

# Rat Pups and Random Robots Generate Similar Self-Organized and Intentional Behavior

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*Biorobotic research continually demonstrates that behavior and cognition can be the emergent products of (1) embodied agents that are (2) dynamically embedded within an environment and (3) equipped with simple sensorimotor rules. Thigmotaxis is an orientation response to contact manifested in infant rats by wall following, corner burrowing, and group aggregation. Orientation responses have been long thought to be mediated only by sensory or central processes. Here we show that a random control architecture in a morphologically similar robot embedded in a scaled environment can reproduce thigmotactic behaviors seen in infant rats. We conclude that (1) and (2) may play a larger role than previously thought in the generation of complex behaviors. © 2006 Wiley Periodicals, Inc. Complexity 12: 53–66, 2006*

**Key Words:** biorobotics; animal Behavior; *Rattus norvegicus*; randomness; dynamical systems; embodied cognition

## INTRODUCTION

In the now classic and widely read "Vehicles," Valentino Braitenberg forcefully demonstrated that high-level descriptions of behavior often can be effected by fairly simple electromechanical devices [1]. As an example, take a

rectangular cart with two light sensors placed on opposite sides of the front end of a vehicle and two motors placed on opposite sides of the back end. The sensory-motor connections on such a vehicle are excitatory, such that increased input to a sensor causes increased rotation of the wheel to which it is connected. When each sensor is ipsilaterally wired to its respective motor, the vehicle will tend to move away from a light source. That is, if the light is slightly to the right of the vehicle, that light will activate the right sensor,

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which will trigger the right wheel, causing the vehicle to veer left. Over repeated trials, or in the presence of multiple light sources, observers often think that the vehicle fears light, dislikes light, is a coward, or has an avoidant personality. Alternatively, if the sensors are wired to the contralateral wheels, the vehicle is viewed as aggressive, liking light, or being highly extroverted. Even knowing precisely how the vehicle's behavior is produced, we are still inexorably drawn to use high-level psychological language in describing behavior.

The problem with such high-level concepts is that, although descriptive of behavior, they offer few, if any, mechanistic insights. As a result, the complexity of a system or behavior is typically masked. Recognition of this bias led C. Lloyd Morgan to formulate his famous canon [2] and Paul Churchland to take the radical step of advocating eliminative materialism [3], the view that we should eliminate all folk psychological theorizing in favor of the more explanatorily potent languages of neurobiology. Despite these advisories, anthropomorphism is still ubiquitous in animal behavior research. It becomes crucially important, therefore, to describe a system in conceptually neutral languages to avoid this bias. To this end, we have developed a biorobotic platform for the investigation of rat behavior. Building robots forces a researcher to confront assumptions implicit in higher-order descriptions.

There remains, in addition to the anthropomorphic bias, a further problem in the explanation of behavior. This is the centralization bias: a tendency to localize processes in a minimal number of physical structures. The centralization bias typically amounts to a reduction of processes to structures, a consequent denial of emergentism, and, therefore, a masking of systemic complexity. The centralization bias is most explicitly seen in the still-dominant computational theory of mind (CTM), pervasive both in the cognitive and behavioral sciences. Accordingly, brains are thought of as black boxes, implementing computational functions that map inputs to outputs. Inputs are typically just parameters used to seed or trigger the computational engine that is the brain, whereas behaviors are the outputs produced by the black box. The chore then becomes to determine what computational functions the black box is executing and ultimately how these functions are neurally, hormonally, or genetically implemented. The entire computational and generative cause for a given behavior is localized within the black box of the brain.

In contrast, we label the behavior of a Braitenberg vehicle as "aggressive" or "fearful," not because of a rule in a black box, but because of the wiring of sensors to motors from which emerge patterns of behavior via the dynamic interaction of vehicle and environment. In the case of apparent fear behavior, the arc away from a light source results only from how sensors are wired to motors and the arrangement structure of light in the environment. Thus,

there is no internal computation required to generate "fear behavior." It is a product of sensorimotor wiring, agent-environment interactions, and our interpretations of behavioral patterns. In short, the brain of a Braitenberg vehicle is the embodiment of sensorimotor contingencies, rather than an internal fear module, which computes fear responses to sensory input. Indeed, an emerging theme of biorobotics research is that reactive architectures implementing simple rules can give rise to a wide variety of apparently complex emergent behavior [4]. Critically important for emergence is that organisms (1) are embodied and (2) dynamically interact with their environment (for a comprehensive explication, see [5]).

An important example of embodiment is Barbara Webb's biorobotic reproduction of cricket phonotaxis [6]. Taxes are directed orientation reactions [7] defined as input-output relationships in the behaviorist tradition of the early- to mid-twentieth century. The advantage of cataloguing taxes as behavioral descriptors is that they make no presumptions about internal mechanisms. Cricket phonotaxis, in particular, refers to the ability of a female cricket to locate a conspecific male by walking toward the calling song emitted by the male. A typical CTM decomposition of this behavior would be as follows: (1) recognize the calling song as that of a conspecific male and (2) locomote toward its source. The former requires a dedicated recognition processor, whereas the latter requires comparisons of stimulus intensity and latency differences between two ears located on a cricket's legs to direct movement toward the sound source. By constructing an acoustic system to emulate a cricket's auditory system, Webb found that such a system was only responsive to one sound: the calling song of a male conspecific. Thus, in contrast to a CTM decomposition, there is no need for a complex recognition processor in the cricket's brain.

Dynamic environmental interactions is the theme of J. J. Gibson's work, which pioneered the field of ecological psychology [8]. According to Gibson [9], these interactions produce affordances (i.e., features of an environment providing opportunities for action). Affordances are emergent products of sensorimotor routines implemented within a particular agent morphology in a particular kind of environment. A principal conclusion of Gibson's work, seen in the Braitenberg example as well, is that the more information is embedded in or produced by the organism-environment complex, the less information production or internal computation is required of the organism. Brains are grounded in information exploitation rather than information representation and production [10]. This makes sense from an evolutionary perspective because if information already exists in agent-environment sensorimotor interactions, there is no reason to evolve representation and production structures. Such structures should only evolve when the information cannot be directly exploited from these interactions. Thus, surprisingly simple brains or control systems can give rise to

very intelligent-looking behavior. On this view, both behavior and cognition are distributed across brain, body, and environment. Cognition, in many respects, is in the eye of the beholder [11].

If, on this view of behavior and cognition, the explanatory space has been widened from brains, to brains, bodies, and dynamic environmental exchanges, all of which co-emerge, co-develop, and co-evolve; then gaining a foothold on behavior will prove to be even more difficult than previously thought. How are we to get anywhere with almost intractably complex organisms such as mammals? We believe that tractability can be gained by studying organisms whose behavioral-possibility space is naturally constricted and progressively expands. This is provided by studying the development of organisms that have initially impoverished sensory and motor development.

