WHEN ROBOTS FAIL:
THE COMPLEX PROCESSES OF LEARNING
AND DEVELOPMENT

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3) for physical coupling: shape changing to eat or grasp the resource (e.g., depression of the lower jaw of fish to create negative buccal pressure for prey capture; bats flipping the tail membrane up to bring an insect to their mouth).

Animals exhibit an astonishing sophistication in their manipulation of the mechanical properties of their world to achieve these ends. For example, shape changing for sensing in electric fish can be seen in rolling behavior following prey detection (MacIver et al. 2001). This behavior centers the fish's top edge – a region of high sensor density – under the prey; allows the fish to approach the prey by slicing its narrowest cross-section through the water, thereby minimizing added-mass effects; and may provide a simple control strategy for reaching the prey by balancing the stimulus between the two sides of its body and ascending the gradient of sensory signal strength (MacIver et al. 2001; Nelson & MacIver 1999). As described further below, investigations of shape change for locomotion in insects and fish are demonstrating that these animals utilize phenomena within fluids quite beyond those that we utilize in our flying and underwater machines, phenomena that we are still discovering, to say nothing of having a good analytical approach toward.

Shape changing for resource detection and acquisition is clearly fundamental to the sensorimotor intelligence of animals that we so desire to understand. As the examples indicate, these shape changes are tightly coupled to the sensory and mechanical ecology of the animal. Yet, modeling the environment, which animals have demonstrated an unerring capacity to exploit in ways we are hardly aware of, let alone capable of simulating accurately, presents a high obstacle to the integrative computer simulations that are currently our best shot at understanding these coupled sensorimotor processes.

As Webb and others have pointed out (target article, sects. 3.7 & 4.7; Beckers et al. 1996; Flynn & Brooks 1989; Quinn & Espenschied 1993), a great advantage of building physical models is that this allows us to prescind from modeling the undiscovered or unabstracted aspects of the environment on which the target behavior depends. Although Webb's article is very helpful in clarifying the maze of issues surrounding the building of physical models, I believe that this key point is one which merits further elaboration. In what follows, I place the building of physical models in the broader context of the acquisition of scientific knowledge, inquire into the nature of their contribution to this process, and briefly describe some recent examples.

Understanding involves abstraction. These abstractions are expressed in some language for communication and verification. Mathematics provides one such language, but what follows applies to abstractions expressed in any language. Suppose we express our abstractions of some biological phenomenon using the language of mathematics. The next logical step is to calculate predictions from these expressions in order to test their fidelity to the phenomenon (in the case of a spoken language, we would use practices of informal logic to derive verbal predictions). The expressions may need to be approximated to make them computable in finite memory machines in finite time. The calculated predictions are compared to empirically obtained observations, and an interwoven process of theory adjustment, algorithm development, and experimental work ensues. Where can building physical models contribute?

The tragedy of abstraction is that it requires the loss of information. Otherwise, we haven't abstracted. In the process of generating predictions from abstractions, there will be some predictions that will therefore not be computed; namely, those that rely upon the information excluded from our abstractions, or lost in the approximations of those abstractions required by computational expediency. I will use the phrase "abstraction load" (in analogy to "cognitive load") to refer to the work needed to obtain the abstractions and computational methods that will generate the observations we have failed to compute.

Building physical models has the advantage of reducing the po-

tentially insurmountable abstraction load associated with computing all the aspects of the environment on which the target phenomenon depends (where "environment" refers to any aspect external to the phenomenon we are trying to abstract). To simulate the phenomenon adequately, this work would have to be done; but building the object and letting reality supply the physics obviates the need to do some of this work. The crucial point is, we haven't thereby given up the game completely – we are neither pinned into the muck and goo of pure experimentation, nor caged in the assumption-permeated world of pure simulation, but find ourselves at some interesting halfway point.

For example, following similar work by McGeer, Ruina and colleagues developed computational models of a "passive walker" – a walker that has a human-like bipedal gait down inclined planes without actuation or control. The simulations predicted that the walker would not be stable, but it was built in order to test some other issues. To their surprise, the model did walk (Coleman & Ruina 1998). The functioning of the physical model directed the development of a simple quantitative model to explain its stability (Coleman et al. 2001). Similarly, in recent work on fish swimming and insect flying, a number of fluid phenomena have either been discovered or made more observable as a result of the use of robotic devices that approximate the movement of these animals (Ahlborn et al. 1997; Bandyopadhyay et al. 2000; Barrett et al. 1999; Birch & Dickinson 2001; Dickinson et al. 1999).

In allowing the full complexity of the environment to work on what could be called "reduced robotic preparations," this research is cracking open the black box of complex deformable-body and fluid dynamics phenomena to new theoretical advances. The epistemic accessibility afforded by building these robotic devices is analogous to that obtained by traditional instruments such as the microscope and telescope. The building of physical models not only reduces abstraction load, but in illuminating that part of nature we most urgently need to abstract in order to account for a phenomenon, it provides a saliency filter for the immense richness of opportunities for abstraction effort that arise at every turn in the course of experimental work.

When robots fail: The complex processes of learning and development

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Abstract: Although robots can contribute to the understanding of biological behavior, they fail to model the processes by which humans cope with their environment. Both development and learning are characterized by complex relationships that require constant modification. Given present technology, robots can only model behaviors in specific situations and during discrete stages. Robots cannot master the complex relationships that are the hallmark of human behavior.

