

Behavior-based robotics as a tool for synthesis of artificial behavior and analysis of natural behavior

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Work in behavior-based systems focuses on functional modeling, that is, the synthesis of life-like and/or biologically inspired behavior that is robust, repeatable and adaptive. Inspiration from cognitive science, neuroscience and biology drives the development of new methods and models in behavior-based robotics, and the results tie together several related fields including artificial life, evolutionary computation, and multi-agent systems. Ideas from artificial intelligence and engineering continue to be explored actively and applied to behavior-based robots as their role in animal modeling and practical applications is being developed.

This article is an overview of behavior-based robotics, a field of robotics that is guided by principles from nature and aims to develop methods for synthesizing artificial systems, ranging from physical robots to autonomous software agents, and use robotics to model and analyze natural systems, ranging from insects to humans. The article defines the key principles of behavior-based robotics, and overviews a variety of examples of its practical applications and its models of natural systems. The overlap between the two is described, but the article focuses on biologically inspired robotics work, giving details of several new areas of research.

Behavior-based robotics is a branch of robotics that bridges artificial intelligence (AI), engineering and cognitive science. Its dual goals are: (1) to develop methods for controlling artificial systems, ranging from physical robots to simulated ones and other autonomous software agents; and (2) to use robotics to model and understand biological systems more fully, typically, animals ranging from insects to humans. This article focuses mainly on work towards satisfying the first goal, giving a brief review of the key approaches and types of systems that have been implemented with a strong biological inspiration.

In the field of robotics, 'control architectures' are methodologies that supply structure and impose constraints on the way that robots are controlled. The behavior-based approach is a methodology for designing robot architectures and controllers for endowing robots with intelligent behavior. The methodology is based on a biologically-inspired philosophy that favors parallel, decentralized architectures,

and allows for some freedom of interpretation. The approach is general and fits well within other powerful frameworks such as schema theory¹.

In behavior-based systems, the robot controller consists of a collection of 'behaviors', each of which achieves and/or maintains a specific goal. For example, the 'avoid-obstacles' behavior maintains the goal of preventing collisions with objects in the environment, and the 'go-home' behavior achieves the goal of reaching some home region. Each behavior is a processing element or a procedure, also called a control law in the engineering field of 'control theory', that can be implemented either in software or hardware; each can take inputs from the robot's sensors (for example, cameras and ultrasound, infra-red or tactile sensors) and/or from other behaviors, and send outputs to the robot's effectors (such as wheels, grippers, arms or speech) and/or to other behaviors in the system. Consequently, a behavior-based robot is controlled by a structured network of interacting behaviors.

System organization

The organizational methodology of behavior-based systems differs from other robot control methods in its approach to modularity, that is, the way in which the system is organized and subdivided. The behavior-based philosophy mandates that behaviors are relatively simple, incrementally added to the system and not executed in a serial fashion. The systems are meant to be constructed in a bottom-up fashion, resembling evolution in its incremental refinement as well as its utilitarian exploitation of existing modules.

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Behaviors are activated in response to external and/or internal conditions, that is, sensory inputs and internal state. The system as a whole activates entire subsets of behaviors so that parallelism can be exploited, both in speed of computation and in the resulting dynamics. The latter is a critical aspect of behavior-based control: as multiple behaviors or modules are active, dynamics of interaction arise both within the system itself (from the interaction among the behaviors) and within the environment (from the interaction of the behaviors with the external world). Inspired by biological organisms, designers of behavior-based systems exploit these dynamics to create (by hand or automatically through the use of learning, described below) repeatable, stable and, ultimately, intelligent behavior without relying on top-down, centralized and often even hierarchical control (Refs 2,3; and P.E. Agre, PhD thesis, 1988, MIT).

The design of behaviors

A methodological constraint of behavior-based systems is their use of state and representation: information is not centralized or centrally manipulated. Instead, various forms of distributed representations are used, ranging from static table structures and networks, to active, procedural processes, providing a rich medium for innovative interpretations.

Behaviors can be designed at a variety of levels of abstraction. In general, they are made to be higher than the robot's atomic actions (that is, typically above 'go-forward-by-a-small-increment' or 'turn-by-a-small-angle'), and they extend in time and space. Effectively, this elevates the representational level of the system, which has been shown to facilitate higher-level cognition and learning^{4,5}. Some commonly implemented behaviors include: 'go-home', 'find-object', 'get-recharged', 'avoid-collisions' and 'pick-up-object'. More specialized behaviors include: 'avoid-the-light', 'aggregate-with-group', 'find-mate', 'follow-edge', etc.