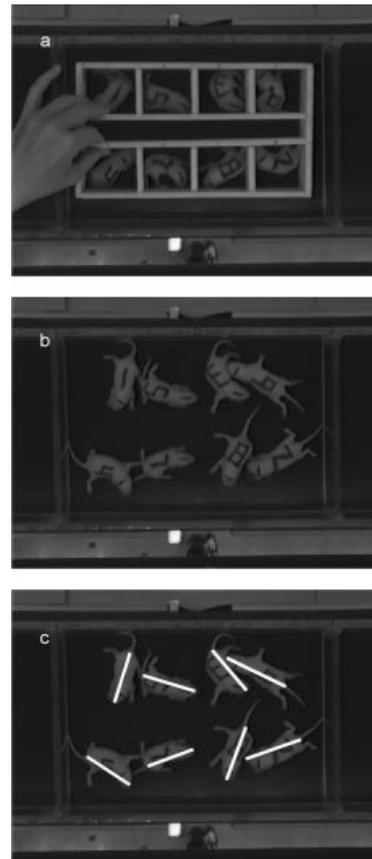
Infant Norway rats (*Rattus norvegicus*) are ideal mammals for this purpose. They are born very immature with very limited sensorimotor abilities, and are well-suited as subjects for robotic models with Braitenberg-style reactive architectures. We briefly review our previous results with reactive architectures and then present the results of an even simpler architecture intended to overcome the limitation observed in reactive architectures, with results that even Braitenberg might find surprising.

### RAT PUPS

Norway rats (*Rattus norvegicus*) are well-studied laboratory animals that are born altricial [12]. At birth, they are deaf and blind and have limited locomotor capabilities for the first 2 weeks of life [13]. Behaviorally, rats are referred to as a contact species [12]. They follow walls, burrow in corners, and aggregate in huddles throughout life. Because they are born in relatively large litters, we can study contact and aggregative and social behavior in infant rats [14–16]. Although contact with objects and conspecifics is under multisensory control [17], huddling and wall following are believed to be primarily due to topotaxis (movement towards a stimulus) and thigmotaxis (orientation to contact) [14]. Taxes make no presumptions about the nature of the generative mechanisms. However, it is typically assumed that central processing of some sort mediates the orienting response.

One hundred sixteen 7- and 10-day-old male and female Sprague-Dawley, Norway rats were run as individuals, and 18 litters of 8 pups of the same ages were run as groups. Pups were placed in a temperature-controlled rectangular arena ( $20.32 \times 30.48 \times 5.08$  cm) for 10 min. Individual pups were placed in the center, and litters of pups were placed in stalls and then released (see Figure 1). The temperature control chamber [18] held both ambient and surface temperature of the arena constant at  $34^{\circ}\text{C}$ , which is slightly cooler than normal body temperature for rats ( $36.5^{\circ}\text{C}$ ) and minimizes effects of cooling on behavior. Pup movements

FIGURE 1

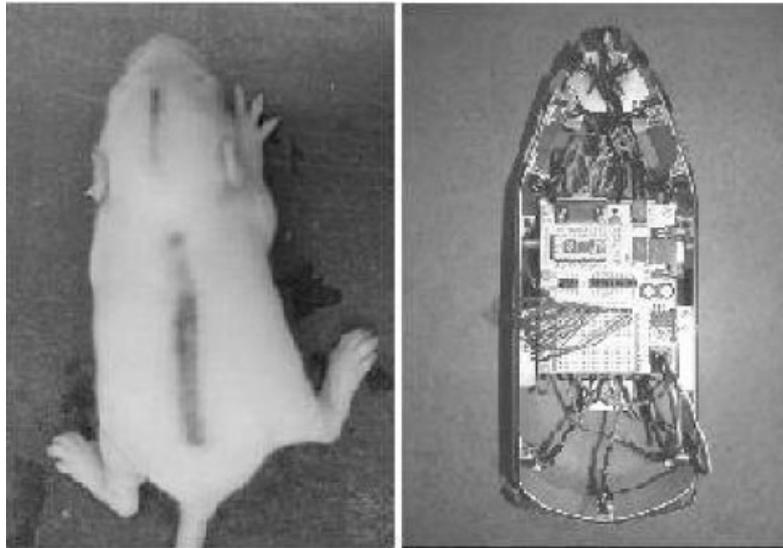


Images illustrating how groups of eight pups were released in the arena. Pups were placed in the stalls of the rack and then the rack was lifted straight up and placed to the side (a). Five seconds later, the pups are moving in the arena (b). Illustration of how nose and base-of-tail coordinates are recorded (c).

in the arena were recorded by a video camera placed directly above it [11,14,15]. Pup behavior was analyzed by digitizing frames and extracting images at 5-s intervals. Images were then coded using a modified version of NIH Image [16] that records clicks an observer makes on the tip of the nose and base of the tail of the pups as depicted in Figure 1. From nose and base-of-tail coordinates, contact among pups, activity, orientation, and how far pups moved in a given time interval were computed by a custom-made algorithm.

### ROBOTS

Robotic designs embody assumptions about the behaviorally relevant morphological, sensory, and motor characteristics of a system [19]. For rat pups, we hypothesized that body shape is an important constraint on behavior, influencing how rats interact with walls, corners, and conspecific-

**FIGURE 2**

Overhead comparison of rat pup and robot (scaled). Ten-day-old rat pup (left), one of eight identical robots we constructed for our robotic experiments (right).

ics. Consequently, robots were outfitted with a long metal body, tapering to a rounded snout beginning approximately 2/3 of the distance from the caudal pole (see Figures 2 and 3). Electromechanical size constraints limited our ability to build robots at the same scale as pups. Therefore, robots were scaled by a factor of four (i.e.,  $7.62 \times 2.54$  to  $23.39 \times 10.80$  cm), as was the robot arena (i.e., from  $20.32 \times 30.48$  to  $81.28 \times 121.92$ ).

Tactile sensing was implemented using 14 binary micro-switch bump sensors mounted along the periphery of the robot. Sensors were clustered along the nose of the robot both to model the rat pup sensory montage, where there is greater tactile sensitivity at the snout, as well as to model an observed rostral-caudal development of tactile responsivity in the first weeks of life in the rat pup [13]. Brass strips were mounted on all of the sensors to create 360° sensing.

