

# Brain-Based Devices: Intelligent Systems Based on Principles of the Nervous System

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**Abstract** – Our group has constructed a series of brain-based devices (BBDs); i.e. physical devices with simulated nervous systems that guide behavior, to serve as a heuristic for understanding brain function. Unlike conventional robots designed by engineering principles, BBDs are based on biological principles and alter their behavior to the environment through self-learning. The resulting systems autonomously generalize signals from the environment into perceptual categories and through adaptive behavior become increasingly successful in coping with the environment. Although the principal focus of developing BBDs has been to test theories of the nervous system, this approach may also provide a basis for robotic design and practical applications.

## I. INTRODUCTION

The development of intelligent systems has received a lot of attention, but only marginal success. The hope was to build systems that could automate tasks in an intelligent manner, extend human intelligence, or behave autonomously. In this paper, we review a novel approach that takes inspiration from biology at the systems neuroscience level to create a class of brain-based devices (BBDs), i.e. physical devices whose behavior is controlled by a simulated nervous system, that demonstrate adaptive behavior in rich environments.

BBDs are not programmed by instructions like computers, but instead, like biological systems, they operate according to selectional principles that allow them to adapt to the environment [1]. This design, which possesses neuroanatomical structure and large-scale neural dynamics, differs fundamentally from that of robots designed for engineering purposes. Rather, BBDs are constrained by the following design principles: (i) The device must engage in a behavioral task. (ii) The device's behavior must be controlled by a simulated nervous system having a design that reflects the brain's architecture and dynamics. (iii) The device's behavior is modified by a reward or value system that signals the salience of environmental cues to the BBD's nervous system. (iv) The device must be situated in the real world.

These features result in a system that autonomously generalizes signals from the environment into perceptual categories and adapts its behavior so that it becomes increasingly successful in coping with its environment. Because of these constraints, BBD simulations tend to require large-scale networks of neuronal elements that reflect the brain's anatomy and physiology, high performance computing to run the network in real-time, and the engineering of specialized physical devices to embody the network.

Over the last 12 years, we have constructed a series of BBDs designated the Darwin automata [2-6]. In this paper, we describe the two most recent BBDs in the series, Darwin VII and Darwin VIII, with the aim of conveying the principles underlying these devices and the potential of the BBD approach.

## II. DARWIN VII - PERCEPTUAL CATEGORIZATION AND OPERANT CONDITIONING IN A BBD

The behavior of Darwin VII showed that a synthetic brain-based device operating on biological principles and without pre-specified instructions could carry out object recognition and conditioned responses (for more details regarding Darwin VII experiments and methodology, see [4]). The successful performance of the device rests on the selectional modulation of its neuronal activity by behavior interacting with constraints provided by its value system. The development of categorical responses required exploration of the environment and sensorimotor adaptation through specific and highly individual changes in connection strengths.



Fig. 1 Darwin VII consists of a mobile base equipped with several sensors and effectors and a neural simulation running on a remote computer workstation. (From [4]).

Darwin VII consists of a mobile base equipped with a CCD camera for vision, microphones for hearing, conductivity sensors for taste, and effectors for movement of its base, of its head, and of a gripping manipulator having one degree-of-freedom (Figure 1).

Darwin VII's behavior is guided by a nervous system modeled on the vertebrate nervous system, but obviously

with far fewer neurons and simpler architecture (see Figure 2). Six major systems make up the simulated brain: an auditory system (*LCoch*, *RCoch*, *A1*), a visual system (*R*, *VA<sub>p</sub>B*, *VA<sub>p</sub>H*, *VA<sub>p</sub>V*, *IT*), a taste system (*T<sub>app</sub>*, *T<sub>ave</sub>*), sets of motor neurons capable of triggering behavior (*M<sub>app</sub>*, *M<sub>ave</sub>*), a visual tracking system (*C*), and a value system (*S*). The complete nervous system contained 18 neuronal areas, 19,556 neuronal units, and approximately 450,000 synaptic connections between neuronal units.

