

Biology Inspired Robot Behavior Selection Mechanism: Using Genetic Algorithm

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Abstract. Since behavior selection is a crucial issue not only in biology, but also in robotics, especially in behavior-based robotics, it is nature to consider the behavior selection problem both in biological view and robotic view. In recent years, accumulative evidences from neurobiology and anatomy have given rise to proposals that the basal ganglia-a group of subcortex nuclei in vertebrate brains- serve as a central selection mechanism. This paper introduces a robot behavior selection mechanism inspired by basal ganglia and makes explorations of applying genetic algorithm to the optimization of model parameters. The proposed method demonstrates its efficiency through a simulated robot foraging task and casts light on designing more intelligent and fluent behavior selection mechanism in the future.

1 Introduction

Behavior-based robotics (BBR) dates back to the early days of psychology, ethology, neuroscience and cybernetics. Ablib[1] is generally considered as a precursor in this area. In the middle 1980s, Brooks[2-3] introduced a complete new mode of thought for building intelligent mobile robots, which was later called behavior-based robotics.

In behavior-based robotics, the control of a robot is shared between a set of purposive perception-reaction modules called behaviors. Due to limited motor resources, behaviors with different and possibly incompatible objectives may produce conflicting control commands. Thus a major issue in the design of behavior-based control systems is the formulation of effective mechanisms for selecting behaviors.

Many behavior selection mechanisms have been proposed over the last two decades and they can be classified into two categories[4]: competitive mechanisms[2, 5 6] and cooperative mechanisms [7-9] respectively.

All the selection mechanisms mentioned above were considered in engineering view. But how do cockroaches, rats or even human beings select an appropriate behavior from a set of available behaviors? Why can they behave gracefully when encounter conflicts caused by two or more behaviors. What is the neural substrate of behavior selection? Recent progress in neurobiology and anatomy has indicated that

the basal ganglia play a crucial role in behavior selection for vertebrate and this is the primary focus of this paper.

This paper is organized as follows. In Sect. 2, two well-known computational models of basal ganglia are introduced. In Sect. 3, genetic algorithm optimized version of the two models mentioned above is proposed. Sect. 4, a robot behavior selection mechanism based on the optimized basal ganglia model is implemented and simulation experiments are carried out to demonstrate its efficiency. Conclusions are also provided in Sect. 5.

2 Models of the Basal Ganglia

2.1 Introduction to the Basal Ganglia

The basal ganglia are a collection of highly interconnected subcortex nuclei located in central brain, consisting of the striatum, the subthalamic nucleus (STN), the globus pallidus (GP, including the internal segment GPi and the external segment GPe), the substantia nigra (SN, including the pars reticulata SNr and the pars compacta SNc). Anatomical studies demonstrate that the basal ganglia take massive inputs originated from cerebral cortex, the brainstem, and the limbic system, process it in a complex way, and then pass it back to the cerebral cortex. Further more, studies from amphibiology suggest that basal ganglia are ancient structures and exist in the majority of vertebrate species. The above two facts imply that the basal ganglia can fulfill its role as an action selection mechanism (see Humphries[10] for details).

2.2 Qualitative Modeling

In order to support the hypothesis that the basal ganglia act as a central behavior selection mechanism in the brain, qualitative models of the basal ganglia should be constructed and analyzed. Although there are numerous models, only two of them will be discussed in this paper.

The first and most prevalent model of the basal ganglia termed direct-indirect pathway model (DIPM) was proposed by Albin et al.[11], and it had successfully explained some basal ganglia related movement disorders such as Parkinson's disease. In DIPM, the internal connections of basal ganglia were divided into two pathways: the inhibitory direct pathway projects from the D1-type cells in striatum to the GPi; the indirect pathway is inhibitory from the D2-type cells in striatum to the GPe, inhibitory from there to the STN, and excitatory to the GPi (Fig. 1 (a)).

As research goes on, some new connections in the basal ganglia have been found and confirmed. Gurney et al.[12], developed a new model called select-control pathway model (SCPM) of the basal ganglia to include those recently discovered connections such as the inhibitory connection from the GPe to the GPi and the excitatory connections from the STN to the GPe (Fig. 1 (b)). Humphries and Gurney[13] extended SCPM to include the thalamic complex, but since this extended model is rather complex and the thalamic complex are generally not regard as a part of the intrinsic basal ganglia, it will not be discussed here.