Infant rats primarily use their back legs for locomotion and their front legs for orientation movements [14,15]. This was modeled using two rear-driven wheels with differential drive on the chassis and continuous rotation servomotors (see Figure 3). The robot microcontrollers were Parallax 25 MHz Java stamp 24-pin DIP modules. Java code was downloaded to the robot controller so that behavior was fully autonomous (see [20], for more on the design specifications).

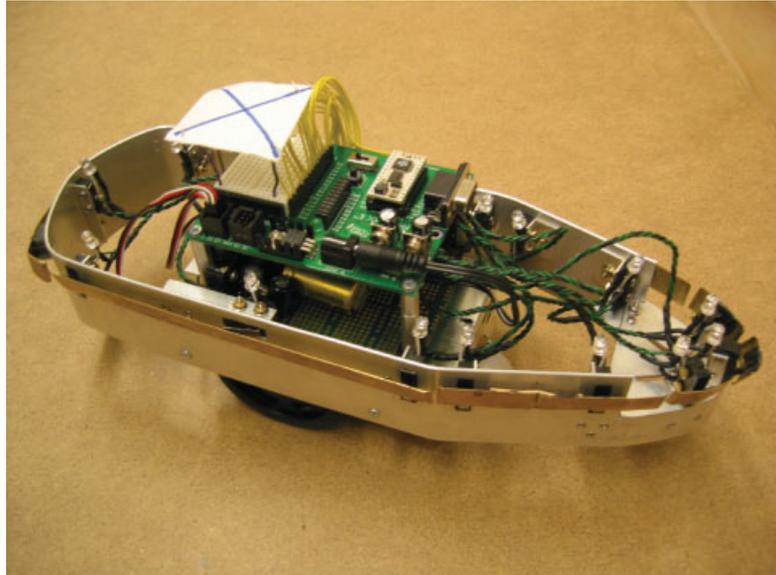
### METRICS

We used three types of metrics to compare robot and pup behavior. These were aggregation, wall and corner contact, and distance traveled in an interval of time,  $\tau$ . Two measures

of aggregation were used based on our previous research [14,15]. The first was a measure of aggregates of various contact groups formed by pups or robots moving about in an arena. For example, if there are 8 pups or robots, 4 may form one contact group and 3 another, while 1 is alone. Thus, we have three aggregons with 4, 3, and 1 animals or robots. Greater aggregation is characterized by a fewer number of aggregons and more pups within a given aggregon. This allows the ordering of aggregons into a measure of aggregation. For example, a group of 8 that forms an aggregon pattern of (4, 3, 1) is less aggregated than a group forming two aggregons of (5, 3), but more aggregated than a group forming four aggregons of (3, 2, 2, 1). All 22 possible aggregon patterns for groups of eight are illustrated in Table 1. A second, closely related measure of aggregation is the number of subgroups that form, ignoring the number of individuals in each subgroup (Table 1). Average aggregon and subgroup measures were obtained for each trial.

When pups or robots move around in an arena they contact walls and corners (the intersection of walls). Because corners are walls, we also kept track of wall contact excluding corners. Wall contact was defined as the head point falling within approximately one head-length of the wall (i.e., in the range of 2.3 to 2.4 cm, depending on pup size; see Figure 5, dotted black lines for wall contact). Corner contact was defined as the head point falling within one head-length from the corner along either wall, and the intersection of the two wall contact lines (see Figure 5, red lines). For groups, wall and corner contact were averaged across agents for a given trial. The metrics of aggregation,

**FIGURE 3**



Lateral view of the robot. [Color figure can be viewed in the online issue, which is available at [www.interscience.wiley.com](http://www.interscience.wiley.com).]

**TABLE 1**

Aggregon Patterns for  $N = 8$  Agents

Aggregon Patterns	Index	Subgroup Patterns	Index
(1, 1, 1, 1, 1, 1, 1, 1)	1	{{(1, 1, 1, 1, 1, 1, 1, 1)}}	8
(2, 1, 1, 1, 1, 1, 1, 1)	2		
(2, 2, 1, 1, 1, 1, 1, 1)	3	{{(2, 1, 1, 1, 1, 1, 1, 1)}}	7
(2, 2, 2, 1, 1)	4		
(2, 2, 2, 2)	5	{{(2, 2, 1, 1, 1, 1, 1, 1), (3, 1, 1, 1, 1, 1, 1)}}	6
(3, 1, 1, 1, 1, 1, 1, 1)	6		
(3, 2, 1, 1, 1, 1, 1, 1)	7		
(3, 2, 2, 1)	8	{{(2, 2, 2, 1, 1, 1, 1, 1), (3, 2, 1, 1, 1, 1, 1, 1), (4, 1, 1, 1, 1, 1, 1)}}	5
(3, 3, 1, 1)	9		
(3, 3, 2)	10		
(4, 1, 1, 1, 1, 1, 1, 1)	11	{{(2, 2, 2, 2), (3, 2, 2, 1), (3, 3, 1, 1), (4, 2, 1, 1), (5, 1, 1, 1, 1)}}	4
(4, 2, 1, 1)	12		
(4, 2, 2)	13		
(4, 3, 1)	14		
(4, 4)	15	{{(3, 3, 2), (4, 2, 2), (4, 3, 1), (5, 2, 1), (6, 1, 1)}}	3
(5, 1, 1, 1)	16		
(5, 2, 1)	17		
(5, 3)	18	{{(4, 4), (5, 3), (6, 2), (7, 1)}}	2
(6, 1, 1)	19		
(6, 2)	20	{{(8)}}	1
(7, 1)	21		
(8)	22		