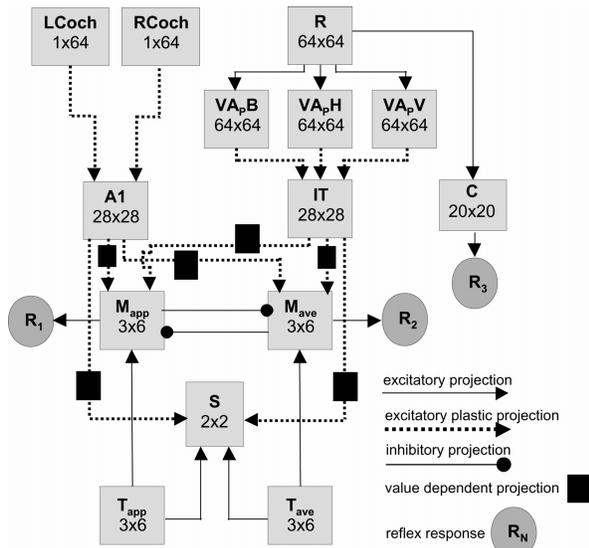


Fig. 2 Schematic of the regional and functional neuroanatomy of Darwin VII. Each box denotes a neural area and the numbers signify the number of neuronal units in that area (height x width). Arrows denote synaptic projections from neuronal units in one area to neuronal units in another. (Adapted from [4]).

A neuronal unit in Darwin VII was simulated by a mean firing rate model; the activity of each unit corresponds roughly to the average activity of a group of neurons (approximately 10 to 100 neurons) over a time period of approximately 200 milliseconds. The mean firing rate model was chosen because it captures many of the attributes of real neurons at a level of resolution consistent with electrophysiological measurements, while being sufficiently simple to allow computation in real-time. In the model, updates were based on a simulation cycle: the period of time during which the current sensory input is processed, the activities of all neuronal units are computed, the connection strengths of all plastic connections are computed, and motor output is generated (see [4] for details). Each simulation cycle in Darwin VII took approximately 200 ms of real time, which is sufficiently fast in that the device does not wait for commands from the nervous system and can respond to stimuli without delays.

The strength of connections between two units can change based on the activity of the sending unit, called the pre-synaptic neuronal unit, and the receiving unit, called the post-synaptic unit. If the sending and receiving units are simultaneously strongly active, the connection between them is strengthened. If the sending and receiving units are simultaneously weakly active the connection is weakened. Some connections are also affected by the value system. The

connection strength between these units is amplified when the value system was active.

Activation of the simulated value system (Area *S*, Figure 2) signals the occurrence of salient sensory events and contributes to the modulation, at that time, of connection strengths of all active synapses in the value-dependent pathways. For example, “tasting” a block picked up by Darwin VII’s gripper is a salient event affecting subsequent behavior that is reinforced or weakened through synaptic change. Area *S* is thus analogous to an ascending neuromodulatory value or reward system [7].

Darwin VII’s environment consisted of an enclosed area with black walls and a floor covered with opaque black plastic panels, on which we distributed stimulus blocks (6 cm metallic cubes) in various arrangements (Figure 1). The top surfaces of the blocks were covered with two basic patterns: *blobs* (several white patches 2-3 cm in diameter) and *stripes* (width 0.6 cm, evenly spaced). *Stripes* on blocks in the gripper could be viewed in either horizontal or vertical orientations, yielding a total of three stimulus classes of visual patterns to be discriminated (*blob*, *horizontal* and *vertical*). A flashlight mounted on Darwin VII and aligned with its gripper caused the blocks, which contained a photodetector, to emit a beeping tone when Darwin VII was in the vicinity. The sides of the stimulus blocks were metallic and could be rendered either strongly conductive (appetitive or “good taste”) or weakly conductive (aversive or “bad taste”). Gripping of stimulus blocks activated the appropriate taste neuronal units (either *T<sub>app</sub>* or *T<sub>ave</sub>* in Figure 2) to a level sufficient to drive the motor areas above a behavioral threshold. In the experiments, strongly conductive blocks with a striped pattern and a 3.9 kHz tone were chosen arbitrarily to be positive value exemplars, whereas weakly conductive blocks with a blob pattern and a 3.3 kHz tone represented negative value exemplars.