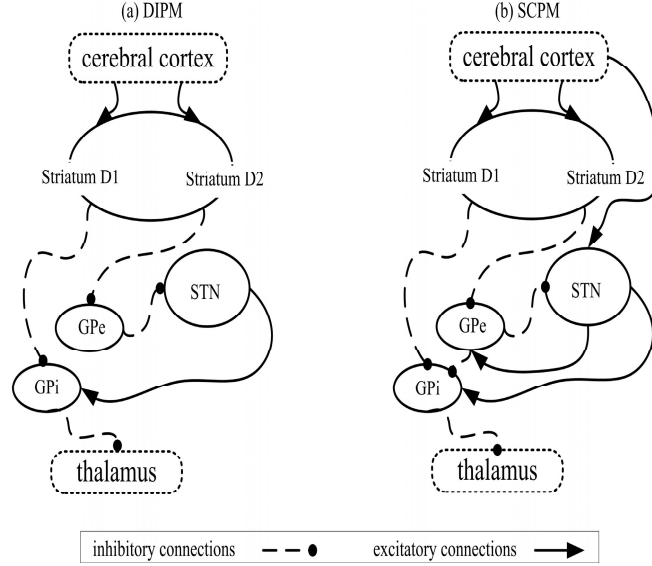


Fig. 1. Two qualitative models of the basal ganglia. (a) is DIPM, (b) is SCPM. Excitatory: solid line. Inhibitory: dashed line.

2.3 Quantitative Modeling

In quantitative models, leaky-integrator artificial neurons are used to simulate the real neurons. Let u be the total post-synaptic potential generated by the afferent input, and k be the constant determining the rate of activation, the activation a of a leaky integrator is then

$$\frac{da}{dt} = -k(a - u) \quad (1)$$

y is the output of the neuron and given by

$$y = m(a - \theta)H(a - \theta) \quad (2)$$

where θ is a threshold for activation, $H(\cdot)$ is the Heaviside step function and m is a slope parameter.

It is supposed that the basal ganglia are processing in a parallel manner, just like the other parts of the brain. When the numerous neural information streams or channels originated in the cerebral cortex, each channel may potentially request for a particular behavior to be expressed, reach the basal ganglia, only a small number of them will be released according to their importance or salience. In this way, the basal ganglia allow the most urgent behavior to be selected and executed.

	DIPM	SCPM
Cortex	$y_i^C = S_i$	$y_i^C = S_i$
StriatumD1	$\begin{cases} u_i^{d1} = w_{CS1} * y_i^C \\ y_i^{d1} = m(a_i^{d1} - \theta_{d1}) H(a_i^{d1} - \theta_{d1}) \end{cases}$	$\begin{cases} u_i^{d1} = w_{CS1} * y_i^C \\ y_i^{d1} = m(a_i^{d1} - \theta_{d1}) H(a_i^{d1} - \theta_{d1}) \end{cases}$
StriatumD2	$\begin{cases} u_i^{d2} = w_{CS2} * y_i^C \\ y_i^{d2} = m(a_i^{d2} - \theta_{d2}) H(a_i^{d2} - \theta_{d2}) \end{cases}$	$\begin{cases} u_i^{d2} = w_{CS2} * y_i^C \\ y_i^{d2} = m(a_i^{d2} - \theta_{d2}) H(a_i^{d2} - \theta_{d2}) \end{cases}$
GPe	$\begin{cases} u_i^{GPe} = -w_{Sd2-GPe} * y_i^{d2} \\ y_i^{GPe} = m(a_i^{GPe} - \theta_{GPe}) H(a_i^{GPe} - \theta_{GPe}) \end{cases}$	$\begin{cases} u_i^{GPe} = -w_{Sd2-GPe} * y_i^{d2} + w_{STN-GPe} * \sum_i y_i^{STN} \\ y_i^{GPe} = m(a_i^{GPe} - \theta_{GPe}) H(a_i^{GPe} - \theta_{GPe}) \end{cases}$
STN	$\begin{cases} u_i^{STN} = -w_{GPe-STN} * y_i^{GPe} \\ y_i^{STN} = m(a_i^{STN} - \theta_{STN}) H(a_i^{STN} - \theta_{STN}) \end{cases}$	$\begin{cases} u_i^{STN} = w_{C-STN} * y_i^C - w_{GPe-STN} * y_i^{GPe} \\ y_i^{STN} = m(a_i^{STN} - \theta_{STN}) H(a_i^{STN} - \theta_{STN}) \end{cases}$
GPI	$\begin{cases} u_i^{GPI} = -w_{Sd1-GPI} * y_i^{Sd1} + w_{STN-GPI} * \sum_i y_i^{STN} \\ y_i^{GPI} = m(a_i^{GPI} - \theta_{GPI}) H(a_i^{GPI} - \theta_{GPI}) \end{cases}$	$\begin{cases} u_i^{GPI} = -w_{Sd1-GPI} * y_i^{Sd1} + w_{STN-GPI} * \sum_i y_i^{STN} - w_{GPe-GPI} * y_i^{GPe} \\ y_i^{GPI} = m(a_i^{GPI} - \theta_{GPI}) H(a_i^{GPI} - \theta_{GPI}) \end{cases}$

