

PROJECT DESCRIPTION

1 Introduction



Figure 1: Inferring Stimulus Properties from Neural Activity. A simple perceptual agent with a single sensory neuron is illustrated. The neuron performs a transformation $f : I \rightarrow S$, where I is the input stimulus and S the spike output (the encoded internal state). The problem of inferring the stimulus property represented by S (for example, orientation of a line segment) can be posed to either an external observer (a) or an internal observer (b). As we can see, the task is much harder (or may even seem impossible) for the internal observer which does not have direct access to the actual stimulus I . Note that the raw input I is available only at the immediate sensory surface (such as the retina).

The main research problem of this proposal is that of grounding: “How can the semantic interpretation of a formal symbol system be made intrinsic to the system, rather than just parasitic on the meanings in our heads?” (Harnad, *Physica D* 42:335-346, 1990). How can internal representations be linked to external stimulus properties (semantic interpretation), within the confines of the brain of an agent (intrinsicness, or autonomy)? Stimulus properties represented by sensory cortical neurons are well known to neuroscientists. For example, extensive experiments have uncovered that visual cortical neurons respond to orientation (Blasdel 1992; Blasdel and Salama 1986; Grinvald et al. 1994; Hubel and Wiesel 1962, 1968; Ts’o et al. 1990), spatial frequency (Issa et al. 2001; Landisman and Ts’o 2002), direction of motion (Shmuel and Grinvald 1996; Weliky et al. 1996), and other stimulus dimensions. Also, latest results in self-organization models and natural image statistics research have shown an intricate relationship between the tuned stimulus properties (or receptive field properties) in these neurons and the statistical properties of visual elements in the environment (Bell and Sejnowski 1997; Choe and Miikkulainen 2004; Geisler et al. 2001; Karklin and Lewicki 2003; Olshausen and Field 1997).

Thus, it seems that scientists have a good understanding of what stimulus properties are represented by neural spikes, and how the specificity to such properties may arise through development. What enabled such an understanding is our ability to conduct experiments as an external observer, with simultaneous access to both the environmental stimulus and the neural spikes (figure 1a). Such experiments provided the stimulus and response data that were needed by analysis frameworks such as those based on Bayesian methods or information theory (Rieke et al. 1997; Warland and Meister 1995; see Oram et al. 1998 for a review).

However, the question of how these encoded sensory representations can be interpreted within the confines of the brain has not been given much attention. How can the brain itself learn about the stimulus properties carried by its own neural spikes when direct access to the environmental stimulus is not available? This problem is illustrated in figure 1b, which is distinctively different from the one faced by neuroscientists (figure 1a). With access to only the spikes (and none to the environmental stimulus), it seems impossible to conduct the kind of analyses as mentioned above, which require direct knowledge of the stimulus. This is basically an instance of the problem of *grounding*. Understanding how natural agents achieve grounding despite such a severe limitation is of prime importance because it will allow us to identify key ingredients that enable intrinsic grounding, leading to the construction of robust, autonomous, intelligent agents that have their own semantics and not programmed by humans.

The main hypothesis of this proposal is that motor primitives (stereotypical patterns of motor sequence;

Matarić 2001) serve as a key ingredient in inferring the stimulus properties when only the brain’s internal state is observable. This project will bring us one step closer to solving the grounding problem. By observing the changes in the internal spikes while performing action, and relating that pattern of action to those changes, an internal observer can infer stimulus properties without direct access to the raw environmental stimulus (figure 2). Through action, the agent-environment loop gets closed, and only through such an interaction can the agent find grounding for its internal state. Our view is not the first to emphasize the importance of action since active vision precedes us (Aloimonos et al. 1988; Bajcsy 1988; Ballard 1991; Findlay and Gilchrist 2003; Harris and Jenkin 1998). However, this project is the first to recognize its importance in relation to grounding and development of grounding in neural systems.

Several important questions arise from the above observation, including (1) how to link internal states to motor primitives in a grounded manner, (2) what is the developmental origin of sensory receptive fields and motor primitives. The **objectives** of this project, motivated by the above, are as follows:

1. **Action-based grounding of simple stimulus properties:** *Investigate motor-primitive-based grounding of internal sensory states.*

How can sensory states be linked to motor primitives that have a similar property is an important question. What kind of biological principle can guide such a linkage will be the main point of investigation for this objective.

2. **Action-based grounding of complex stimulus properties:** *Extend action-based grounding to deal with complex object properties.*

Can the action-based grounding approach generalize to deal with complex object properties? In its original form, the approach is basically reactive, thus the stimulus properties recoverable are limited to simple orientations. With the addition of memory capacity, this limitation can be lifted. The main focus of this objective will be to extend the action-based grounding to encompass more complex stimulus properties.

3. **Co-development of sensorimotor primitives and grounding:** *Derive learning rules to self-organize sensory receptive fields and motor primitives that together maximize grounding.*

The sensory receptive fields and motor primitives adapt over time throughout development. How can the two developmental processes co-direct each other so that the degree of grounding is maximized? This question will be addressed within a cortical self-organization paradigm.