Basic modes of behavior built into Darwin VII included IR sensor-dependent obstacle avoidance, visual exploration, visual approach and tracking, gripping and “tasting”, and two main classes of innate behavioral reflex responses (appetitive and aversive). With the exception of obstacle avoidance, selection among the above behaviors was under control of the simulated nervous system. Appetitive and aversive responses were triggered initially by taste, but after training or conditioning, these responses could be triggered by auditory or visual stimuli. After conditioning, Darwin VII continued to grip and “taste” appetitive blocks, but learned to back away without picking up aversive blocks avoiding these blocks over 90% of the time. Thus, during the conditioning experiments, in which many stimuli were encountered over an extended period of time, Darwin VII developed perceptual categories that modified its behavioral responses in an adaptive fashion.

Furthermore, we were able to carry out second-order conditioning experiments with Darwin VII. After associating the initially neutral visual pattern with an innate value-loaded taste, the visual pattern was paired with a tone that emitted from the block. Darwin VII successfully learned this association, and avoided blocks with a tone predictive of bad taste and approached blocks with a tone predictive of good taste over 90% of the time (see [4] for details).

While performance improved with training, it never reached perfection and occasional “mistakes” were made. This unpredictability is a general property of selectionist systems, that is, systems consisting of a population of variant repertoires which are differentially amplified, thus yielding responses to unpredicted or novel events. The unpredictability of behavioral responses in Darwin VII coupled with the variability of a complex environment allowed the device to learn after mistakes, to generalize over sensory inputs, and to deal with novel situations.

Categorical responses in Darwin VII’s “higher” visual areas were essential for success in conditioning tasks. Object recognition, resulting from a persistent *IT* pattern of activity in response to a class of object, was invariant to changes in rotation, scale, and position in its visual field (see Figure 3).

Darwin VII’s nervous system had three features that were critical for perceptual categorization: (i) Connectivity from a topographically mapped primary area with transient activity to a non-topographically mapped higher area with more persistent activity (e.g. see  $VAP \rightarrow IT$  in Figure 2). (ii) Sensory input that is continuous and temporally correlated with self-generated movement. (iii) Activity-dependent learning in which competitive mechanisms categorize sensory information and select for appropriate behavioral repertoires. These features allowed Darwin VII to achieve invariant object recognition, which is a system property that emerges dynamically from competitive neuronal group interactions within and between neural areas.

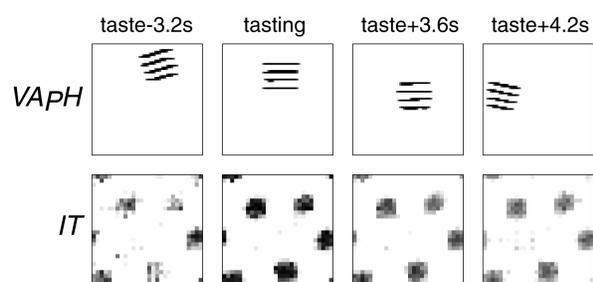


Fig. 3 Invariance with respect to position, scale and rotation emerges from a persistent pattern of activity in area *IT* as the pattern of activity in the *VAP* areas moves sequentially across Darwin VII’s field of vision. Shown in the figure is sequential activity of *VAPH* and *IT* during a stimulus encounter with a striped block. Activity in neuronal area *VAPH* is shown in the top row and that in area *IT* is shown in the bottom row as Darwin VII approaches, grasps and tastes, and moves away. (Adapted from [4]).