**FIGURE 4**

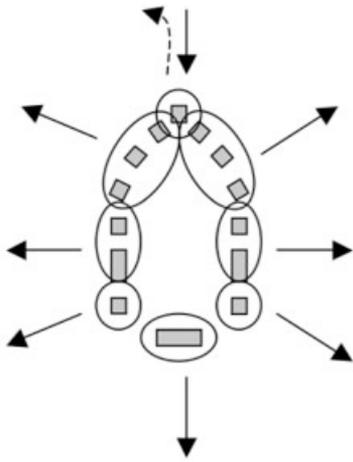


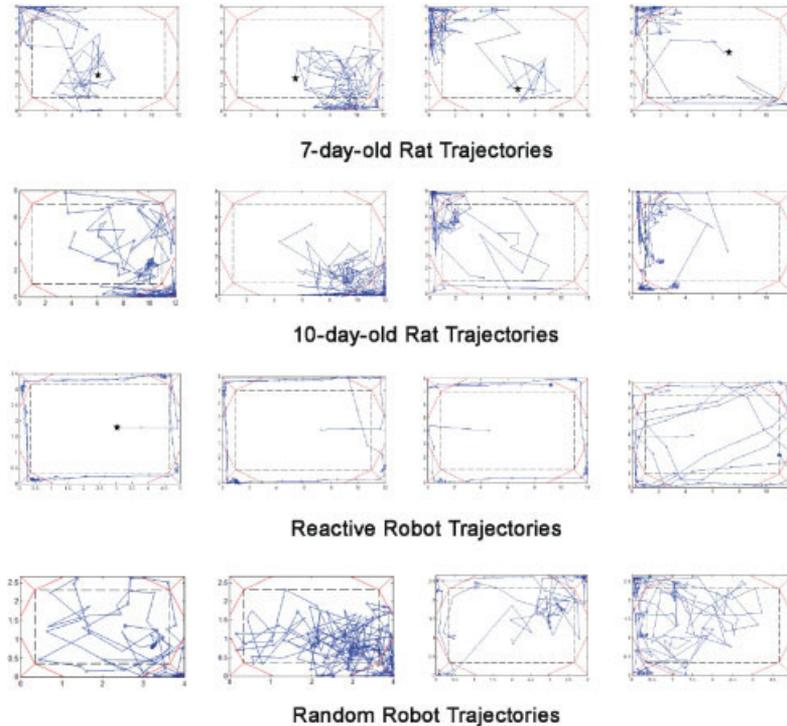
Diagram of the sensorimotor contingencies for the reactive agent. If one of the sensors (blocks) in a sensor group (circle) is activated, the robot moves in the direction of the arrow.

wall contact, and corner contact are all indices of thigmotaxis. In addition, we measured the distance traveled every 5 s when active from (i) tip-of-the nose at time  $t$  to tip-of-the nose at time  $t + 1$ , (ii) base-of-the tail at time  $t$  to base-of-the tail at time  $t + 1$ , and (iii) the midpoints between (i) and (ii) from time  $t$  to  $t + 1$ . This we used as an additional validation measure for rat-to-robot fit.

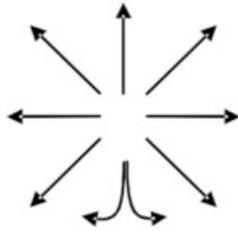
### REACTIVE ARCHITECTURE

We previously [20] reported results from a Braitenberg-style reactive architecture to model thigmotaxis using simple rules. This architecture employed priority-based arbitration in which rostral sensory contact overrode more caudal contact. Additionally, more sensorimotor representation was given to less extreme behaviors. Agents were programmed to move toward tactile contact according to the scheme in Figure 4. Specifically, every 2 s, a robot selected a direction of movement based on sensory input from the preceding interval (2 s was judged to be a reasonable decision interval to model rat pup behavior; unpublished observations). All behaviors were executed for 2 s, with the exception of move-

**FIGURE 5**



Trajectory plots of (from top-to-bottom) 7-day-old rat pups, 10-day-old rat pups, reactive robots, and random robots. Plots consist of lines between successive head coordinates. The arena wall is represented by the outer box. The dashed lines within the arena are tolerance lines demarcating wall contact, whereas triangles in the corners demarcate corner events.

**FIGURE 6**

Directional movements available to random robots individually and in groups.

ments resulting from contact with the front sensor. In this case, robots back up for 1 s and then turn left for another second (see [20] for justification). In the absence of tactile stimulation, agents moved forward.

As illustrated in Figure 5, robots implementing this reactive architecture produced very rigid and highly stereotyped behavior. For most runs, agents would quickly move to the wall, and then circumnavigate the arena for the remainder of the run. Although visually different from rat pup trajectories, these results serendipitously highlighted a previously unrecognized pattern in the animal data, namely that rat pup movement is not symmetrically distributed in the corners. Pups spend more time along one wall of the corner than the other wall (for more, see [20]). Nonetheless, it is clear that this architecture provides a poor model of rat pup behavior in an arena.

A clue pointing to a better architecture was revealed by noticing that not all of the runs had such rigidly stereotyped behavior. Certain behavioral patterns deviated from the norm (e.g., see the rightmost plot under reactive robot in Figure 5), which we attributed to random variation in the robot-environment interactions. These include part deterioration, imperfections in the floor, dust accumulation on the floor, and slight difference in the construction of robots. This suggested that we should explicitly model indeterminacy in the robot-environment complex.

#### RANDOM ARCHITECTURE FOR INDIVIDUAL ROBOTS

Indeterminacy was modeled with a completely random control architecture in which robots did not use their sensors. Every 2 s, robots randomly chose 1 of 10 movements: stop moving or 1 of the 7 forward or 2 back-up directions depicted in Figure 6. Note that rat pups can flex their body and turn away from a corner. Rigid-body robots cannot escape a corner in this way. Therefore, to model the ability of rat pups to escape corners, we implemented the two

back-up directions of movement. This is also a more principled implementation of backing up than the two sub-behavior routine implemented in the reactive architecture [20]. Thus, when moving, a robot moved forward 78% and backed up 22% of the time.

Eight robots implementing the random architecture were individually run in 18 experimental sessions. For each experimental session, each robot's pseudo-random number generator was seeded with a different pseudo-random number. Each robot was placed in the middle of an arena scaled four times larger than the rat-pup arena ( $81.28 \times 121.92$  cm) for 10 min. All statistical comparisons between robots and rat-pups used two-tailed *t*-tests.