Scope: The problem of grounding is prevalent in the various sensory modalities and the conceptual constructs in cognition and language. Certain modalities such as color or smell pose an acutely difficult problem for grounding in general (the problem of “qualia”), and for the approach presented in this proposal in particular. That is, it is hard to see how actions can have color-like or smell-like properties. Although there are good arguments about how even the sensation of color may be tightly coupled with a certain type of action (the book “Seeing Red” by Humphrey 2006 is especially relevant; also see Humphrey 1992; Nöe 2004; O’Regan and Noë 2001), in this project the project team will focus on *grounding of geometric properties only*, as a concrete first step. Finally, we emphasize that our main hypothesis is about action being a *necessary condition* of grounding with no claim made about it being a sufficient condition. For a complete account of grounding, agency and autonomy should be incorporate at the very least. These are hard problems on their own, requiring an investigation much larger in scale than what is proposed here.

Intellectual merit: Grounding is a foundational issue in artificial intelligence and cognitive science, and has yet to become one in neuroscience. The key insight in this proposal is that making the problem of spike interpretation intrinsic to the brain is important in understanding the problem of grounding. The results from this project are expected to elucidate the role of motor primitives in grounding in neural systems. The

project links theoretical, biological, and developmental perspectives of grounding firmly anchored at the neural level, providing a cross-disciplinary perspective on grounding.

Broader impacts: This project contains outreach activities specifically targeted at underrepresented groups among the undergraduate population. The project’s outcome can, in the long run, lead to the development of truly autonomous agents, with potential applications in space exploration, care-giving to patients, and operation in hazardous environments. The framework can shed light on neuroscience research, with its emphasis on analysis intrinsic to the brain, which will help redefine the research problems in neuroscience (cf. “23 Problems in Systems Neuroscience” edited by van Hemmen and Sejnowski 2006) and also provide unique solutions.

2 Background

In this section, we will briefly review relevant background that provide motivation for our project.

2.1 Natural image statistics and theory of receptive field formation

As briefly discussed earlier, the sensory receptive field properties and how they can develop have been intensively studied (section 1). In fact, there are more work being done in this hot area than the references listed in section 1. For example, see the special issue of *Network: Computations in Neural Systems* on natural scene statistics edited by Reinagel and Laughlin (2001). However, in most of these works, it is unclear what is to be done with the resulting output, or how the encoded representations are to be interpreted by subsequent stages. Also missing is the link between these learned receptive field properties and that of action and behavior. Even when we ignore goal-directed behavior and higher cognitive functions, the problem persists.

Furthermore, stimulus statistics can be altered by specific patterns of action, thus biasing the input distribution. For example, Reinagel and Zador (1999) showed that contrast distribution near the center of gaze (following saccades) is distinctly different from neighboring regions. Thus, deriving receptive field properties solely on the basis of randomly sampled input image patches cannot tell the complete story. For example, Floreano et al. (2005) and Wyss et al. (2006) have shown how the motor module in exploratory robots affects learned receptive field properties. The implications of the above on the understanding grounding will be addressed in this proposal, by incorporating action into the investigation.

2.2 Inferring stimulus properties from spikes

What stimulus property does a spike convey (Rieke et al. 1997)? A very successful approach in answering this question has been through associating the neural spikes with the stimulus that triggered those spikes (Warland and Meister 1995; see Oram et al. 1998 for a review). This method involves the experimenter systematically varying the environmental stimulus while measuring the neural response (see, e.g., Rieke et al. 1997 chapter 2), so that at a later time when only the spike train is observed, something can be said about the property of the stimulus. Mathematically, this is conveniently written using the Bayes rule (Rieke et al. 1997): $P(I|S) = \frac{P(S|I)P(I)}{P(S)}$, where I is the input stimulus and S the spike activity (figure 1a). Note that the likelihood term $P(S|I)$ and the prior $P(I)$ require that we have either an empirical statistic or a reasonable prior knowledge of the stimulus I . Thus, the interpretation of the current spike train $P(I|S)$ seems to *depend* on a priori or direct knowledge about the stimulus properties, which introduces the problem of circularity (cf. Hacker 1987): to know about X, one must already know about X.

However, such an approach requiring direct access to the environmental stimulus (figure 1a) has limitations as mentioned in the introduction (section 1, figure 1b). Thus, such a strategy cannot form the basis of grounding.

2.3 Relationship between action and perception

Given the discussion in the previous section, the question then is, “what is missing from this picture?” (figure 1b). A potential answer is *action*. An action-oriented approach may be able to solve this problem. Even when the stimulus I is not directly accessible, through action and the associated change in S , some properties of the stimulus can be recovered. Experimental results suggest that action and the motor cortex actually play an important role in perception (Bach y Rita 1972, 1983; Hecht et al. 2001; Held and Hein 1963; Naito et al. 2002), providing support for this idea. The implication is that sensorimotor coordination may be a necessity for autonomous learning of sensory properties conveyed through the internal state.

