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A Neural Approach to Adaptive Behavior and Multi-Sensor Action Selection in a Mobile Device

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Abstract. *Sampling multisensory information and taking the appropriate motor action is critical for a biological organism's survival, but a difficult task for robots. We present a Neurally Organized Mobile Adaptive Device (NOMAD), whose behavior is controlled by a simulated nervous system based on the anatomy and physiology of the vertebrate brain, that is capable of action selection in a real world environment. NOMAD's nervous system consists of an auditory system, a visual system, a taste system, sets of motor neurons capable of triggering behavior, a tracking system driven by visual stimuli, and a value system. The device itself, which moves autonomously, has a CCD camera for vision, microphones for hearing, and a gripper manipulator to pick up and taste objects by measuring the object's conductivity. Similar to a biological organism, NOMAD learns to categorize sensory information from its environment with no prior instruction, associate positive and negative value with this sensory information, and then learn to select the appropriate motor actions. We suggest that this neurobiological approach to action selection may be generalized to other robot systems.*

1. Introduction

Integrating and categorizing novel information sampled by different sensory modalities and then selecting the appropriate action is a difficult task for robots. In contrast, biological organisms categorize multisensory information and take the appropriate motor action seemingly easily and naturally. One way that organisms may achieve this sensory to motor mapping is by associating the value of objects that they sense with an appropriate motor behavior. For example, an organism may learn to seek objects that contain good value (e.g. sweet tasting food) but avoid objects that are of bad value (e.g. bitter tasting food).

We have constructed a Neurally Organized Mobile Adaptive Device (NOMAD) that autonomously explored its environment and through learning was able to develop adaptive behaviors. NOMAD is a part of the Darwin series of automata in which theories of the nervous system are tested by implementing "brain-based" devices [10, 5, 1, 8]. NOMAD's behavior is guided by a simulated nervous system based on the anatomy and physiology of the vertebrate brain. NOMAD's simulated nervous system has attributes in common with biological counterparts that are critical for action selection behavior: 1) Higher order areas that cluster and categorize sensory information without instruction. 2) A value system that reinforces behavior when a salient event occurs. 3) A nervous system that is in close interaction with a phenotype (i.e. a set of innate behaviors) and a morphology (i.e. a physical device). In the present implementation, we demonstrate that NOMAD can categorize (i.e. perceive and classify) novel auditory and visual information from its environment, associate those categories with value-loaded taste cues, and then take the appropriate action.

2. Implementation

2.1 Device. The robotic device (NOMAD) consisted of a mobile base equipped with several sensors and effectors, and was capable of communicating with a neural simulation running on a remote computer. The mobile device was constructed on a circular platform (developed by Nomadic Technologies Inc., Mountain View CA) with wheels that permitted independent translational and rotational motion, pan/tilt movement for its camera and microphones, and object gripping with a one degree-of-freedom manipulator (see Figure 1). An onboard microcontroller (PIC17C756A) sampled input and status from the sensors and controlled RS-232 communication between the NOMAD base and a host computer running the neural simulation. The CCD camera, two microphones on either side of the camera, and sensors embedded in the gripper that measured the surface conductivity of stimuli provided sensory input to the neural simulation. Eight infrared (IR) sensors were mounted at 45-degree intervals around the mobile platform. The IR sensors were responsive to the boundaries of the environment and were used to trigger reflexes for obstacle avoidance. All behavioral activity other than obstacle avoidance was triggered by signals received from the neural simulation.

Sensory information was sent to the neural simulation computer via RF transmission and allowed for untethered movement. Input to the visual system consisted of a 320x240 video image sampled by the CCD camera at a rate of 30 frames/sec sent via an RF transmitter to an ImageNation PXC200 frame grabber attached to the neural simulation computer. Input to the auditory system consisted of measuring the frequency and amplitude of signals picked up by the microphones. An RMS chip measured the amplitude of the signal and a comparator chip produced a square waveform which allowed frequency to be measured. Every millisecond, the microcontroller on NOMAD calculated the overall microphone amplitude by averaging the current amplitude measurement with the previous three amplitude measurements. The microcontroller calculated the frequency of the microphone signal by inverting the average period of the last eight square waves. Input to the taste system consisted of measuring conductivity of objects in NOMAD's gripper. If IR sensors located in the gripper indicated that an object was between its two manipulators, the gripper closed, the object was picked up, and conductivity was measured across its exposed contacts.