#### Results

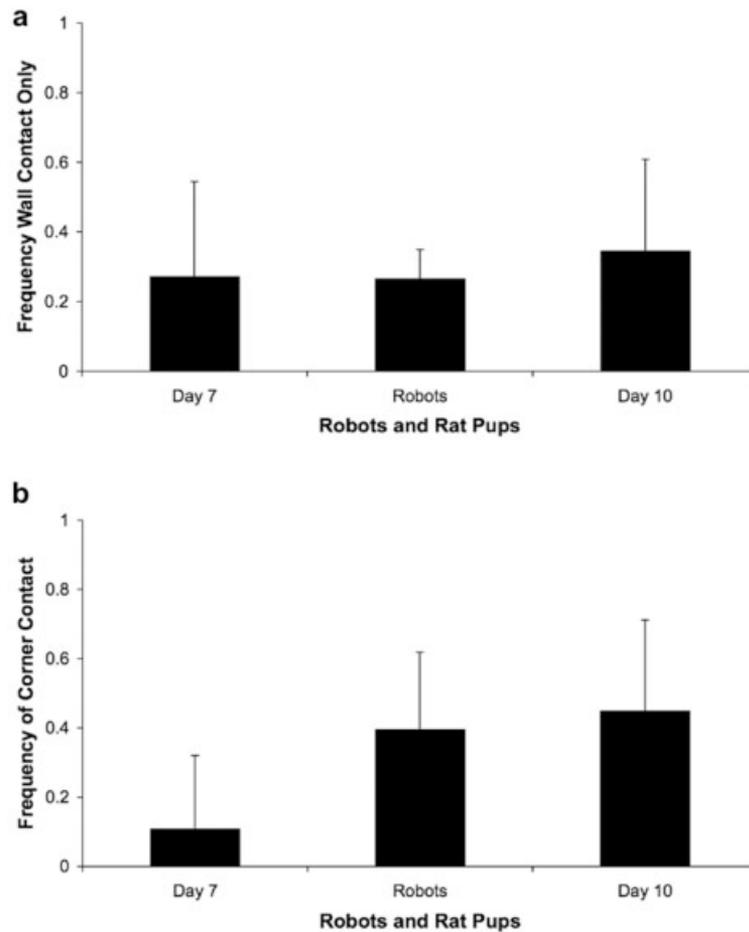
It is striking how well the trajectory plots of random robots visually matched the plots for both 7- and 10-day-old pups (Figure 5). Robots and 7-day-old pups did not differ in frequency of wall contact [excluding corner contact;  $t = 0.25$ ,  $df = 81$ ,  $p = 0.81$ , unequal variance; Figure 7(a)]. Ten-day-old pups contacted walls about 23% more often than robots ( $t = 2.92$ ,  $df = 59$ ,  $p = 0.005$ ) and 7-day-old pups [ $t = 2.35$ ,  $df = 242$ ,  $p = 0.02$ ; Figure 8(a)].

However, for frequency of corner contact, robots did not differ from 10-day-old pups [ $t = 0.82$ ,  $df = 132$ ,  $p = 0.42$ ; Figure 7(b)]. Robots contacted corners 73% more than 7-day-old pups [ $t = 5.39$ ,  $df = 144$ ,  $p < 0.001$ ; Figure 7(b)]. Ten-day-old pups also contacted corners about 76% more than 7-day-old pups [ $t = 11.26$ ,  $df = 242$ ,  $p < 0.001$ ; Figure 7(b)]. Thus, individual robots in the arena matched aspects of both 7- and 10-day-old contact behavior, falling between the two age classes, but closer to 10-day-old pups.

The rotational speed of the servo-motors (forward and reverse) on the robots was restricted to integer units in the Parallax Java Stamps. Because there was a limited range of settings, we systematically tested different combinations of settings to identify one setting that looked most like 10-day-old pups. To test these servo-motor settings, we compared the distances moved in time intervals of 5 s. Given that a pup or robot moved at time  $t$ , we measured three distances moved in 5 s ( $t + 1$ ): from nose to nose, base-of-tail to base-of-tail, and body midpoint to body midpoint (see Figure 8).

In Figure 8(a and c), 10-day-old pups and robots did not significantly differ in the distance moved ( $t = 0.35$ ,  $df = 37$ ,  $p = 0.72$ , unequal variances), but 7-day-old pups moved significantly less from nose to nose than did 10-day-old pups ( $t = 3.85$ ,  $df = 242$ ,  $p < 0.001$ ) and robots ( $t = 3.14$ ,  $df = 144$ ,  $p = 0.002$ ). This is not surprising given that we matched the robots speed to the 10-day-old pups. Measuring from midpoint to midpoint, 10-day-old pups and robots again did not significantly differ in the distance moved ( $t =$

**FIGURE 7**



The average frequency ( $\pm$ SD) of wall contact (a) and corner contact (b) for rat pups and robots. The frequency of wall contact was the same for robots and 7-day-old pups, but robots contacted walls about 23% less than 10-day-old pups. For corners, robots did not differ from 10-day-old pups, but contacted corners much more than 7-day-old pups (as did 10-day-old pups, b).

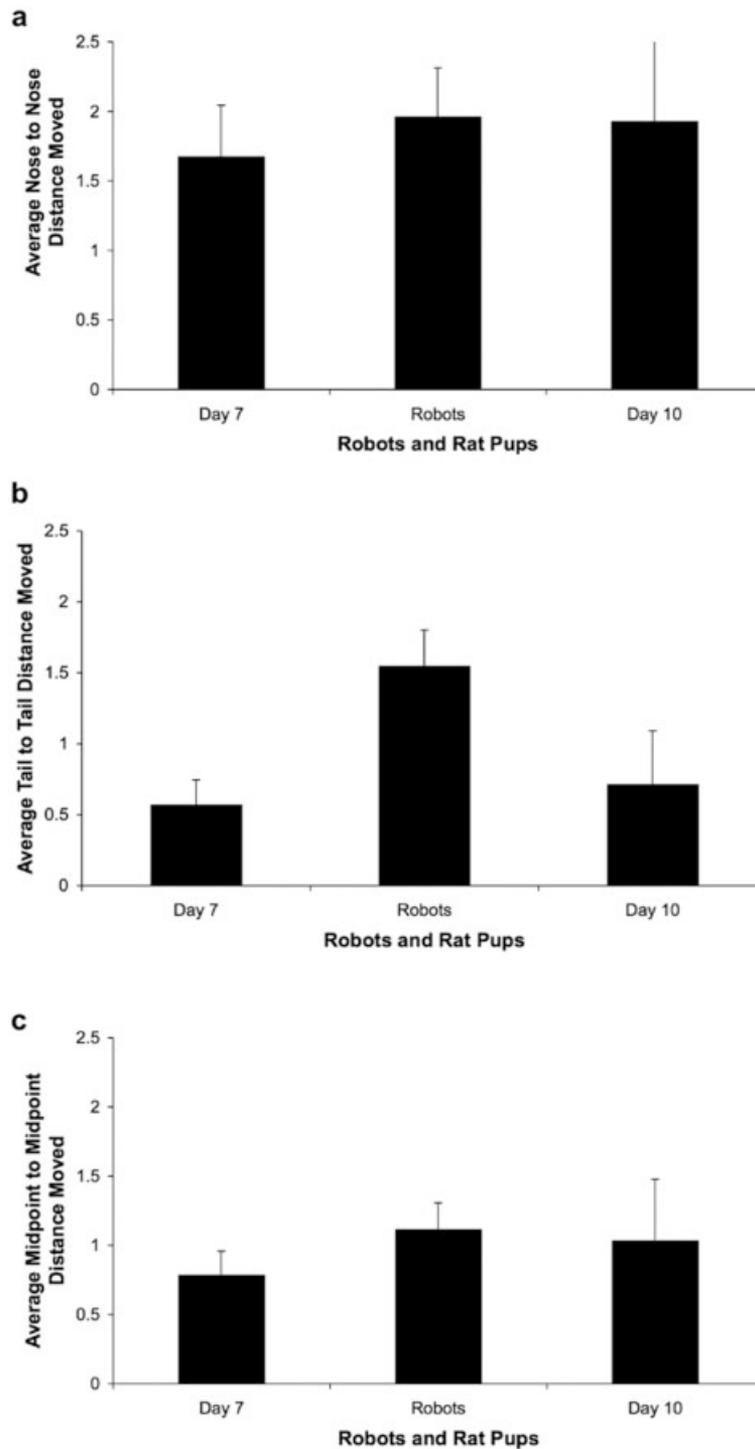
1.35,  $df = 51$ ,  $p = 0.18$ , unequal variances), and 7-day-old pups moved significantly less than from 10-day-old pups ( $t = 5.67$ ,  $df = 145$ ,  $p < 0.001$ , unequal variances) and robots ( $t = 7.63$ ,  $df = 144$ ,  $p < 0.001$ ). Ten-day-old pups moved from base-of-tail to base-of-tail significantly more than did 7-day-old pups ( $t = 3.951$ ,  $df = 242$ ,  $p < 0.001$ ). However, robots moved considerably more from base-of-tail to base-of-tail than either 7-day-olds ( $t = 20.93$ ,  $df = 144$ ,  $p < 0.001$ ) or 10-day-olds ( $t = 9.1$ ,  $df = 132$ ,  $p < 0.001$ ). This was the largest mismatch between robot and pup behavior observed. This difference is likely due to the lack of flexibility in our robots. If a robot's nose end moves from side to side, then its back end must also move from side to side, which is not true for pups. Taken together, these results indicate that the speed of the robots was generally a good approximation of the speed of 10-day-old pups in a rectangular arena.