The internal behavior structure of a system does not necessarily need to mirror its externally manifested behavior. For example, a robot that flocks with other robots may not have a specific internal 'flocking' behavior; instead, its interaction with the environment and other robots may produce flocking. Typically, behavior-based systems are designed so that the effects of the behaviors interact in the environment, rather than internally through the system, so as to take advantage of the richness of the interaction dynamics. These dynamics are sometimes called 'emergent' because they result from the interactions and are not internally specified by the robot's program⁶.

Coordinating multiple behaviors

A key issue in behavior-based systems concerns the coordination of the multiple behaviors, thus making 'arbitration' (deciding what behavior to execute at each point in time) one of the central challenges. For the sake of simplicity, most implemented systems use a built-in, fixed priority ordering of behaviors. More flexible solutions, which can be less computationally efficient and harder to analyze, have been suggested, commonly based on selecting a behavior by computing some function of the behavior activation levels, such as voting or activation spreading^{7,8}.

A historical overview

Behavior-based systems were founded on the work in reactive robotics and in particular on the 'subsumption architecture'⁹, which achieves rapid real-time responses by embedding the robot's controller into a collection of preprogrammed parallel condition-action rules, or reflexes, with minimal internal state (for example, 'if bumped, stop')^{2,10}. In contrast to these so-called bottom-up systems, traditional AI deliberative planner-based systems are top-down, and require the robot to perform a serial sequence of processing sense-plan-act steps (for example, 'combine the sensory data into a model of the world, then use the planner to find a path in the model, then send each of the steps of the plan to the robot's wheels')¹¹⁻¹³. Hybrid systems attempt a compromise between the 'thinking' and 'acting' extremes by using a reactive system for low-level control and a planner for higher-level decision making¹⁴⁻¹⁹.

Hybrid systems tend to separate the control system into two or more communicating but largely independent parts. Behavior-based systems are an alternative to hybrid systems; they enable fast real-time responses through simple reactive behaviors that directly link sensors and effectors, but also provide for higher-level deliberation by distributing the representation and computation over more sophisticated concurrent behavior processes. The power, elegance and complexity of behavior-based systems all stem from the ways in which their constituent behaviors are defined and used. Some proponents of behavior-based systems claim that they model cognition better, while others use them purely from pragmatic motivations, including their ease of system development and the robustness of the results.

Learning and adaptation

Learning has been called the hallmark of intelligence; thus, achieving adaptive and learning capabilities in artificial systems is one of the greatest challenges of AI. Learning is particularly difficult in robotics, because sensing and acting in the physical world involve a great deal of uncertainty, owing to incomplete and noisy information and dynamically changing environment conditions. It is often difficult for robots to perceive correctly (owing to limited sensory technology) and act on (owing to limited effectors) the variety of situations that arise in the physical world. Nonetheless, robot learning is an active branch of robotics, and is one of the variations and adaptations of standard machine learning techniques (in particular reinforcement learning) that have been applied effectively to robots. Behavior-based robots have learnt to walk²⁰, navigate²¹⁻²³, communicate²⁴, divide tasks²⁵, behave socially²⁶ and even identify opponents and score goals in robot soccer²⁷.

Reinforcement learning is the most popular method for learning in mobile robotics^{28,29}. It refers to a set of problems (rather than methods), in which the robot must improve its behavior based on rewards or punishment from the environment. The reinforcement learning model is based on early conditioning work in psychology, and recently an increasing number of robot learning systems have used related concepts from biological reinforcement learning, most notably shaping^{5,30,31} and operant conditioning^{32,33}. Supervised learning methods using neural networks have also been used



Fig. 1 The nerd herd. A group of 13 flocking mobile robots. These robots also demonstrated wandering, following, aggregation, dispersion, chain-formation and foraging.

extensively^{23,34,35}. Some of the most effective demonstrations of learning in mobile robots have been inspired by biological learning systems.

Demonstrations and applications

Consistent with the dual goal of the field itself, behavior-based robotics has been used both in practical applications and in futuristic exploratory endeavors. Behavior-based robots have demonstrated various standard robotic capabilities, including obstacle avoidance, navigation, terrain mapping, following, chasing/pursuit, object manipulation, task division and cooperation, and learning maps and walking. Application domains have included mobile robots, underwater vehicles, space robotics (most recently the Mars Sojourner, the robot that autonomously explored the surface of Mars), as well as robots capable of manipulation, grasping, walking and running.