Figure 1. NOMAD in its environment.

2.2 Environment. The environment consisted of an enclosed area with black cloth-covered walls and a floor covered with opaque black plastic panels, on which we distributed stimulus blocks (6 cm metallic cubes; Figure 1). The top surfaces of these blocks were covered with removable black and white patterns. All other surfaces of the cubes were featureless and black. All experiments reported in this paper were carried out with block stimulus exemplars of two basic designs: *blobs* (several white patches 2-3 cm in diameter) and *stripes* (width 0.6 cm, evenly spaced). *Stripes*, when picked up with NOMAD's gripper, could be viewed either in a horizontal or vertical orientation, yielding a total of three stimulus classes (*blob*, *horizontal* and *vertical*) of visual patterns to be discriminated. A flashlight, mounted on NOMAD and aligned with the CCD camera, caused the blocks, which contained photodetectors, to emit a tone when NOMAD was in the general area. The sides of the stimulus blocks were metallic and could be rendered either strongly or weakly conductive. In the experiments described in this paper, negative value blocks were weakly conductive with a blob visual pattern and a 3.3 kHz tone, whereas positive value blocks were strongly conductive with a striped visual pattern and a 3.9 kHz tone.

2.3 Simulated Nervous System. There were six major components that made up the simulated nervous system: an auditory system, a visual system, a taste system, sets of motor neurons capable of triggering behavior, a visual tracking system, and a value system. In the instantiation used in the present experiments, the simulated nervous system contained 19,556 neuronal units and approximately 450,000 synaptic connections. The model of a neuronal unit in the simulation corresponded to the mean activity of about 100 real neurons over approximately 200 ms. Figure 2 shows a high-level anatomical view of the simulated nervous system and it diagrams the different neural areas and the connectivity between areas. Table 1 contains further details on the neural areas as well as details on the neuronal units.

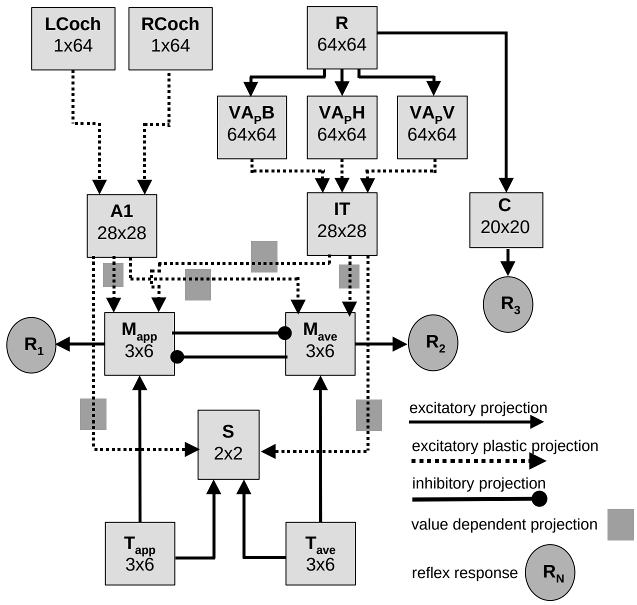

Figure 2. Schematic of the anatomy of NOMAD's nervous system. The neural areas and the number of neuronal units in each neural area are given in the shaded boxes in the figure. R_1 and R_2 correspond to appetitive and aversive behavioral responses, and R_3 corresponds to a visual tracking response. The lateral inhibition between the sub-sections of VA_P, inhibitory interneurons in *IT* and *A1*, and the connections to S_i and S_o are omitted for clarity. See text for discussion of areas and Tables 1 and 2 for parameter settings.