Fig. 2. The net input and output for the i th channel of each component in DIPM and SCPM

Thus, according to Fig. 1, the net input u_i and output y_i for the i th channel in each component of DIPM and SCPM are computed in the equations shown in Fig. 2. w_{CS1} , w_{CS2} , $w_{Sd2-GPe}$, $w_{STN-GPe}$, w_{C-STN} , $w_{GPe-STN}$, $w_{Sd1-GPI}$, $w_{STN-GPI}$ and $w_{GPe-GPI}$ are the weights of the respective connections with the basal ganglia. θ_{d1} , θ_{d2} , θ_{GPe} , θ_{STN} and θ_{GPI} are the thresholds of the respective components in the basal ganglia.

2.4 Simulation Results

Two simulation experiments are conducted for each model. The first experiment uses three channels, and amplitude of the inputs on the three channels represented the salience of three behaviors which are competing for expressing themselves. At time $t=1$, the salience of behavior 1 increases from 0 to 0.4, when $t=2$, the salience of behavior 2 increases to 0.6, exceeds behavior 1, at $t=3$, the salience of behavior 1 increases to 0.6 and soon falls back to 0.4 at $t=4$, the salience of behavior 3 is always 0. If the channel's output is under the threshold, the corresponding behavior was selected (see Fig. 3). All the simulation parameters are the same as those used in Humphries in order to compare the simulation results with the GA optimized models proposed in Sect. 3.

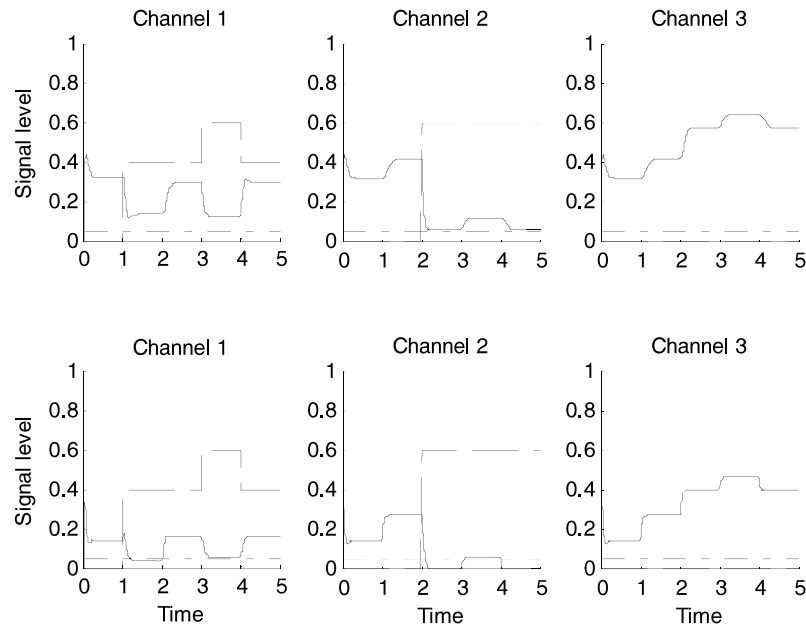


Fig. 3. Simulation results for DIPM (top) and SCPM (bottom). They show that DIPM doesn't have the selection (at $t=1$) and switching (at $t=2$) capabilities, while the SCPM possesses these capabilities. The simulation results of SCPM are the same as those in Humphries[10]. Output of GPI: solid line. Saliency of each behavior: dashed line. Selection threshold: dash-dot line.