Object recognition in Darwin VII had similar properties to that of biological organisms; experience and individuality shaped its perception of different objects. Differences in an individual’s perceptual history had a profound effect on the organization and response of the nervous system. Using Darwin VII, we performed experiments concerned with experience-dependent effects on categorization during the development of perceptual categories as well as after such development [8]. In these experiments, Darwin VII started with an identical simulated nervous system operating in the same physical platform ensuring that any differences would only be due to experiential history. One set of experiments investigated the effect of variations in stimulus order and frequency on early development. The experiments began with a visually “naïve” Darwin VII exploring an

environment that was partially divided into two sub-areas with disparate distributions of stimuli. The number of neuronal units in *IT* selectively responding to a given stimulus (whether blob, horizontal stripe, or vertical stripe) increased with an increase in the frequency of presentation of that stimulus class [4, 8]. These findings are similar to the results of neuronal recordings in the monkey inferotemporal cortex in which more neurons respond to familiar than to unfamiliar objects in recognition tasks [9].

Another set of experiments investigated the effect of stimulus frequency on a BBD that had previous visual experience. The experience consisted of exemplars of the three stimulus classes presented in equal proportion until categorization was achieved with high accuracy. This “adult” Darwin VII was then presented with exemplars of only two out of the three stimulus classes. In contrast to the previous experiments on early development, after extensive experience, the number of neuronal units in *IT* responding to more frequently sampled stimuli did not change significantly suggesting that responses in *IT* had become “saturated” with respect to the familiar stimuli. However, when Darwin VII responded to the less frequently sampled stimulus, the number of *IT* neuronal units was significantly less than that in the controls (Table 1). In essence, Darwin VII had forgotten these perceptual categories.

<i>Effect of stimulus presentation frequency on IT activity after development of visual categorization</i>				
<i>Test Stimuli</i>	control	stripes only	horizontal and blob	vertical and blob
blob	88.8	72.9*	89.9	91.6
horizontal	54	55.6	57.7	31.5*
vertical	24.2	24.4	17.9*	23.8

Table 1. Role of history in perceptual categorization. After visual categories had been developed (8 presentations of each stimulus class), the activity in *IT* stayed relatively constant for stimuli presented in higher proportions, but decreased for stimuli presented in lower proportions. Each row in the table shows the median number of *IT* neuronal units that respond to stimuli for a control group (8 additional presentations of blob, horizontal, and vertical stimuli) and three experimental groups in which 8 additional stimuli from two out of the three classes were presented. There were 10 trials for each group with identical initial conditions in the simulated nervous system. The asterisks denote a significant difference ( $p < 0.05$ ) in medians between the control group and an experimental group using the Wilcoxon Rank Sum test of medians. (Adapted from [8]).

Similar to biological organisms, different Darwin VII subjects (i.e. instantiations of the simulated nervous system with slight variations in initial conditions) and cloned Darwin VII subjects with different experiences never displayed identical patterns of neural activity, even during repetitions of the same behavior. However, the adaptive behaviors tend to remain similar despite variation in system properties resulting from multiple interactions across circuitry, plastic synaptic connections, fluctuating value systems, and variable object encounters. In this respect, Darwin VII is an example of a degenerate system: different circuits and dynamics can yield similar behavior. Degeneracy is a ubiquitous property of biological systems and is necessary for natural selection [10].

### III. DARWIN VIII - VISUAL BINDING THROUGH REENTRANT CONNECTIVITY AND SYNCHRONIZATION

Our most recent BBD, Darwin VIII, demonstrated the ability to bind the attributes of stimuli in a scene to form coherent perceptual categories [5, 6]. Thus, Darwin VIII solves the so-called binding problem, that is, it shows how different brain areas and modalities can yield a coherent perceptual response in the absence of any superordinate control.