Visual images from the frame grabber were clipped, such that only the center square of the image remained, spatially averaged to produce a 64x64 pixel image with each pixel normalized between 0 (black) and 1 (white), and mapped directly to neuronal units of area *R* in the neural simulation. For visual tracking, the image was mapped directly to area *RC* in a similar fashion as area *R*, but without clipping, such that *RC* had a wide-angle view.

The activity of neuronal units in VA_P, which were selective for blob-like features, short horizontal, or vertical line segments, were calculated by performing a 2-dimensional convolution on area *R*. Neuronal units within VA_P were retinotopic, i.e. topographically mapped to the visual image, and projected non-topographically via activity-dependent plastic connections to a secondary visual area, analogous to the inferotemporal cortex (*IT*). *IT* contained local excitatory and inhibitory interactions producing activity patterns that were characterized by focal regions of excitation surrounded by inhibition.

The frequency and amplitude information captured by Darwin VII's microphones was relayed to a simulated cochlea area (*LCoch* and *RCoch*). *LCoch* and *RCoch* each had 64 neuronal units and each cochlear neuronal unit had a cosine tuning curve with a tuning width of 1 kHz and a preferred frequency which over the ensemble of units ranged from 2.9 kHz to 4.2 kHz. Activity of a cochlear neuronal unit was obtained by multiplying the value from the cosine tuning curve with the amplitude of the microphone signal. Cochlear neuronal units projected tonotopically (i.e. frequency mapped) to neuronal units in neural area *A1*. Similar to area *IT*, *A1* contained local excitatory and inhibitory interactions.

Two neuronal areas were capable of triggering appetitive (M_{app}) or aversive (M_{ave}) behaviors. The behavioral responses were triggered if the difference in instantaneous activity between motor areas M_{app} and M_{ave} exceeded a behavioral threshold (b = 0.3). The taste system consisted of two kinds of sensory units responsive to either strong conductivity (T_{app}) or weak conductivity (T_{ave}). The taste system sent non-plastic projections to the motor areas (M_{app} and M_{ave}) and the value system (*S*). *A1* and *IT* sent plastic projections to the motor areas (M_{app} and M_{ave}) and the value system (*S*). Initially, only the taste system was strong enough to elicit a motor behavior. Area *S* projected diffusely, with long-lasting value-dependent activity to the auditory, visual and motor behavior neurons. The visual tracking system, which controlled the approach to objects identified by brightness contrast with respect to the background, was achieved by connections from the retinal area *RC* to area *C* ("colliculus"), which in turn sent motor commands to the device's wheels. The connection strengths to achieve tracking behavior were fixed based on learning experiments in a previous study [5].

2.4 Neuronal Unit Activation and Synaptic Connection Plasticity. After each simulation cycle, the activities of all neuronal units and the connection strengths between neuronal units were recomputed. The total contribution of input to unit *i* is given by:

$$A_i(t) = \sum_{l=1}^{M} \sum_{j=1}^{N_l} c_{ij} s_j(t)$$

Where *M* was the number of different anatomically defined connection types and N_l is the number of connections per type *M* projecting to unit *i*. Negative values for c_{ij} corresponded to inhibitory connections.

The activity level of unit *i* was given by:

$$s_i(t+1) = f\left(\tanh\left(g_i\left(A_i(t) + w\, s_i(t)\right)\right)\right)$$

$$f(x) = \begin{cases} 0; & x < s_i \\ x; & otherwise \end{cases}$$

Where *w* determined the persistence of unit activity from one cycle to the next; σ_i is a unit specific firing threshold and g_i is a scale factor. Specific parameter values for neuronal units are given in Table 1.

Area	*size*	*g*	*s*	*w*
R	64x64	1.50	0.20	0.00
RC	64x64	1.50	0.20	0.00
VA_P-*B*	64x64	-	-	-
VA_P-*H*, VA_P-*V*	64x64	-	-	-
IT	28x28	1.10	0.04	0.03
IT_i	14x14	1.35	0.02	0.15
LCoch, *RCoch*	1x64	2.00	0.10	0.30
A1	28x28	1.50	0.50	0.50
$A1_i$	28x28	1.35	0.02	0.15
M_{app}, M_{ave}	3x6	2.00	0.10	0.30
T_{app}, T_{ave}	3x6	2.00	0.10	0.30
S	2x2	2.00	0.05	0.15
S_o	4x4	3.00	0.15	0.22
S_i	2x2	2.00	0.10	0.22
C	20x20	1.33	0.65	0.50

Table 1. Parameters defining neuronal units properties. The parameters were chosen such that the firing behavior of these neural areas was similar to their biological counterparts.

