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chapter 11

NEUROROBOTICS: NEUROBIOLOGICALLY INSPIRED ROBOTS

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Neurorobots[1] are robotic devices that have control systems based on principles of the nervous system. These models operate on the premise that the "brain is embodied and the body is embedded in the environment." Therefore, neurorobots are grounded and situated in a real environment. The real environment is required for two reasons. First, simulating an environment can introduce unwanted and unintentional biases to the model. For example, a computer-generated object presented to a vision model has its shape and segmentation defined by the modeler and directly presented to the model, whereas a device that views an object hanging on a wall has to discern the shape and figure from ground segmentation based on its on active vision. Second, real environments are rich, multimodal, and noisy; an artificial design of such an environment would be computationally intensive and difficult to simulate. However, all these interesting features of the environment come for "free" when a neurorobot is placed in the real world.

A neurorobot has the following properties:

- It engages in a behavioral task.
- It is situated in a real-world environment.
- It has a means to sense environmental cues and act upon its environment.
- Its behavior is controlled by a simulated nervous system having a design that reflects, at some level, the brain's architecture and dynamics.

As a result of these properties, neurorobotic models provide heuristics for developing and testing theories of brain function in the context of phenotypic and environmental interactions.

Although there have been great advances in autonomous systems,[2, 3, 4, 5] the controllers of these machines are still very much tailored to specific missions and do not have the behavioral repertoire we normally associate with that of biological organisms. Behavior-based robotics[6] do not learn from experience and cannot adapt to environmental change. Probabilistic robot controllers[7] need an accurate model of their sensors and actuators. Robots controlled by reinforcement learning or machine learning[8] are driven by reward expectation and do not address attention, novelty, and threat assessment.

Neurorobotic models may provide a foundation for the development of more effective robots, based on an improved understanding of the biological bases of adaptive behavior. A robotic controller modeled after the vertebrate nervous system, in which the robot's behavior approaches the complexity and flexibility associated with higher order animals, would be a major step forward in the design of autonomous systems. Advances in computational models of the brain as well as computation power are making this a distinct possibility in the not too distant future. Neurally inspired robotic control would be flexible, experience-dependent, and autonomous—just like a biological organism.

Classes of Neurorobotic Models

There are too many examples of neurobiologically inspired robotic devices to exhaustively list in this brief review. However, the approach has been applied to several distinct areas of neuroscience research:

- motor control and locomotion
- learning and memory systems
- value systems and action selection.

The remainder of this article will briefly touch on a few representative examples.

Motor Control and Locomotion

Neurorobots have proved useful for investigating animal locomotion and motor control and for designing robot controllers. Neural models of central pattern generators, pools of motorneurons that drive a repetitive behavior, have been used to control locomotion in robots.[9, 10, 11] Kimura and colleagues have shown how neurorobotics can provide a bridge between neuroscience and biomechanics by demonstrating emergent four-legged locomotion based on central pattern generator mechanisms modulated by reflexes. Their group developed a model of a *learnable* pattern generator and demonstrated its viability using a series of synthetic and humanoid robotic examples. Ijspeert and colleagues constructed an amphibious salamander-like robot that is capable of both swimming and walking, and therefore represents a key stage in the evolution of vertebrate-legged locomotion. A neurorobotic implementation was found necessary for testing whether the models could produce locomotion both in water and on ground and investigating how sensory feedback affects dynamic pattern generation.

An intriguing neural inspiration for the design of robot controllers is the mirror neuron system found in primates. Mirror neurons in the premotor cortex are active both when a monkey grasps or manipulates objects and when it watches another animal performing similar actions.[12] Neuroroboticists, using this notion of mirror neurons, have suggested that complex movements such as reaching and locomotion may be achieved through imitation.[13, 14, 15, 16, 17]

Another strategy for motor control in neurally inspired robots is to use a predictive controller to convert awkward, error-prone movements into smooth, accurate ones. Recent theories of motor control suggest that the cerebellum learns to replace primitive reflexes with predictive motor signals. The idea is that the outcomes of reflexive motor commands provide error signals for a predictive controller, which then learns to produce a correct motor control signal prior to the less adaptive reflex response. Neurally inspired models have used these ideas in the design of robots that learn to avoid obstacles,[18, 19] produce accurate eye,[20] and generate adaptive arm movements.[21, 22, 23]

Learning and Memory Systems

A major theme in neurorobotics is neurally inspired models of learning and memory. One area of particular interest is navigation systems based on the rodent hippocampus. Rats have exquisite navigation capabilities in both the light and the dark. Moreover, the finding of place cells in the rodent hippocampus, which fire specifically at a spatial location, have been of theoretical interest for models of memory and route planning.[24] Robots with models of the hippocampal place cells have been shown to be viable for navigation in mazes and environments similar to those used in rat spatial memory studies.[25, 26, 27, 28] Recently, large-scale systems-level models of the hippocampus and its surrounding regions have been embedded on robots to investigate the role of these regions in the acquisition and recall of episodic memory.[29, 30, 31]

Another learning and memory property of importance to the development of neurorobotics is the ability to organize the unlabeled signals that robots receive from the environment into categories. This organization of signals, which in general depends on a combination of sensory modalities (for example, vision, sound, taste, or touch), is called *perceptual categorization*. Several neurorobots have been constructed that build up such categories, without instruction, by combining auditory, tactile, taste, and visual cues from the environment.[32, 33, 34]

Value Systems and Action Selection

Biological organisms adapt their behavior through value systems that provide nonspecific, modulatory signals to the rest of the brain that bias the outcome of local changes in synaptic efficacy in the direction needed to satisfy global needs. Examples of value systems in the brain include the dopaminergic, cholinergic, and noradrenergic systems.[35, 36, 37] Behavior that evokes positive responses in value systems biases synaptic change to make production of the same behavior more likely when the situation in the environment (and thus the local synaptic inputs) is similar; behavior that evokes negative value biases synaptic change in the opposite direction. The dopamine system and its role in shaping icrosys making has been explored in neurorobots and brain-based devices.[38, 39, 40] Doya's group has been investigating the effect of multiple neuromodulators in the "cyber-rodent," a two-wheeled robot that moves autonomously in an environment.[41] These robots have drives for self-preservation and self-reproduction exemplified by searching for and recharging from battery packs on the floor and then communicating this information to other robots nearby through their infrared communication ports. In addition to examining how neuromodulators such as dopamine can influence decisionmaking, neuroroboticists have been investigating the basal ganglia as a model that mediates action selection.[42] Based on the architecture of the basal ganglia, Prescott and colleagues embedded a model of it in a robot that had to select from several actions depending on the environmental context.

Conclusion

Higher brain functions depend on the cooperative activity of an entire nervous system, reflecting its morphology, its dynamics, and its interaction with the environment. Neurorobots are designed to incorporate these attributes such that they can test theories of brain function. The behavior of neurorobots and the activity of their simulated nervous systems allow for comparisons with experimental data acquired from animals. The comparison can be made at the behavioral level, the systems level, and the neuronal level. These comparisons serve two purposes: first, neurorobots can generate hypotheses and test theories of brain function. The construction of a complete behaving model forces the designer to specify theoretical and implementation details that can be easy to overlook in an ungrounded or disembodied theoretical model. Moreover, it forces these details to be consistent. Second, by using the animal nervous system as a metric, neurorobot designers can continually make their simulated nervous systems and resulting behavior closer to those of the model animal. This, in turn, allows the eventual creation of practical devices that may approach the sophistication of living organisms.

NOTES

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