced if the framework for their competition, cooperation, and sequencing is known. This collective behavior is a higher-level schema called an *assemblage*. Not only are the behaviors of animals describable by schemas but also are the control systems of behavior-based robots. BBRs are, given their modular architectures, particularly amenable to such description. The theory of behavior-based robotics is grounded on the idea that complex behavior in an agent emerges through the competition and cooperation of simple behaviors in the context of an environment, which is precisely the idea of assemblage in schema theory.

To the extent that function can be separated from structure, a schema representation enables a specific behavior to be performed by agents with dissimilar computational hardware. In particular, a behavior observed in an animal that can be described accurately by schemas could be implemented on an appropriately structured robot. Schemas, therefore, provide for comparative analysis of similar behaviors on dissimilar agents, be they bio-chemical or electro-mechanical.

Arbib *et al.* group schemas in two categories. *Motor schemas* are "the control systems which can be coordinated to effect the wide variety of movement. A set of basic motor schemas is hypothesized to provide simple, prototypical patterns of movement." *Perceptual schemas* "are those used for perceptual analysis. They embody the processes whereby the system determines whether a given domain of interaction is present in the environment. They not only serve as pattern-recognition routines but can also provide the appropriate parameters concerning the current relationship of the organism with its environment." [4] (p. 42).

Research in the ontogenesis of animals has demonstrated that the ability to move exists prior to an animal's ability to sense its environment. Arbib *et al.* state that this "does not, however, imply that motility is an end in itself. Rather this, 'motor foundation' serves to group the later development of sensory maps and sensorimotor representations in a self-directed manner." [4] (p.10). Thus, in animals the formation of the musculo-skeletal system and the neuro-circuits for motor control precedes the development of perceptual schemas. Such a development schedule makes sense. Perceptual schemas in animals, even if passed on phylogentically, must be tuned; sensory stimuli is required for a perceptual modality to develop. Other perceptual schemas (*e.g.*, a semantic description of a visual object) must be learned. On the other hand, an animal must, to a certain extent, "hit the ground running" to survive. Motion must precede perception so that the animal can move at birth and so that the effects of its motion can be perceived and learned. Perceptual schemas, must therefore be learned or tuned in concert with motion. Simultaneously, motor schemas must be tuned to enable efficient sensing. Thus, sensory-motor coordination requires the coupling of perceptual schemas and motor schemas into assemblages. Perceptual schemas provide goal and trajectory information to the motor schemas, whereas the latter provide a physical framework within which a perceptual schema can extract salient information. Arbib *et al.* place motor schemas and perceptual schemas at the foundation of animal function. Under the influence of the environment these schemas self-organize to control an animal's behavior.

For the designers of robots the main implication of the onset of motility prior to sensation in animals is that reflexes are not primary. (See [4] Sec. 2.1.1, p. 13 f.f.) Put in another way, basic behaviors are not truly basic. Motion is primary; it can happen without sensing. Reflexes develop with the onset of sensing. Then sensory signals modulate the signaling of motor circuits and reflexes emerge.

SCHEMAS AND SMC IN BEHAVIOR BASED ROBOTS

The following four examples of behavior-based robot control systems depend on SMC and can be described through assemblages of schemas. Each of the architectures has basic behaviors at its foundation. In each case, the basic behaviors are selected by the designer of the robot. Each of the architectures can be designed to learn, and as a result exhibit emergent SMC. The learning, however, occurs at levels above basic behaviors.

Brooks' subsumption architecture

Brooks' subsumption architecture controls a robot through a collection of augmented finite state machines (AFSM) organized into layers [5]. A subsumptive robot has no central planner or controller. Each AFSM can be activated by sensory inputs and produces outputs that drive actuators or are passed to the inputs of other modules. Within subsumption, the AFSMs are motor schemas. The sensory inputs are perceptual schemas. An AFSM with well-defined sensory input implements a basic behavior. Assemblages are formed dynamically as AFSMs at one level are activated or inhibited by AFSMs at a higher level. Usually the basic behaviors in the lowest layer are preprogrammed; the sensory signals that trigger an AFSM are not learned. Learning can take place in a subsumption architecture, (*e.g.*, Brooks' robot, Ghengis [12]) but generally this occurs in layers above the first.

Mataric's action-oriented representations.

Mataric designed, using subsumption, a mobile robot that learns to navigate an environment through the use of action-oriented representations [13]. The robot both generates and operates from an "action map" of the environment. While wandering in the environment and reacting to sensory input according to its basic behaviors (*e.g.*, wall following, object avoidance, etc.) the robot generates the map by building up a directed graph. Each node of the graph contains a description of the motor state at the time of its formation and description of the sensory data that was received as the robot performed the actions described by the motor state. Adjacent nodes in the graph correspond to adjacent areas in the environment. Once the environment has been mapped, the robot can reach a physical location by activating the corresponding node of the graph. The graph is searched (using spreading activation) back from the goal node to the node that represents the current position of the robot. The nodes along the shortest connecting path are enabled. The robot reaches the goal by moving according to the motor commands of its current node until its sensory input more closely matches the data from the next node. Then it executes the motor commands from next node and proceeds successively from node to node until the goal is reached.