Connections between and within neuronal areas were subject to activity-dependent modification that was determined by both pre- and post-synaptic neuronal unit activity and resulted in either strengthening or weakening of the synaptic efficacy between two neuronal units:

$$\Delta c_{ij}(t) = e\left(c_{ij}(0) - c_{ij}(t)\right) + h\, s_j(t) F\left(s_i(t)\right)$$

Where $s_i(t)$ and $s_j(t)$ are activities of post- and pre-synaptic units, respectively, ***h*** is a fixed learning rate, ***e*** is a decay constant, and $c_{ij}(0)$ is the initial ($t=0$) weight of connection c_{ij}. The decay constant ***e*** governed a passive, uniform decay of synaptic weights to their original starting values. The function *F*, based on the BCM learning rule [2], determines limits on potentiation and depression depending upon postsynaptic activity:

$$F(s) = \begin{cases} 0; & s < q_1 \\ k_1(q_1 - s); & q_1 \le s < (q_1 + q_2)/2 \\ k_1(s - q_2); & (q_1 + q_2)/2 \le s < q_2 \\ k_2 \tanh(r(s - q_2))/r & otherwise \end{cases}$$

Implemented as a piecewise linear function defined by two thresholds ($0 < q_1 < q_2 < 1$), two inclinations (k_1, k_2) and a saturation parameter r (r = 6 throughout). Specific parameter settings for synaptic connections are given in Table 2.

Projection	*Prob.*	*Arbor*	$c_{ij}(0)$	h	e	q_1	q_2	k_1	k_2
$VA_PB \rightarrow IT$	0.01	non-topo	0.04,0.08	0.125	0.00125	0.10	0.25	0.45	0.45
$VA_PH, VA_PV \rightarrow IT$	0.0175	non-topo	0.04,0.08	0.125	0.00125	0.10	0.25	0.45	0.45
$IT \rightarrow IT_i$	1.00	Θ 2,3	0.06-0.06	0.0	0.0	0.0	0.0	0.0	0.0
$IT_i \rightarrow IT$	1.00	[] 1x1	-0.36,-0.50	0.0	0.0	0.0	0.0	0.0	0.0
$IT \rightarrow IT$	1.00	O 1	0.10,0.14	0.0	0.0	0.0	0.0	0.0	0.0
$IT \rightarrow M_{app}, M_{ave}$ #	0.15	non-topo	0.0006,0.0010	0.006	0.00006	0.01	0.16	0.1	0.16
$IT \rightarrow S_o$ #	0.05	non-topo	0.0005,0.0015	0.02	0.002	0.01	0.18	0.05	0.05
$R \rightarrow C$	0.50	[] 2x2	0.10,0.10	0.0	0.0	0.0	0.0	0.0	0.0
$LCoch, RCoch \rightarrow A1$	0.65	[] 13x2	0.10,0.13	0.01	0.0001	0.14	0.29	0.45	0.15
$A1 \rightarrow A1_i$	1.00	[] 8x18	0.06,0.06	0.0	0.0	0.0	0.0	0.0	0.0
$A1_i \rightarrow A1$	1.00	O 1	-0.30,-0.46	0.0	0.0	0.0	0.0	0.0	0.0
$A1 \rightarrow A1$	0.25	O 1	0.05,0.075	0.0	0.0	0.0	0.0	0.0	0.0
$A1 \rightarrow M_{app}, M_{ave}$ #	0.15	non-topo	0.0006,0.0010	0.006	0.00006	0.01	0.16	0.1	0.16
$A1 \rightarrow S_o$ #	0.05	non-topo	0.0005,0.0015	0.02	0.002	0.01	0.18	0.05	0.05
$T_{app}, T_{ave} \rightarrow S_o, M_{app}, M_{ave}$	1.00	O 1	0.12,0.12	0.0	0.0	0.0	0.0	0.0	0.0
M_{app} « M_{ave}	1.00	non-topo	-0.12,0.12	0.0	0.0	0.0	0.0	0.0	0.0
$S_i \rightarrow S$	1.00	[] 2x2	-0.27,-0.30	0.0	0.0	0.0	0.0	0.0	0.0
$S_o \rightarrow S$	1.00	[] 2x2	0.09,0.11	0.0	0.0	0.0	0.0	0.0	0.0
$S_o \rightarrow S_i$	0.80	[] 2x2	0.05,0.06	0.0	0.0	0.0	0.0	0.0	0.0