### RANDOM ARCHITECTURE FOR GROUPS OF ROBOTS

To examine the behavior of groups of 8-random robots, we conducted 15 10-min trials. Pseudo-random number generators in each robot were seeded with different numbers at the beginning of each trial. Thus, no two robots on any two runs had identical behavioral sequences. Robots were placed in the center of the arena in 2 rows of 4 with randomly determined initial orientations. Assuming the top of the arena is north (see Figure 1), these orientations were north, northeast, east, southeast, south, southwest, west, and northwest.

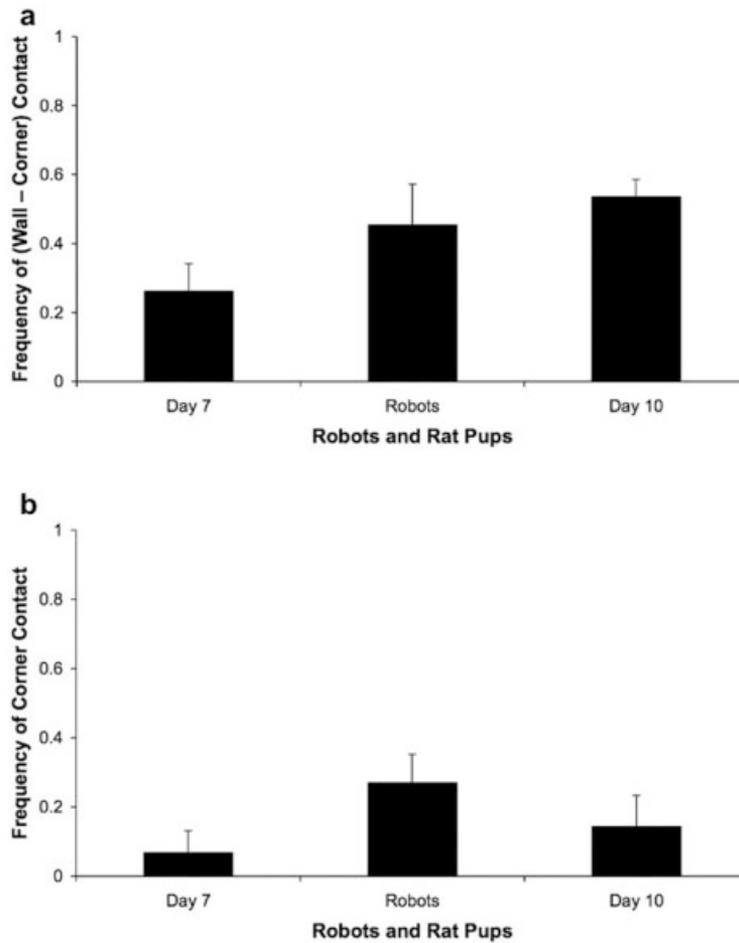
### Results

For groups of eight pups and robots, robots contacted walls excluding corners more than 7-day-old pups [ $t = 5.69$ ,  $df =$

**FIGURE 8**

Plots of mean distances moved for tip-of-nose, base-of-tail, and midpoints ( $\pm$ SD). Distances are in scaled units. For rat pups, 1 unit is 2.54 cm and for robots it is 7.62 cm in 5 s. The distances moved in intervals of 5 s are the same for robots and 10-day-old pups for nose-to-nose and midpoint to midpoint, and although there was a statistical difference for robots and 7-day-old pups, it was only 15% less for nose to nose and 31% less for midpoint to midpoint. For base-of-tail, 7-day-old pups moved 63% less than robots, and 10-day-old pups move 54% less.

**FIGURE 9**



Average frequency ( $\pm$ SD) of wall contact (a) and corners (b) for rat pups and robots. Wall contact did not differ for groups of robots and 10-day-old pups, but robot and 10-day-old pups contacted corners more than 7-day-old pups. Corner contact in group provided the greatest mismatch between robot and pup behavior with robot contacting about twice as often as 10-day-old pups and three times more than 7-day-old pups.