Mataric's robot learns while acting by forming a spatio-temporal sensory-motor description of the environment. The map indicates the sensory and motor status of the robot at a particular point in space at a particular time relative to the current position. Thus, the robot learns how to sequence and basic behaviors from sensory input. This is undoubtedly a form of SMC but it learns the sequencing of basic behaviors rather than the SMC that defines the basic behaviors themselves.

Arkin's Motor Schema.

A robot controlled by Arkin's motor schema[3] architecture follows gradients in a vector field map of its environment [14]. Computational modules such collision detectors and obstacle or object recognizers are perceptual schemas since they compute the vectors at points in space that serve to impel the robot. Motor schemas (in Arbib's sense) within Arkin's architecture are assemblages of motor controllers that respond individually to components of the vector field map. A motor controller generally has a fixed response

[3] *Motor Schema* is the name that Arkin has given his control architecture. It makes use of both perceptual schemas and motor schemas in the sense that Arbib describes them.

to its input vector. The response is a function of the magnitude and direction of the input vector, but that function is generally preprogrammed and does not change. Any learning that occurs happens in the perceptual schemas that compute the vector field.

Pfeifer's SMC-based categorization.

Pfeifer's robots are based on an extended Braitenberg architecture, another type of BBR [15]. A number of basic behavior modules (Pfeifer calls these "reflexes") operate in parallel, receiving sensory inputs (including proprioception) and summing their outputs onto the motor controllers [8]. The response of each behavior module to its inputs is preprogrammed. The overall robot system does learn, however, as it interacts with the environment, guided by a "value system." Values are, essentially, the preprogrammed reflexes and reinforcement schemes, that cause the robot to seek some sensory stimuli and to avoid others. Learning occurs through the adaptive modulation of sensory signals that are fed to the behavior modules.

Pfeifer defines categorization of an object as the robot's appropriate interaction with the object. Through the value-based learning scheme the robot learns how to couple sensing with actuation so that appropriate behaviors are learned for different stimulus patterns. Thus the objects that project the different stimulus patterns are classified *de facto* without forming an abstract model of the object. Pfeifer's robot learns about objects by finding the correlations between sensory signals and behaviors that lead to favorable results and by decoupling behaviors from stimuli when that coupling leads to unfavorable results. Thus, an appropriate linkage between sensing and action at the task level is learned by trial and error.

LEARNING BASIC BEHAVIORS

Behavior-based robots employ schemas implicitly. Their complex behaviors emerge through the interaction of a canonical set of basic behaviors, each of which is a sensory-driven motor controller. Therefore, in a BBR high-level behavior emerges from assemblages of perceptual schemas linked to motor schemas, just as in animals. In terms of schema theory, the practice of designing BBRs differs from the ontogenesis of animals. The designer of a BBR must decide *ad hoc* or through trial and error, exactly which coupling of sensory data to motor controller constitutes a useful basic behavior. And the designer must decide which basic behaviors to include in the canonical set. He or she determines the perceptual to motor schema linkage at the base level and decides which of these first-order assemblages to include on the robot.[4] In other words, the designer programs SMC into the robot at the lowest level.

BBRs that learn, such as those described in the previous section, learn at the level above basic behaviors. They learn which behaviors to activate and which to inhibit or to suppress under various sensory conditions, or they learn an appropriate sequence of be-

[4] In some BBRs the higher-order assemblages are also completely specified by the designer. Such robots cannot learn.

haviors in response to sensory input, or they learn a control function that modulates the sensory signals before they reach the basic behaviors. While these robots might work well, they are still subject to the errors and oversights of their designers in programming SMC into the functional base-level of the robot.

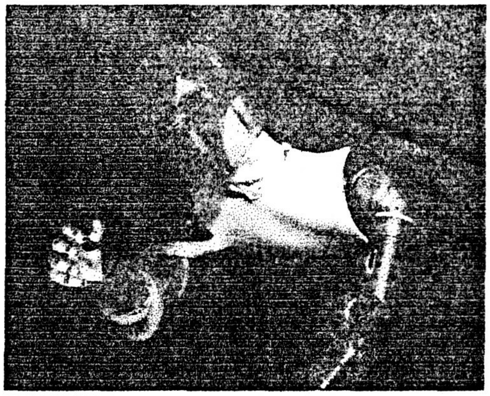
How, then, does one enable a robot to learn SMC at the level of basic behaviors? There are at least two possibilities:

1. Design and implement on the robot the fundamental motor circuits that enable actuation. Have the robot move randomly while sensing. Reinforce any sensory-motor coupling (a temporal coincidence of sensory signals and motor actions) that leads to purposeful motion. approach such as this is necessary for a fully autonomous agent, like an animal. This approach has been used successfully by researchers in artificial life [16]. Learning SMC this way with a robot could require much time.
2. Take advantage of the fact that a robot can be teleoperated. When a person teleoperates a robot, the person's SMC causes the robot to act purposefully. If the robot records all of its sensory signals during repeated teleoperations, through signal analysis it should be able to identify the sensory-motor couplings that accompany purposeful motion.