Interestingly, as the behavior-based approach is being explored for modeling natural systems, the resulting research is demonstrating methods with immediate practical applications. For example, models of large-scale group behavior, that have been developed with behavior-based systems, appear to be the methodology of choice for deploying robots in hazardous or inaccessible environments, including under water, in mine fields, under ground and in space. These domains require a combination of individual independence and group cohesion capable of adapting to varying group sizes and organizations, as in natural societies. Consequently, behavior-based approaches have presented popular options for addressing analysis of natural behavior and synthesis of practical artificial behavior.

Faithful simulation and robotic models have been developed for a diverse range of natural behaviors including: reflexive behavior selection strategies³⁶; cricket phonotaxis for flight and mating behaviors³⁷; lobster odor location³⁸; fly³⁹ and hover-fly⁴⁰ vision; insect navigation, trail formation and path-finding^{41,42}; the application of the schema theory to modeling navigation⁴³ and frog behavior⁴⁴; the use of evolutionary computation methods, modeled after natural selection, to develop individual robotic behaviors⁴⁵; group behaviors⁴⁶ and many

others. A bi-annual international conference, 'Simulation of Adaptive Behavior', is devoted to the subject, and has been convening since 1990; its proceedings provide a more representative review of the various activities in this field⁴⁷⁻⁵⁰.

An example of biologically inspired navigation

Our own work has used behavior-based systems to model navigation, map learning and path-finding mechanisms loosely modeled on the rat's hippocampal place cells⁴. In this system, the behaviors served not only for general movement and obstacle avoidance, but also for landmark detection and representation. As new landmarks were discovered, behaviors became associated with them, and subsequently became activated whenever the robot returned to the same location, much like hippocampal place cells in rats⁵¹⁻⁵⁴. Unlike its neural counterpart, whose network topology has no obvious mapping to the physical space it represents, our synthetic navigation system maintained a clear isomorphic mapping between the two. Consequently, the resulting robot-generated maps were easily readable by humans interacting with the robot. The landmark behaviors also served as predictors that allowed the robot to localize more precisely in its environment; an active landmark used context to activate its network neighbor in the robot's direction of travel, thus 'priming' it and generating expectation. A lack of expectation indicated novel locations or incorrect localization.

An example of ethologically inspired group behavior

Our more recent work has focused on using behavior-based systems to model group behavior. Inspired by ethologically common natural behaviors, we have used groups of up to 13 robots to demonstrate aggregation, dispersion, following, flocking, foraging, task division, specialization and dominance hierarchy formation (see Fig. 1). The robotic implementations resemble the equivalent behaviors found in species ranging from ants, crabs and chickens to chimps and humans^{55,56}, but are not designed to be careful mechanistic models. Instead, they serve as demonstrations of possible mechanisms that push the state of the art in robotics, as well as allowing us to postulate theories about their inspirations from nature.

Current developments: biologically inspired imitation

Our most recent work with behavior-based systems extends the control spectrum from planar mobile robots to articulated, anthropomorphic bodies. Again inspired by certain neuroscience theories of motor control^{57,58} (which demonstrate evidence of a finite set of additive force fields controlling the movement repertoire of frogs and rats), we are developing behaviors for the control of three-dimensional movement. As with our work on group behavior, we are using 'basis-behavior' primitives as a substrate for a broader repertoire of higher-level behaviors, obtained by sequencing and combining the basis set⁵⁹. Our current basis set includes behaviors for movement to a destination point, posture maintenance and oscillatory movements, all based on theories of human motor control⁶⁰⁻⁶³, with the eventual goal of modeling learning by imitation.

Acquiring new skills by imitation is a well-known robotics problem. It is usually classified as learning by demonstration,

where the robot uses vision sensors to interpret the behavior of a human user and thus acquire a new task. Historically, assembly tasks have been learned by demonstration, without an effort to model precisely the observed behavior, but focusing on achieving the demonstrated goals⁶⁴⁻⁶⁷. More recently, imitation learning between two mobile robots has been demonstrated⁶⁸, as has skill learning between a human demonstrator and an articulated robot arm with human kinematics, such as learning to balance a pole⁶⁹ and play Kendama⁷⁰. The latter was an instantiation of the bi-directional theory of motor control⁷¹, another example of a robotic implementation of a neuroscience model. Modeling human skill acquisition, while a tremendously challenging task, is gaining popularity in robotics. It has recently been approached from a Piagetian perspective, using developmental stages in order to simplify the complex learning problem⁷²⁻⁷⁴. Computational modeling of motor control and learning is an active research area outside the scope of this review.