Darwin VIII was constructed to bind features such as colors and line segments into objects and discriminate between these objects in a visual scene. Darwin VIII's simulated nervous system was similar to that depicted in Figure 2, but with a more extensive visual system for detecting color and shape, and the addition of reentry; reciprocal connections within and between neural areas. In order to represent the relative timing of neuronal activity, each neuronal unit in Darwin VIII was described by both a firing rate variable, and a phase variable, where similar phases reflect synchronous firing. This modeling strategy provides the high temporal precision needed to represent neural synchrony, without incurring the computational costs associated with explicit modeling of the spiking activity of neurons. The simulated nervous system contained 28 neural areas, 53,450 neuronal units, and approximately 1.7 million synaptic connections. Darwin VIII used the same mobile platform as Darwin VII (see Figure 1).

In a scene segmentation task, Darwin VIII autonomously approached and viewed multiple visual shapes, hung from the walls of its enclosure, which contained overlapping features. It was trained to prefer one of these shapes by pairing the preferred shape with a positive value tone, and it demonstrated this preference by orienting toward the preferred object. When confronted by a pair of these shapes, Darwin VIII learned to successfully track towards the preferred object, designated the target, and avoid the other objects, designated the distracters.

Figure 4 shows a snapshot of Darwin VIII's neural dynamics during an approach to a red diamond target and a green diamond distracter towards the end of a training session. The panels next to Darwin VIII depict selected neural areas in the simulation. The visual system is based on the primate nervous system (in our model  $V1 \rightarrow V2 \rightarrow V4 \rightarrow IT$ ), in which neurons in successive areas have progressively larger receptive fields until the inferotemporal cortex (*IT*) is reached in which receptive fields cover nearly the entire visual field. The tracking system (area *C*) allows Darwin VIII to orient towards auditory and visual stimuli. The activity of area *C* (analogous to the superior colliculus in the primate) dictates where Darwin VIII centers its gaze or camera. Similar to Darwin VII, activation of the simulated value system (area *S*) signaled the occurrence of salient sensory events causing modulatory changes in value-dependent connections. These neural areas have both inter-area and intra-area reentrant connections (i.e. reciprocal, excitatory synaptic projections) between neuronal units. Each pixel in the depicted neural areas represents the activity and phase of a single neuronal

unit. The phase is given by the color of the pixel and the activity is given by brightness of the pixel (black is no activity; very bright is maximum activity). Neuronal units with similar phase have similar colors so that regions of consistent coloration reflect synchronous activity.

Figure 4 shows two neural circuits which are differentiated by their distinct relative phases as indicated by red/orange and blue/green colors, corresponding respectively to the red diamond and the green diamond shapes. The neuronal units which make up these circuits are distributed throughout the nervous system. As shown in the figure, the activity of the value system (area *S* in Figure 4) is in phase with the target and is therefore predictive of the visual object's saliency or value. Moreover, *IT* has two patterns of activity, based on the two different phase colors, reflecting two perceptual categories; activity in motor area *C*, which was biased toward the object on the left, lead to an orientating movement towards the target (i.e. the red diamond) and away from a distracter.

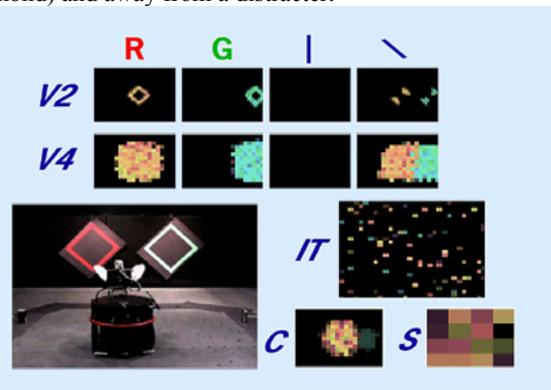


Fig. 4 Snapshot of Darwin VIII's neuronal unit activity during a behavioral experiment. Darwin VIII is approaching a red diamond target (left) and a green diamond distracter (right) towards the end of a training session. The panels next to Darwin VIII show the activity and phase of selected neural areas in the simulation (top row; *V2*-red, *V2*-green, *V2*-vertical, *V2*-diagonal, second row; *V4*-red, *V4*-green, *V4*-vertical, *V4*-diagonal, third row to the right of Darwin VIII; *IT*, fourth row to the right of Darwin VIII; *C* and *S*). Each pixel in the selected neural area represents a neuronal unit; the activity is normalized from no activity (black) to maximum activity (bright colors), and the timing of that activity (i.e. phase) is represented by the color of the pixel. Neuronal units with similar phase have similar colors. The neuronal units responding to the attributes of the red diamond are firing predominately in one phase (red-orange tinted neuronal units), whereas the neuronal units responding to the green diamond are firing at another phase (blue-green tinted neuronal units). (Adapted from [6]).