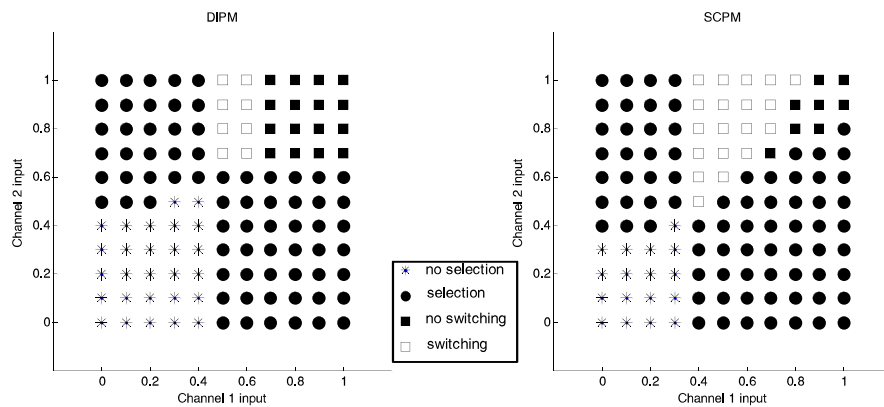


Fig. 4. Selection and switching abilities of DIPM (left) and SCPM (right)

It should be noted that DIPM was not originally proposed for studying basal ganglia's behavior selection properties, and has never being quantitatively simulated. But

since the main purpose of this paper is to develop biology inspired robot selection mechanisms, it is important to remember that biological studies are not necessarily viewed as constraints for robotics, but nonetheless serve as inspirations.

In the second experiment, 121 simulations are run on each model, consisting of the salience input pairs (S1, S2) where S1 and S2 increase from 0 to 1 in the step of 0.1. The input to channel 1 started at time $t=1$; the input to channel 2 started at $t=2$. The simulation results are shown in Fig. 4. No selection means neither of the two channels becomes selected. Selection: only one channel becomes selected, for example, channel 1 becomes selected at $t=1$ or channel 2 becomes selected at $t=2$; No switching: channel 1 becomes selected at $t=1$ and remains selected from that time on and channel 2 also becomes selected at $t=2$; Switching: channel 1 first becomes selected at $t=1$ but becomes deselected at $t=2$ while channel 2 becomes selected at $t=2$.

3 Genetic Algorithm Optimization of the Basal Ganglia Models

3.1 Details of the Genetic Algorithm

In order to enhance the performance of DIPM and SCPM, which considerably depends on the weights and thresholds, the genetic algorithm (GA) is applied as a means of optimization. The initial population is first generated at random. The genome of each individual in the population is simply a chain of all the weights and thresholds in the two models. Each weight or threshold is a single gene within the genome and is a real number in range [0, 1]. The fitness value of each individual is calculated in the below way: apply the parameters contained in the individual to DIPM and SCPM, then run the second simulation experiment discussed in section 2 to see how many selection results in the 121 simulations match an ideal selection results diagram, the more the larger fitness value will be. When all the individuals in the population have had their fitness evaluated, selection operator, crossover operator and mutation operator were performed in sequence. The whole process will be repeated until reach the maximum generation.

3.2 Optimization Results

Three genetic operators employed in this paper are roulette wheel selector, one-point crossover and simple mutation respectively. Elitism is also used to protect the best individual that had ever found. Parameters of GA are as follows: population size is 100, maximum generation is 100, crossover probability is 0.8 and mutation probability is 0.02. Simulation results of optimized DIPM and SCPM are shown Fig. 5 and Fig.6.

Compared with Humphries [10], the simulation results show that the GA optimized DIPM has the ability to select between the sample input signals. Thus DIPM is also a candidate for the selection model of the basal ganglia. Fig. 6 shows that both of the two GA optimized model have a considered improved selection and switching performance than the two original models shown in Fig. 4.