Inspired by data from neuroscience and psychophysics that provide evidence for combined perceptual and motor activation during movement observation and imagination⁷⁵⁻⁷⁸, we are developing a set of behaviors that not only produce movement, but also facilitate its perception. These behavior primitives simultaneously recognize and plan movements, thus combining perception and generation. Furthermore, the primitives facilitate prediction, in that they represent complete movements and when presented with an incomplete visual input, can complete it based on their own model of the movement. Practically, the system functions by continuously classifying the observed movements into its known repertoire, thus enabling imitation.

This approach is an extension of our earlier hippocampus-inspired navigation work, described above, in which landmark behaviors primed and anticipated other landmarks based on their local topology. Similarly, in the current work, partial movement matches recognize and prime complete behaviors. Inspired by developmental psychology work providing evidence for infant prediction of goals implied in observed incomplete and incorrect actions⁷⁹, our primitives infer movement goals by internally matching, predicting and completing the observed movements. The ultimate goal of this work is dual, in a manner typical of behavior-based work, namely to: (1) provide insight into the animal/human imitation process, and (2) facilitate automated programming of new tasks and skills in robotic systems.

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Outstanding questions

While major accomplishments have been made in the development of behavior-based systems (see Ref. 80 for an in-depth review of the foundations, goals and the state of the field in 1991), many interesting and important research questions remain to be addressed.

Among them are:

- What organizational principles will be needed in order to scale-up behavior-based systems so that they are able to handle truly complex problems, such as those involving multiple, very different tasks and goals, akin to animal behavioral repertoires?
- How well will behavior-based systems scale-up to increasingly more cognitive problems, such as those involving symbolic reasoning, including natural language discourse?
- Can researchers in natural and artificial sciences overcome their stylistic, terminological and methodological differences and collaborate more closely and efficiently in order to utilize their complementary expertise more efficiently?

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Spatial hemineglect in humans

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The term 'spatial hemineglect' refers collectively to disorders of spatial cognition, which concern specific sectors of space with reference to a given coordinate system. Patients with cerebral lesions involving the posterior-inferior parietal and the premotor cortex, most often in the right hemisphere, sometimes fail to explore the extra-personal and personal sectors of space contralateral to the side of the lesion, are not aware of stimuli presented in these portions of space, or of contralateral body parts and their disordered function. In addition to these negative signs patients may also show positive pathological manifestations, such as avoidance or withdrawal from the contralateral side of space, and delusional views concerning contralateral body parts. The many varieties of this disorder can occur in dissociated forms, suggesting a multifaceted organization of the internal representation of space, of spatial attention, and of their neural correlates. Many manifestations of hemineglect are modulated in a similar fashion by specific sensory stimulation that also affects visuo-motor processes in normal subjects. This ongoing sensory modulation might update the internal representations of space in a continuously changing environment, and contribute to the formation, around the vertical orientation of gravity, of our subjective unitary experience of space.

Spatial hemineglect refers to the defective ability of patients with unilateral brain damage to explore the side of space contralateral to the lesion (contralesional), and to report stimuli presented in that portion of space. The 'hemi' prefix denotes a main feature of the disorder, which distinguishes spatial neglect from global deficits of spatial exploration and perception. The patients' performance is comparatively preserved in the side ipsilateral to the lesion (ipsilesional), or a lateral gradient may be present. In the more widely used diagnostic tasks, such as line bisection (Fig. 1), target cancellation, copying and drawing (Fig. 2), patients are free to move their

head and eyes. A defective performance, therefore, cannot be attributed to primary sensory or motor deficits, which, in turn, may occur in the absence of hemineglect¹. These patients may also show an ipsilesional displacement of the egocentric frames of reference, such as the perceived mid-sagittal plane (Fig. 3).

In the last 30 years, a number of general interpretations have been put forward, to account for the manifold manifestations of hemineglect, making use of constructs such as 'representation'², 'attention'³, and 'reference frames'^{4,5}. (i) Conscious representations of contralesional space may be more or less completely lost⁶. (ii) Orientation of spatial attention

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