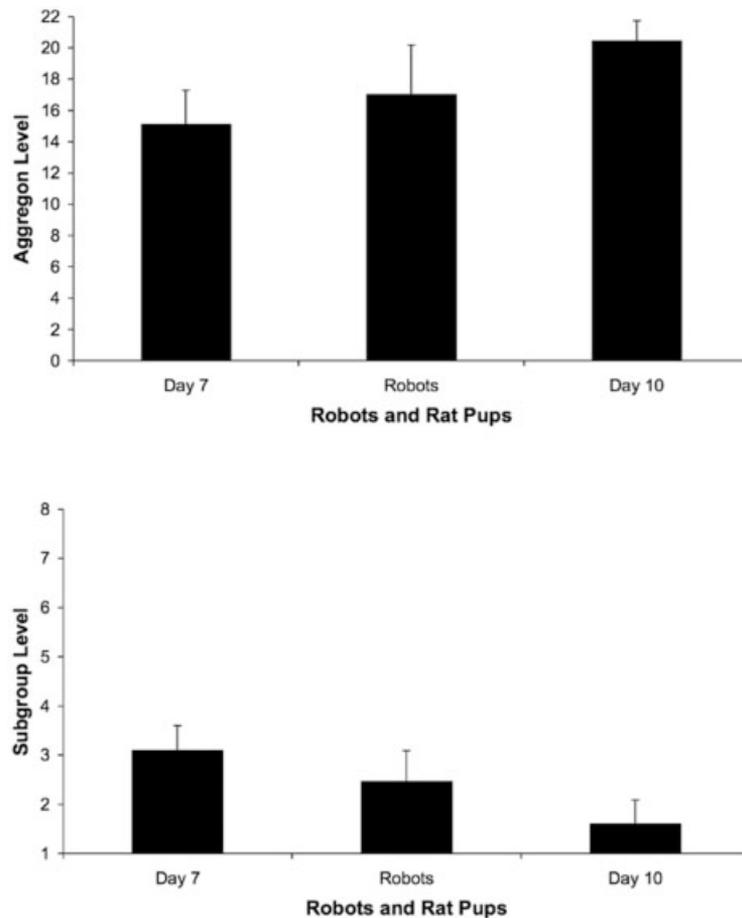
26,  $p < 0.001$ , unequal variances; Figure 9(a)] and marginally less (15%) than 10-day-old pups [ $t = 2.075$ ,  $df = 20$ ,  $p = 0.051$ , unequal variances; Figure 9(a)]. Thus, robots in groups contacted walls intermediate between 7- and 10-day-old pups.

Ten-day-old pups contacted corners more than 7-day-olds [ $t = -2.98$ ,  $df = 33$ ,  $p < 0.01$ ; Figure 9(b)]. Robots contacted corners more (74%) than 7-day-old pups [ $t = 8.53$ ,  $df = 32$ ,  $p < 0.001$ ; Figure 9(b)] and more (46%) than 10-day-old pups [ $t = 4.36$ ,  $df = 31$ ,  $p < 0.001$ ; Figure 9(b)]. Thus, in groups, robots contacted corners more than either 7- or 10-day-old pups, which again may be due to their rigid bodies (see Discussion).

Robots were also intermediate between 7- and 10-day-pups in the level of aggregation they achieved. Using the

aggregation measure, robots aggregated a little more than 7-day-old pups [ $t = 2.081$ ,  $df = 31$ ,  $p = 0.046$ ; Figure 10(a)], but less than 10-day-old pups [ $t = 4.175$ ,  $df = 20$ ,  $p < 0.001$ , unequal variances; Figure 10(a)]. Seven-day-old pups aggregated less than 10-day-old pups ( $t = 8.89$ ,  $df = 32$ ,  $p < 0.001$ ).

Using the subgroup measure, robots aggregated more than 7-day-old pups ( $t = 3.31$ ,  $df = 31$ ,  $p = 0.002$ ) but less than 10-day-old pups [ $t = 4.44$ ,  $df = 30$ ,  $p < 0.001$ ; Figure 10(b)]. Again, 7-day-old pups aggregated less than 10-day-old pups ( $t = 9.19$ ,  $df = 32$ ,  $p < 0.001$ ; Figure 11). The similarities in aggregation between robots and pups were particularly striking when viewed in video as shown in several images in Figure 11.

**FIGURE 10**

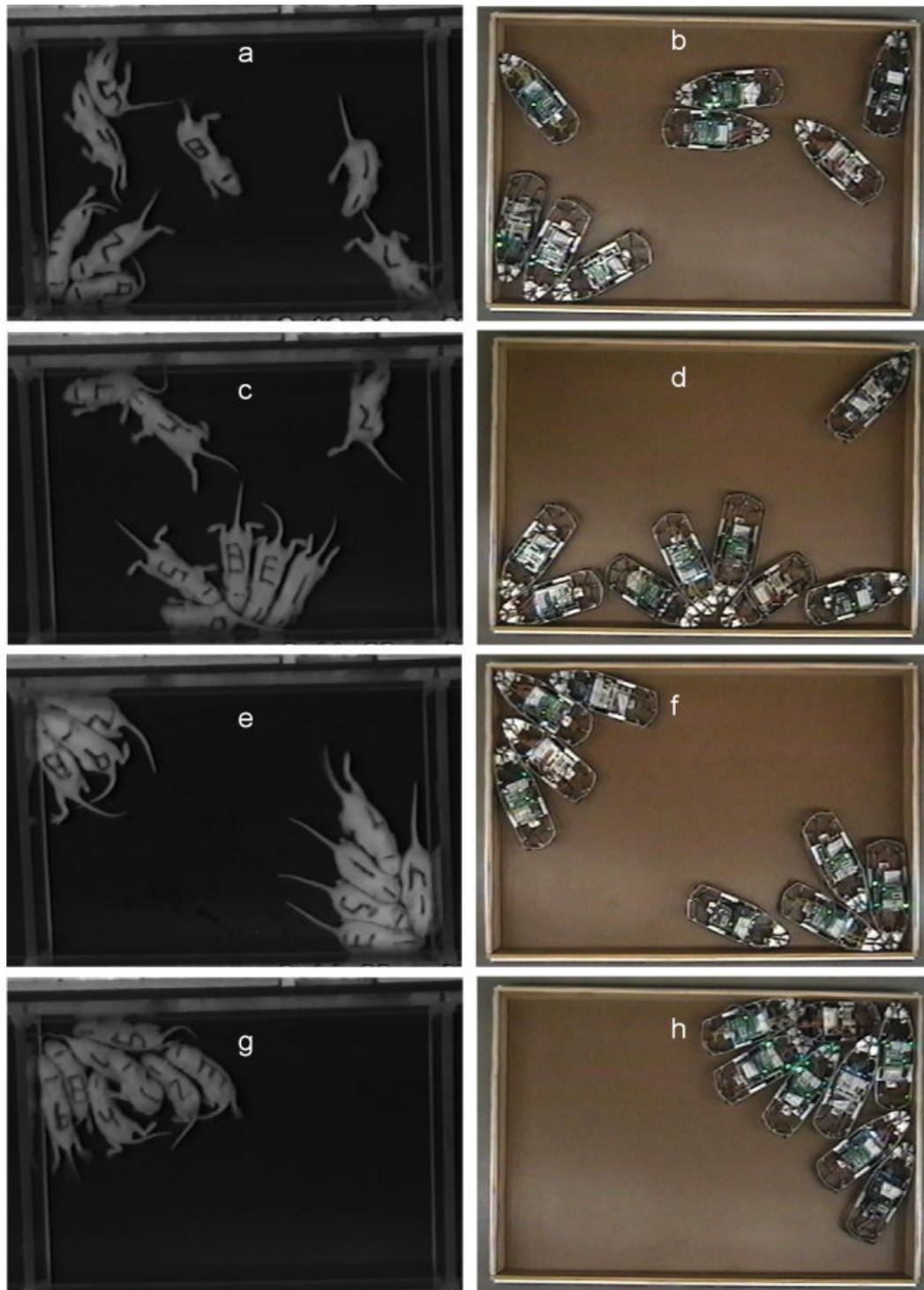
Two measures of aggregation, both indicating that robots aggregated intermediate between 7- and 10-day-old pups.