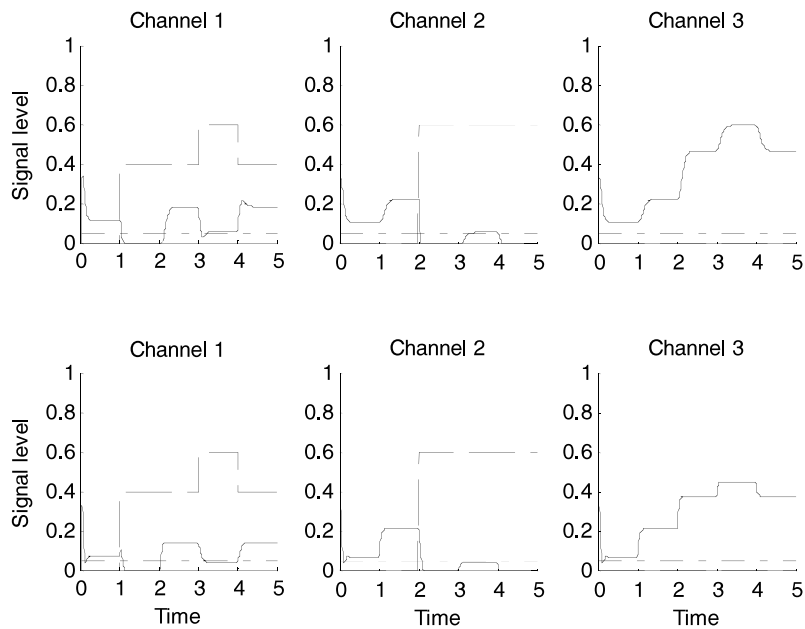


Fig. 5. Simulation results for GA-DIPM (top) and GA-SCPM (bottom). Output of GPI: solid line. Saliency of each behavior: dashed line. Selection threshold: dash-dot line.

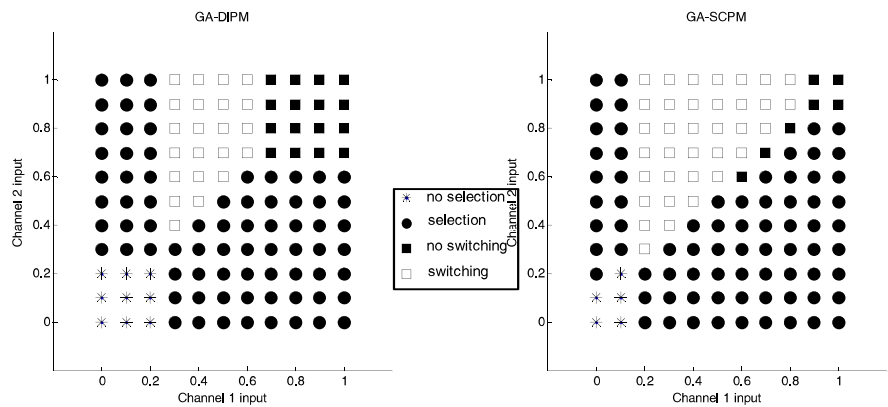


Fig. 6. Selection and switching ability of GA-DIPM (left) and GA-SCPM (right)

4 Robot Implementation and Simulation

4.1 Robot Implementation

Girard et al.[14] and Prescott et al.[15] had made early exploration of applying basal ganglia inspired behavior selection mechanism to robotics and got some valuable results. In this section, GA optimized basal ganglia models are embedded in a robot control system. The robot architecture is typical behavior based control architecture. It has four main parts: the robot sensory system, the behavior system, the basal ganglia and the robot motor system.

The robot motor system is equipped with two driven wheels and a gripper, which is used to pick up targets (food). The sensory system has five range scanners which allow the robot to know whether there are obstacles or targets around it. The gripper is also equipped with two sensors, one tells the robot if something locates in the gripper and the other indicates the gripper's state (closed or open). The behavior system is decomposed into six behaviors: *avoid obstacle*, *search*, *move to target*, *pick up*, *go home* and *put down*, respectively. Each behavior consists of a set of condition-action mappings. The salience signal for each behavior is computed in the below equations:

$$S_{avoid_obstacle}=0.96*P_{obstacle} \quad (3)$$

$$S_{search}=0.6-0.5*P_{obstacle} \quad (4)$$

$$S_{move_to_target}=0.72*P_{target}-0.3*P_{obstacle} \quad (5)$$

$$S_{go_home}=0.34*P_{target_in_grip}+0.56*P_{grip_closed} \quad (6)$$

$$S_{put_down}=0.17*P_{target_in_grip}+0.28*P_{grip_closed}+0.5*P_{home} \quad (7)$$