Both of these approaches require signal analysis algorithms that will detect signal correlations or coincidences. Moreover, the detected sensory-motor couplings must be used to construct basic behavior modules. Both of these problems are open research issues.

ROBONAUT

Robonaut is NASA's most sophisticated humanoid system (See figure 1). Its mechanical systems have been designed to operate within the conditions of space in low-earth orbit. The Robonaut upper body is an articulated torso with two dexterous arms, left and right five-fingered hands, and a head with cameras mounted on an articulated neck, packaged in less volume than an Astronaut's EMU. Robonaut is fully functional at the level of motor control and is operated via full-immersion VR. It has a large set of proprioceptic sensors and an active pan-tilt stereo vision system. Robonaut brings to the project, a high degree of dexterity, sophisticated teleoperability, and a rich sensor suite, but no autonomy. At this point in time it only works through teleoperation



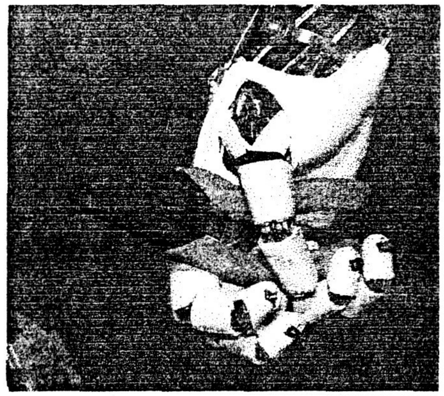


Figure 1. Left: Robonaut; right: Robonaut's hand.

EXPERIMENTS

The objective of the research began during the summer of 2000 is to enable Robonaut to learn the sensory-motor control couplings that define a canonical set of basic behaviors and to learn the sensory signals that precede and follow behavior changes during task execution. The approach is to have a person teleoperate the robot through a task a number of times while the robot records the motor control sequence and the signals from its sensors. For the experiments reported herein, Robonaut's task was to find, to reach toward, and to grasp one stationary object followed by another across the workspace. This was accomplished through teleoperation, wherein the teleoperator controlled the action of the robot through a full-immersion VR station. The signals recorded were the end-effector position and the 6-axis force and torque above the wrist on the forearm.

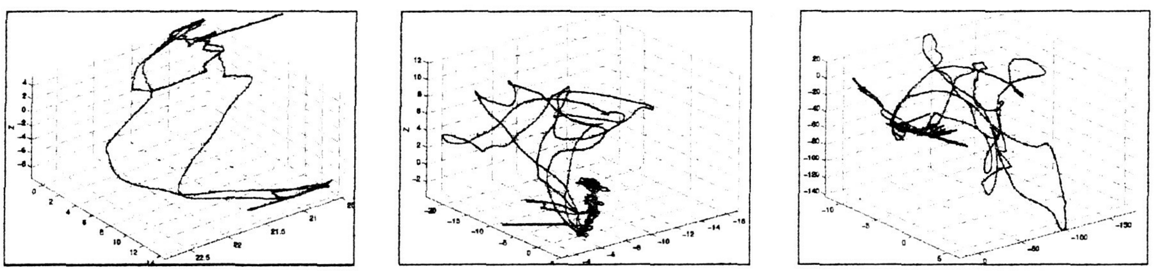


Figure 2. Left: end-effector position; middle: force on wrist; right: torque on wrist

LEARNING SMC

The motor control sequence within each trial will be used to determine the motor events -- the times of transition between continuous motor operation states. The motor events from a trial will be used to partition all the sensory signals within that trial. Since the same task is repeated by the same operator several times there should be the same number of motor events in each trial, although the time between them will vary. After all the trials are completed, the signals will be time warped to align the motor events across trials. Then in a time interval bracketing the motor event, the signals from a single sensor will be correlated across all trials to determine if there is a corresponding sensory event (the signal exhibits a change consistently near the motor event.) Only the signals that exhibit a consistent sensory event within an interval of a motor event will be considered to be salient to that motor event and analyzed further. (A signal that is constant or that changes inconsistently near a motor event across multiple trials of the same task is presumed to be superfluous to the SMC of that event.) Through averaging (or some nonlinear combination such as median filtering) a characteristic signal for that sensory event at the given motor event will be formed. Then the signals from different sensors will be correlated within individual trials to determine which sensors react together near the motor events. To each motor event, the characteristic signals from the salient sensors are coupled to form a sensory-motor coordination event. An SMC event is, therefore, a motor state transition, that is either preceded or followed by a consistent signals in more than one sensor.

CONCLUSIONS AND FUTURE WORK

At the time of this writing, the first experiments in SMC data gathering during teleoperation had been performed. We found that the teleoperation procedure is repeatable in the way needed for the analysis: Having the same number of motor events yet having sufficient variability to detect true sensory events and to average out the spurious ones. It remains to perform the analysis described herein.

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