In her article, Webb offers a convincing argument for instances in which robots can be good models for understanding biological behavior. In her account, mechanical models, like those used in research on other animals, can similarly help researchers gain insight into human behavior. Robots offer experimental advantages in certain situations because robots can be programmed, and even demonstrate very simple learning strategies within a given environment and context. For example, robots can be used as "stand-ins" for humans in experimental situations that are too dangerous for live subjects (e.g., removing the primer of a rocket). Using robots eliminates emotions like fear or anxiety that affect experi-

mental outcome. This said, however, we are not convinced that present technology allows mechanical models of humans to produce one of the most fundamental hallmarks of behavior – adaptation to changes and variations in environmental constraints.

Behavior is affected by both developmental evolution (biological and physiological changes) and learning, or discovering new ways to cope with novel situations in the environment. These variables must be perceived and processed together in order for an appropriate behavior/response to result. As we will attempt to illustrate, the on-line nature of these interactions and the vast amount of variability and complexity within changes of a physiological or an environmental nature are impossible to capture with a mathematical model.

There is no better illustration of variability in behavior than that of babies learning to perform new skills for the first time. Reaching, sitting, crawling, grasping, walking, and throwing are just a few of the plethora of skills babies master in their first few years of life. One major characteristic of these early developmental milestones is that they are manifested in a nonlinear process. We've all seen new parents boast that their baby has taken steps and can walk, even though baby still prefers crawling as a means of getting from point A to B. After the very first steps that a baby takes, it is often a few weeks or even months before the baby is actually described to others as a "walker." During this time, the baby may take ten steps on one day, zero steps on the following two days, and five steps a week later. Motivation for locomotion, as well as the baby's physical ability to put one foot in front of the other in a given moment both factor in to whether the new walker will actually decide to walk rather than crawl, scoot, roll, or slide. Given all this variability, we are not convinced that a robot can take into account the process by which physiological change and contraints in the environment relate to and directly affect each other.

Learning a new skill requires that physiological and biological properties are modified with respect to the constraints of the environment and to the task. Although it is possible, as Webb herself points out, for robots to learn through conditioning, we argue that human learning is fortunately much more complex than simple conditioning. Newell (1986) showed that learning all new skills is based on the interactions among the intrinsic properties of the learner him/herself (morphology, muscle), the environment, and the task constraints. For example, when a gymnast learns a new and complex tumbling skill, he/she must first resolve the relationship between individual and environmental constraints. Furthermore, gymnasts must learn how to constantly modify this relationship with respect to psychological demands like fear, fatigue, and motivation. The interaction of these multiple constraints is very difficult to reproduce in a model because all interactions must first be *identified*. If interaction is not the sum of its parts but, in fact, an original entity (Kelso 1995; Kofka 1935), how is it possible to program and model an interaction without defining, or at the very least identifying each constraint? We maintain that the various elements that contribute to the learning process cannot be gathered in one general model that captures every variation. It is only possible to model the behavior of one given interaction in a specific situation at a given moment with given constraints. As is the case in development, mechanical models are more likely the reflection of one very specific instance (a "snapshot" of a special stage in learning) rather than a model of the learning *processes*.

We maintain that existing experimental methods remain the best way to truly address the questions of human development in the contexts of learning and development. We think that it will remain so, as long as robots are created as computer analogy. Any model for biological behavior must take into account the various interactions that are continually present in learning and development. Some interesting studies have already moved in this direction (Schöner et al. 1995). The new generation of robots, the so-called "animats," are autonomous systems exhibiting self-organizing properties (Kodjabachian & Meyer 1995; Meyer & Wilson

1991). Based on neural network modeling, these robots are non-linear systems that can learn from their environment and lead to "the emergence of interesting and ecologically valid behaviors" (Damper et al. 2000). We expect that future generations of robots will make further progress in accurately representing the processes involved in nonlinear long term change.

Embodiment and complex systems

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Abstract: In agreement with the target article, we would like to point out a few aspects related to embodiment which further support the position of biorobotics. We argue that, especially when complex systems are considered, modeling through a physical implementation can provide hints to comprehend the whole picture behind the specific set of experimental data.

Beside the many examples described in the target article, we argue that one of the possible uses of biorobotics is for the study of complex systems with the aim of elucidating general principles rather than perfectly simulating them in every detail. We agree that the most effective research to date has been devoted to the analysis and simulation of specific subsystems (e.g., chemotaxis in *C. Elegans,* locomotion in insects, simple visual motion detectors, etc.), and consequently it addresses rather specific biological questions. On the other hand, the real potentiality lies mostly in the possibility of further analyzing complexity in general terms by, for instance, devising experiments that could not be carried out on real biological systems for various reasons. One possibility we pursued is that of investigating *development* of sensori-motor coordination and cognition: in particular, the first year of life (Metta 2000; Sandini et al. 1997).

The main hypothesis we put forward is that development can be regarded as controlling the complexity of the learner (Metta 2000). We proposed development in contrast to the classical *modular approach,* not only as a source of inspiration, but rather, as a possible design alternative. The criticism we have against the modular approach, especially in engineering, is that, very often, to make the problems tractable, complex systems are divided in small parts, which are then analyzed in isolation. Complexity is addressed by breaking the system into components. This has been successful so far but it has also hit its own limits (Brooks 2001). Most of the time large-scale system integration has either failed or has been successful only at the expense of generality and adaptation.

A different approach is taken by biological systems. Newborns, for example, are already, at birth, an *integrated* system. Many "modules" are still non-functional or they function differently from their "adult" counterpart: neural growth is not completed (Leary 1992), motor control limited (Konczak et al. 1995), but the sensorial, motor, and cognitive abilities are nicely matched. Submodules develop harmonically, resulting in a system whose components always fit one to another during growth. Adaptation is inherent in the very fabric of the system: we can observe the general tendency of a smooth shift from *simpler to more complicated.* Limitations, such as poor sensory resolution, are thought to be an advantage rather than a drawback (Turkewitz & Kenny 1982). Newborns are maximally efficient in collecting data (making new