Table 2. Properties of connection types in NOMAD. A pre-synaptic neuronal unit is connected to a post-synaptic neuronal unit with a given probability (Prob.) and given projection shape (Arbor). Arborization shape can be a rectangular "[]" with a height and width (h x w), circular "O" with a radius (r), doughnut shaped "Θ" with the shape constrained by an inner and outer radius (r1, r2), or non-topographical "non-topo". The initial connection strengths, $c_{ij}(0)$, are set randomly within a range given by a minimum and maximum value (min, max). A negative value for $c_{ij}(0)$, indicates inhibitory connections. Projections marked # are value-dependent. Non-zero values for *h, e,*q_1,q_2, k_1 *and* k_2 signify activity-dependent plastic connections. The parameters constraining the anatomical projections between neural areas were chosen to reflect similar projections in the vertebrate nervous system.

Activation of the value system (see Area *S* and value dependent projects in Figure 2) signaled the occurrence of salient sensory events and contributed to the modulation of connection strengths of all synapses in the affected pathways. For example, tasting a block is a salient event with the consequence that at that time behavior should be reinforced or weakened through synaptic change. Area *S* thus is analogous to an ascending neuromodulatory system in that its units show uniform phasic responses when activated and its output acts diffusely over multiple pathways by modulating synaptic change [11, 12]. Value-dependent synaptic changes were applied to connections by multiplying Dc_{ij} with the term *V*:

$$V(d) = 1 + f(d)\left(\left(\bar{S} + v(d-1)(d-1)\right)/d\right)$$

Where *d* is the delay of the value term and is incremented every simulation cycle after the onset of area *S* activity with a range of 1 through 9, $\bar{S}$ is the average activity in area *S*, and *v(d-1)* is the value of *V* at time *d-1*. *f* is a convolution function that scales the activity over the delay period with values of 0.1, 0.1, 0.3, 0.7, 1.0, 1.0, 0.7, 0.3 and 0.1 for the 9 delay increments. The effect of this convolution is to delay onset of the value system activity and spread the activity over time.

2.5 Behavior. Basic modes of behavior in NOMAD consisted of IR-sensor driven obstacle avoidance, visual exploration, visual tracking, gripping and "tasting", and two classes of behavioral motor responses. These behavioral motor responses, called appetitive and aversive, could be activated by taste (the unconditioned stimulus, triggering an unconditioned response), or by auditory and visual stimuli (the conditioned stimulus, triggering a conditioned response). Unconditioned appetitive and aversive responses consisted of prolonged gripping and tasting of a stimulus block, releasing the block, and then turning counter-clockwise. Conditioned appetitive responses were the same as unconditioned with the exception of a clockwise turn after tasting. A conditioned aversive response differed from a conditioned appetitive response in that the stimulus block was not picked up. Conditioned appetitive and aversive responses occurred when either auditory or visual system responses activated the motor neuronal units such that the difference in activity between M_{app} and M_{ave} exceeded ***b*** prior to picking up a block.

2.6 Computation. Each simulation cycle lasted approximately 200 ms of clock time. The simulated nervous system was run on a Quad Pentium III Xeon Linux workstation capable of communicating with the mobile base. The workstation received auditory, visual and gripper information via a RF communication.