While performing this task, temporally coherent neuronal circuits were activated for each object in the visual scene. These circuits were comprised of synchronously active neuronal groups distributed throughout different areas in the simulated nervous system. Circuits associated with objects having different combination of features were distinguishable by their temporal characteristics, specifically the relative phase of their neural activity.

A summary of Darwin VIII's behavioral performance is given in Figure 5. Darwin VIII subjects with intact reentrant connections selectively oriented towards targets, but subjects with severed reentrant connections had significant degradation in their tracking performance. These observations indicate that reentrant connectivity was necessary for the reliable discrimination of targets from

visually similar distracters. Darwin VIII autonomously solved the binding problem in a rich environment in which there was self-movement that generated changes in the size and location of visual stimuli.

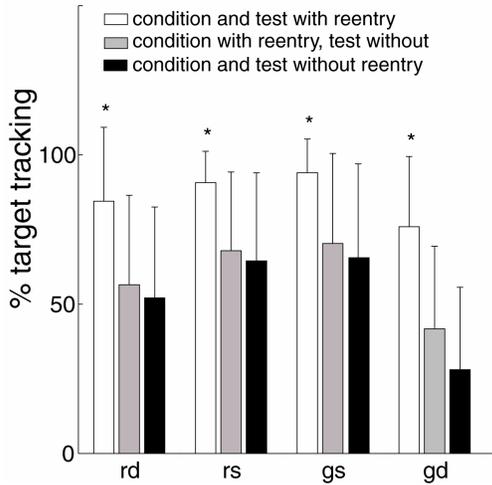


Fig. 5 Darwin VIII behavior following conditioning. Three separate Darwin VIII subjects were conditioned to track towards one of 4 target shapes ('rd' = red diamond, 'rs' = red square, 'gs' = green square, 'gd' = green diamond) in a control and two lesion experiments. Following conditioning, neural data was recorded from each subject as it approached successive target-distracter pairs. Subjects with reentrant connections intact tracked targets significantly better than both lesion groups (Asterisks denote statistically significant differences between intact subjects and both lesion conditions;  $p < 0.01$ , Wilcoxon ranksum test). Intact subjects are shown with white bars, lesions only during test period are shown with light gray bars, and lesions during both conditioning and testing are shown with black bars.

The results of these experiments demonstrated that the interaction between local processes (i.e. activity in each neural area) and global processes (i.e. emergent synchronously active circuits distributed throughout the nervous system) was necessary for binding together features to form a coherent scene, which in turn was critical for successful discriminatory behavior.

#### IV. DISCUSSION

The development of adaptive and autonomous behavior by brain-based devices (BBDs) is novel in its neurally based approach and has implications for the construction of intelligent machines. Without a doubt the most sophisticated behavior seen in either biological or artificial agents is demonstrated by organisms whose behavior is guided by a nervous system. Thus, the construction of behaving devices based on principles of nervous systems may have much to offer. However, this begs the question as to how much neural detail must be incorporated into these devices?

There is a tendency among modelers to apply Occam's razor (i.e. the best theory is the simplest theory with the least assumptions) to their designs. For example, Beer and colleagues have introduced the notion of simple idealized models that show minimally cognitive behavior [11]. These agents are developed through an evolutionary algorithm and contain on the order of tens of artificial neurons. Their agents show sensitivity to the future location of an object

and can act as if they are able to switch attention between objects. Moreover, their model is simple enough that a rigorous dynamical systems analysis can be applied. However, it is difficult to link these results to experimental work revealing neural areas underlying attention and working memory.