Whether the robot is near to an obstacle, a target or the home area are indicated by $P_{obstacle}$ (0 or 1), P_{target} (0 or 1) and P_{home} (0 or 1) respectively. $P_{target_in_grip}$ (0 or 1) indicates whether there is a target in the gripper and P_{grip_closed} (0 or 1) indicates whether the gripper is closed. When the salience value has been computed, the basal ganglia will then select a suitable behavior based on these salience signals and command the robot motor system to execute it.

4.2 Simulation Results

The simulation environment is a 4.5m×6.0m rectangle shaped room, which is surrounded with wall and contains some obstacles. The home area is a circle area whose diameter is 0.9m. Some targets (small circles whose diameter is about 0.15m) are scattered in the room. The range of the scanners is about 0.8m.

Screenshots of the simulation are shown in Fig.7. The simulation results demonstrate that the robot can switch fluently between the six behaviors and validate that the basal ganglia can fulfill its role as a behavior selection mechanism.

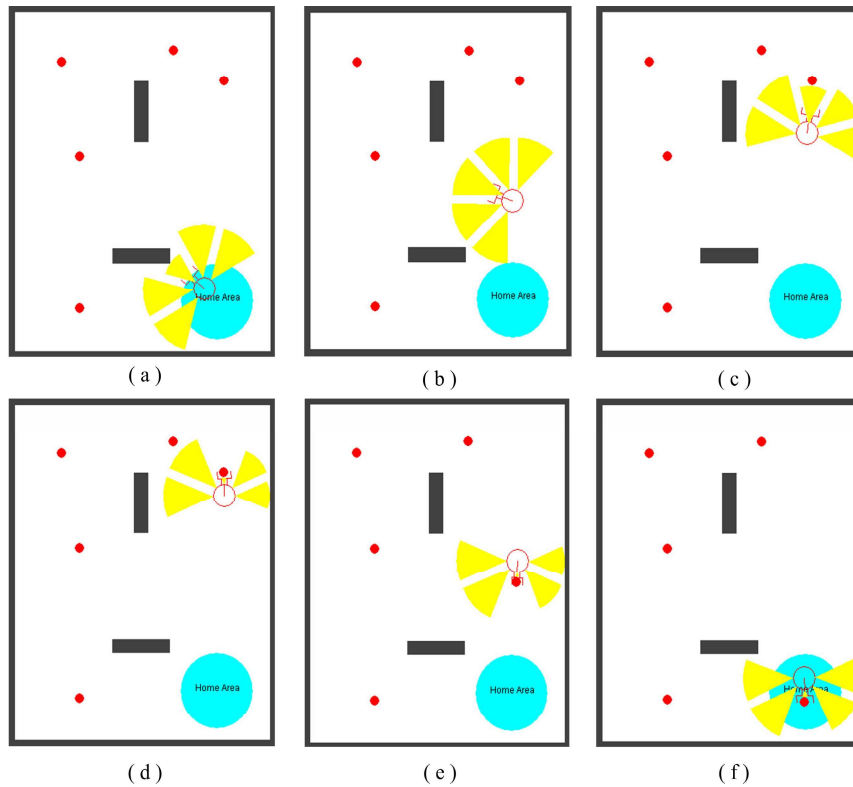


Fig. 7. Screenshots of the simulated foraging task. (a) avoid obstacle, (b) search, (c) move to target, (d) pick up, (e) go home, (f) put down .

5 Conclusions

As stated in the introduction, this paper first introduces a biology-inspired behavior selection mechanism based on the recent research achievements on the basal ganglia. Then, the genetic algorithm is utilized to optimize the weights and thresholds in two basal ganglia models, DIPM and SCPM respectively. A robot is also implemented for a simulated foraging task. Some conclusions drawn from this paper are the following:

- The DIPM can also be considered as a selection model of the basal ganglia although further studies and biological evidence are needed to support this conclusion.
- GA is an effective optimization method and can considerably improve the performance of the computational basal ganglia models.

-The biology inspired behavior selection mechanism can be successfully embedded in behavior-based robot control architecture, and can switch fluently between the robot behaviors.

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