3. Results

In all experiments, NOMAD autonomously explored its environment, sampling stimulus blocks. Approximately eight stimulus exemplars of each block type were randomly placed within the enclosure. Seven different NOMAD "subjects" were used for the experiments. An individual NOMAD subject was an instantiation of the simulated nervous system that had unique individual connections between neuronal units (constrained by a common set of projections), and unique initial connection strengths (constrained over a range of values). See Table 2 for parameter details.

In learning trials, NOMAD quickly learned to associate unconditioned stimuli (taste) with conditioned stimuli (visual or auditory cues). A learning trial consisted of NOMAD autonomously exploring the environment until it encountered ten stimulus blocks. In visual conditioning trials, in which visual stimuli were paired with taste, conditioned responses were above 70% by the sixth stimulus encounter and above 90% by the tenth stimulus encounter (see Figure 3). In auditory conditioning trials, in which auditory stimuli were paired with taste, conditioned responses were above 80% by the sixth stimulus encounter (see Figure 3). After visual and auditory conditioning, NOMAD would take the appropriate behavioral action in response to auditory stimuli, visual stimuli, or both. Specifically, NOMAD continued to pick up and "taste" high frequency tone, stripe-patterned blocks, but avoided low frequency tone, blob-patterned blocks.

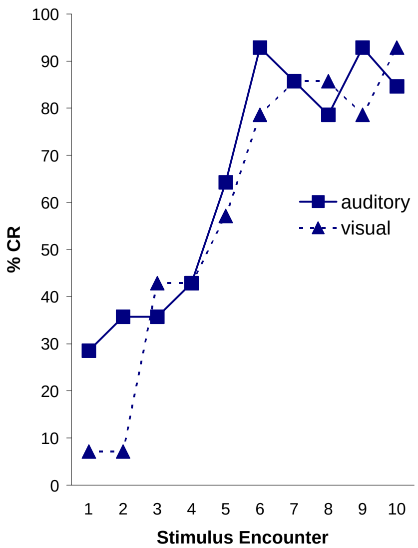

Figure 3. Percentage of conditioned responses during learning trials for both visual and auditory conditioning as a function of stimulus block encounters (seven subjects). The response of aversive and appetitive stimulus encounters were pooled together.

Changes in behavior corresponded with changes in the simulated nervous system. Figure 4 shows the activity in NOMAD's neural areas *IT*, M_{ave}, M_{app} and *S* during the first and tenth stimulus encounters of a negative value block with visual cues (i.e. weakly conductive, blob-patterned). The "snapshots" of activity shown in Figures 4 and 5 coincide with the onset of value system (*S*) activity. When encountering the stimulus for the first time, the activity in area *IT* was insufficient to classify the object and trigger a behavioral response. After several stimulus block encounters, *IT* responded to visual patterns with a sharp, strong pattern of activity that was sufficient to trigger a behavioral response. For example, in the tenth stimulus encounter, *IT*'s categorization of the blob pattern caused a conditioned aversive response prior to gripping the block. As can be seen by contrasting the pattern of activity in *IT* during the first and tenth stimulus block encounters, *IT*'s activity is diffuse with a low level of activity on early stimulus encounters, but after several stimulus encounters, becomes sharp with islands of high activity due to activity-dependent plasticity.

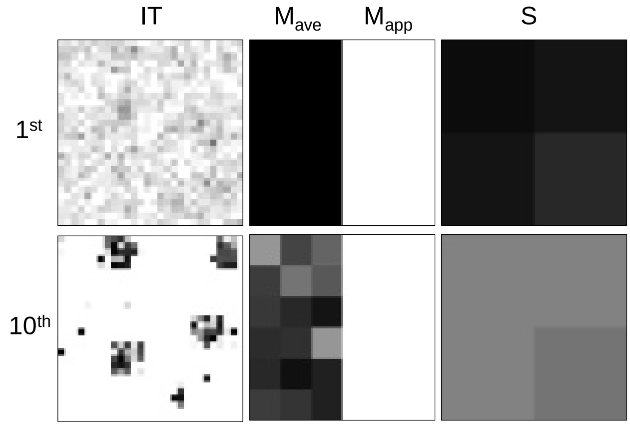

Figure 4. Activity of selected areas in the simulated nervous system during presentation of an aversive stimulus with visual cues during NOMAD's first (top row) and tenth (bottom row) stimulus encounter. Each pixel represents the activity of a neuronal unit normalized from inactive (white) to maximally active (black).