## DISCUSSION

On most measures, random robot behavior was intermediate between, or the same as, observed behavior in 7- and 10-day-old rat pups. This is interesting in that our initial goal in these robot experiments was not to model one or the other age group, but to obtain a first-order estimate. It appears we have succeeded at modeling the behavior of pups with a null model of their behavior. Indeed, because robots had more wall and corner contact than 7-day-old pups, as well as greater aggregation, random robots appear to be more thigmotactic than 7-day-old pups. However, robots also aggregated less than 10-day-old pups. This is consistent with previous research demonstrating that activity levels of 10-day-old pups are coupled, which is not the case for 7-day-old pups [15], nor is it represented in our robot control architecture.

As with the rat pups, movement trajectories in the state-space of the random robots do not appear random (Figure 5). Robots often appear goal-directed, “seeking out” and remaining in corners or along walls. The apparent good fit between rat pup and random robot behavior is initially unintuitive because this presumes that rat pups are moving randomly and that thigmotactic behavior can emerge from random interactions. The explanation lies in the interaction between body morphology and arena geometry. When a robot contacts a wall, it slides along the wall by virtue of its tapered nose. Which direction a robot will travel along the wall (left or right) is determined largely by its angle of approach. Once against the wall, 5/9ths of the robot’s behavioral repertoire will keep it against the wall. The other 4/9ths, namely those movements away from the wall, have compromised effectiveness. For example, in executing a movement away from the wall, the robot’s back end may hit the wall, limiting the extent to which it can move away. It

**FIGURE 11**



Examples of aggregation patterns of rat pups and robots in arenas. Day-7 pups (a) and robots (b) shortly after they are released or started. Day-7 pups (c) and robots (d) forming a subgroup that is not in a corner. Day-10 pups (e) and robots (f) forming two subgroups in opposite corners. Day-7 pups (g) and robots (h) aggregating in a single corner. [Color figure can be viewed in the online issue, which is available at [www.interscience.wiley.com](http://www.interscience.wiley.com).]

still can, and does, leave the wall, but with a probability much lower than 0.5. In a corner, the nose wedges between the two walls, limiting the effectiveness of any movement other than backing up. When in a group, even backing up is compromised because of the presence of other agents. As with rat pups, other agents press in from the sides (see Figure 11). “Wall-following,” then, can be thought of as an attractor and “corner-burrowing” as a much deeper attractor created by the convergence of two wall-following attractors, where both attractors are further deepened in the context of a group. These attractors are born, not of a specific control algorithm, but of the random interactions between a robot and its environment.

We suspect that this finding will turn out to be robust because the random architecture employed here is only one of a large number of random architectures, some of which will fit rat-pup behavior better than our initial random model. For example, although each of the 10 movements was randomly selected, their probability of selection was fixed at 10%. These probabilities could be varied. As with the reactive architecture, less extreme movements could be given higher probability than more extreme movements. Alternatively, activity could be completely decoupled from inactivity. This would effectively create an internal state variable specifying action or inaction, roughly mapping into the behavioral approach system and behavioral inhibition system in animals. That activity level is independent of the kind of activity has been suggested by multiple researchers [15,21]. Probabilities could also change over the course of a robotic run, in accord with an observed decrease in activity in rat pups [14], and movement patterns may be allowed to change across time as well [22].

We are not yet claiming that Norway rats at this stage of development are behaving randomly. Even if the robot data perfectly matched the animal data on all of our metrics, it does not follow that the generative mechanisms are isomorphic. Indefinitely many functions could produce the same behavior, which is the under-determination problem in modeling. Further experiments will have to be conducted to tease out the behavioral implications of a given architecture or morphology to see if those are reflected in similar animal experiments. For example, body rigidity plays a large role in generating the emergent patterns of behavior in groups of robots. If we construct flexible robots, will they generate the same patterns of behavior when programmed to move about randomly? Their behavior will also depend on whether they flex passively or actively.

However, these results do lend further support to the embodied, dynamic environmental interaction paradigm. We found that robot morphology interacted with the environment to produce wall-following, corner-burrowing, and group huddling (see Figure 11). Although rat pups are thigmotactic, our results indicate that they need not be in virtue

of a dedicated neural processor or sensorimotor routine. Morphological and environmental constraints may be so strong that no cognitive control at all is required to produce these behaviors. This is a plausible interpretation if we consider the experimental conditions under which the pups were tested. The arena surface and ambient temperature of the chamber were held constant at 34°C. The surface or skin temperature of a pup under these conditions matches very closely the ambient temperature (unpublished observation with an infrared camera). Thus, temperature of other pups was likely not a salient contact stimulus. Olfactory cues were reduced by cleaning the arena after each session with alcohol, but the odors given off by each pup do play some role in their contact behavior [17]. Other stimuli are known to affect their aggregation [17,18] but these were precisely controlled. The walls of the arena may not have had salient features that would elicit a positive thigmotactic response from the pups. Thus, our experimental setup might have been devoid of stimuli that would elicit positive thigmotactic responses, and so the pups might have been moving nearly randomly in the arena. That the pups still aggregate well and displayed thigmotactic behavior is surprising and constitutes an entirely novel hypothesis about the mechanisms generating rat-pup behavior. It has been believed since at least 1934 that thigmotaxis is a reactive behavior [23]. Before that, thigmotaxis was simply assumed to be innate. Our results suggest patterns of aggregation and wall-following may emerge from random behavior constrained by body morphology and the geometry of the environment.

More generally, we see the hallmark of complexity in the emergence of patterned behavior from total randomness. This result has important implications for behavioral research in the social and biological sciences, where noise is typically thought of as unexplained variance to be minimized or averaged out. However, given that noise is integral to the emergence of behavior and the operation of a system, that understanding will then always be partial. The unappreciated fundamentality of noise is demonstrated here in the role it plays in the generation of “simple” taxes. This dramatically underscores the importance of synthesizing behaviors to really understand them.

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