In neuroscience, however, the simplest explanation is rarely the best explanation. Brains are large in scale, complex in dynamics, and have multiple levels of control (e.g. from molecular events to gross anatomical structure). What should be the proper level of abstraction and complexity for a brain-based device?

The brain can be studied at many different levels (e.g. molecular, synaptic, cellular, and network), but structure at the gross anatomical level is critical for function and, in general, ignored in models of neural function using artificial neural networks or evolutionary algorithms. While chemical changes in the nervous system, such as the effect of Prozac on the serotonin system, serve to modulate brain function, a loss of neuroanatomical structure due to stroke, trauma, or injury can cause serious deficits. For example, an injury to the hippocampal and subhippocampal structures can cause anterograde amnesia, that is, the loss of the ability to form new memories [12]. Lesions of the prefrontal cortex can cause a loss in the ability to plan for the future, make rational decisions, and process emotion [13]. In general, damages to the neuroanatomical structure of the brain whether due to stroke, disease, or trauma can lead to dramatic deficits in function.

Any model of brain function must not only take into consideration the structure of different brain regions, but must also pay attention to the connectivity within and between these brain areas. Brain function is more than the activity of disparate regions; it is the interaction between these areas that is crucial as we have shown in Darwin VII and Darwin VIII. Synaptic connections, which occur within and between neural areas, help define the function of a region. For example, the auditory cortex can be induced to carry out visual processing by re-routing the projection from the optic nerve to the auditory cortex [14]. Additionally, special connectivity that occurs during a critical period of the developing animal allows the visual system to be responsive to orientation [15]. Thus, brains are defined by a distinct neuroanatomy in which there are areas of special function, which are defined by their connectivity to sensory input, motor output, and to each other.

Preserving this structure tends to make the BBD model very large in terms of the number of distinct neural areas and the number of neuronal units within each of these areas. For example, Darwin VII's early visual processing region in its nervous system contained as few neuronal units as possible to resolve the different shapes in its environment (see  $R$  in Figure 2). Because its nervous system was based on the anatomy of the visual stream, this early region, with its 4096 neuronal units, had projections to "higher" regions of the same scale (see  $VAP$ , and  $IT$  in Figure 2) resulting in a large-scale simulation.

By basing the design on neurobiological principles, our BBDs have demonstrated behavior, similar to biological organisms that would have been difficult to achieve with a

conventional approach. For example, invariant object recognition in Darwin VII and Darwin VIII arose mainly as a result of plasticity between topographic feature detectors (e.g. *VAp*) and non-topographic association areas (e.g. *IT*) that were reinforced and expanded by subsequent inputs from stimuli during the BBD's movements. Experience-dependent perceptual categorization emerged by altering the environment. This alteration affected the BBD's object recognition; some categories were over-learned, whereas others were forgotten. We showed that autonomous sampling of salient cues from the environment caused the value system to shift from being activated by an innate unconditioned stimulus (such as "taste" or "sound") to becoming predictive of a stimulus' value and thus modulating the BBD's behavior. Darwin VIII demonstrated the ability to bind visual features into coherent categories in a scene through synchrony and showed that this is feasible in a real-world environment when objects are constantly changing in size and position.

Brain-based devices, such as the Darwin series of automata, embed principles not previously seen in robots or intelligent systems. Their performance provides a solid basis on which to develop autonomous, intelligent agents. Unlike conventional robots, the behavior of these devices is not programmed by computer instructions and is not purely reactive in nature [16, 17]. Instead, like the brain, they operate according to selectional principles through which they form categorical memory, associate these categories with innate value, and adapt to the environment.

We have demonstrated that BBDs can address many difficult and unsolved problems in robotics and computer vision without instruction or intervention, such as object recognition, visual binding of objects in a scene, and operant conditioning. These devices also provide the groundwork for the development of intelligent machines that follow neurobiological rather than computational principles in their construction.

## V. ACKNOWLEDGEMENT

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