Similar to the visual conditioning example, the activity in area *A1* was insufficient to classify the object and trigger a behavioral response in the first stimulus block encounter, but sufficient to trigger an aversive conditioned response prior to gripping in the tenth stimulus encounter. Figure 5 shows the activity in NOMAD's neural areas *A1*, M_{ave}, M_{app} and *S* during the first and tenth stimulus encounters of a negative value block with auditory cues (weakly conductive, low frequency tone).

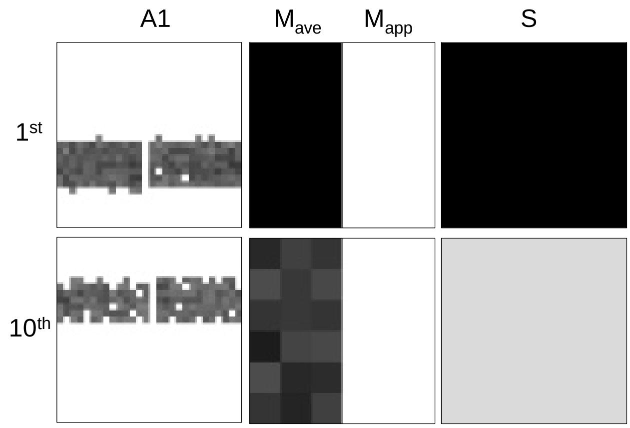

Figure 5. Activity of selected areas in the simulated nervous system during presentation of an aversive stimulus with auditory cues during NOMAD's first (top row) and tenth (bottom row) stimulus encounter.

Because of unsupervised activity-dependent learning and a reinforcing value system, NOMAD learned to categorize objects in its environment and associate the value of objects with their visual and auditory characteristics. Categorization and classification develops due to unsupervised activity-dependent plastic connections from a feature detecting area (e.g. VA_P or *LCoch/RCoch*) to an association area (e.g *IT* or *A1*), and intrinsic connections (excitatory and inhibitory) within an association area. Assigning categories to behavioral responses is accomplished through value-system modulation of plastic connections from association areas to motor behavior areas. Initially, *S* became active only when the block was tasted, and the taste of the block triggered a behavioral response (i.e. T_{ave} triggered M_{ave}). On the tenth stimulus encounter in both the visual and auditory learning trials, area *S* became active at the conditioned stimulus onset (the visual pattern or the tone) prior to gripping the stimulus block (see Figures 4 and 5).

4. Conclusions

In the present report, we show how NOMAD, a robotic device controlled by a neural simulation, developed adaptive behavior and action selection based on its interaction with the environment. NOMAD was able to perceive and categorize objects in its environment with multiple sensors and adapt its behavior appropriately due to activity-dependent plasticity and a reinforcing value system. In agreement with experimental studies of perceptual categorization [3, 6, 7], activity in NOMAD's association areas varied between subjects, and varied as a function of experience in the environment, yet all subjects demonstrated successful performance on learning tasks. Environmental exploration, association areas in the nervous system, and modulatory signals from a value system enabled the organism to generalize and transfer learning from one sensory system to another [11, 12]. The value system, which was activated by environmental cues, resulted in reinforcement learning at critical, salient times. This approach of experience-dependent categorization with environmentally cued reinforcement learning could conceivably be a general problem solving technique for robots in unfamiliar environments where the robot must extract salient cues with little or no prior instruction.

Emulating the activity and connectivity of a biological nervous system provides a useful methodology for modeling and controlling complex behaviors carried out by devices in the real world [8, 9]. The heuristic described above is an example of a device based on biological principles that contains morphology, a nervous system, and a niche within an environment. Similar to a biological organism, NOMAD's memory is selective within a lifetime, is distributed, and differs significantly from trial to trial reflecting individual experience [4]. We suggest that devices, such as NOMAD, provide a novel approach toward robotics and the construction of intelligent machines.

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