There are ongoing research efforts in the theories of the sensorimotor loop (Granlund 1999; Humphrey 1992; Hurley 2001; O’Regan and Noë 2001; Philipona et al. 2003, 2004), developmental robotics (Almássy and Sporns 2001; Brooks 1991; Lugarella et al. 2003; Pfeifer and Scheier 1999; Weng et al. 2001), embodied cognition (Varela et al. 1993), bootstrap learning (Kuipers et al. 2006; Pierce and Kuipers 1997), natural semantics (Cohen and Beal 1999), dynamical systems approach to cognition (Beer 2000; Cariani 2001), schema theory (Arbib 2003), imitation (Arbib 2005; Demiris and Hayes 2001; Matarić 2001; Schaal et al. 2003) etc. that touch upon our topic of interest. However, the question of how could the brain understand itself and how that relates to grounding has not been fully addressed (cf. second-order cybernetics, von Foerster 2003).

Finally, the discovery of “mirror neurons” (neurons in the prefrontal cortex that respond to visually perceived gesture and also to the production of the same kind of gesture) provides a unique opportunity for the investigation of grounding mechanisms in the brain. Mirror neurons have been thought to be involved in imitation and communication, i.e., reading other’s mind (Arbib 2005; Rizzolatti et al. 1996, 2001), but investigation of mirror neurons in relation to the issue of grounding has not been addressed (Choe 2005).

Summary: In this section, we reviewed related works that provided motivation to our research. In so doing, we have identified key research issues such as the status of grounding in neural systems and developmental issues. Our research group at Texas A&M has been addressing these issues in this section, and has been making good progress. Prior results from these early pilot studies are summarized in the following section (section 3).

3 Prior Work

3.1 Sensory-Invariance-Driven Action (SIDA) for Autonomous Semantics

In previous work (Choe and Bhamidipati 2003, 2004), we showed that in a sensorimotor agent as in figure 2a, the stimulus property represented by internal neuronal state can be inferred through the use of motor primitives. Imagine we are inside this agent, isolated from the world outside the box, sitting near the “ π ” symbol, with no access to I nor f . We are then faced with the same problem as depicted in figure 1b.

The only way we can see the problem solved is through action, that is, the movement generated by the agent. This is not entirely obvious at first, so we will elaborate on this point. For example, consider the state of the agent as shown in figure 2b, where a 45° input is presented and the corresponding sensor is activated in the sensory array. Now imagine we move the visual field according to the motor action vector sequence $\nearrow, \nearrow, \nearrow, \searrow, \searrow, \searrow$, which corresponds to a back-and-forth movement along the 45° diagonal (along the slanted input). Such an action will keep only the 45° sensor turned on during the motor act, i.e. the sensory array will stay invariant over time. We can see that this motion, generated while trying to keep the sensor array unchanged, has led the agent to perform an act, the property of which reflects that of the stimulus. Thus, we are led to conclude that associating sensory spikes with the property of this kind of sensory-invariance-driven action can potentially serve as the meaning for each sensory neuron. That is, there is a correspondence between (1) the property of the stimulus I triggering a particular sensory state s and (2) the property of the action a that maintains invariance in the sensory state s . Thus, a *behaviorally meaningful content* (the particular action) can be attached to each sensory state, providing a solution to

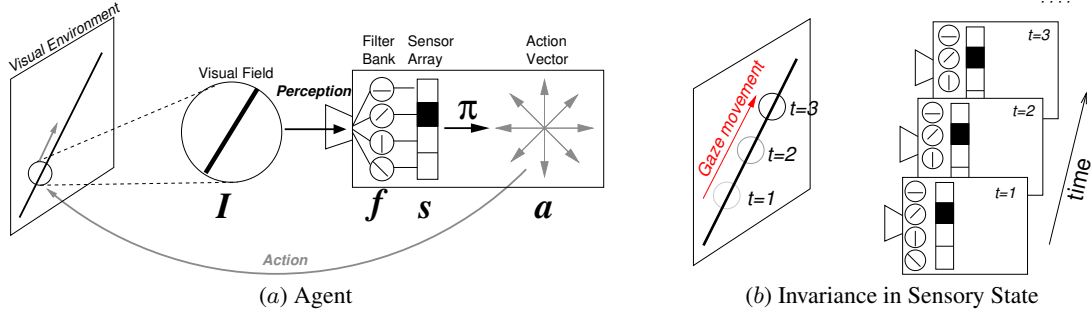


Figure 2: A Sensorimotor Agent. An illustration of a simple sensorimotor agent is shown. (a) The agent has a limited visual field where part of the input from the environment (I) is projected. A set of orientation-tuned units f (sensory primitives) receive that input and transform it to generate a pattern of activity in the sensory array s (black marks active). In the example shown here, the 45° unit is turned on by the input. Based on the sensory array pattern, a mapping π to motor action vector a is determined, resulting in the movement of the visual field in that direction, and then a new input is projected to the agent. Note that the agent is assumed to be aware of only its internal sensory state s , thus it has no knowledge of I , nor that of f . How can this agent attach meaning to such a sensory state? One possible way is to utilize its motor capability, but how? (b) The agent’s internal sensory state does not change over time as the agent’s gaze moves along the diagonal input. The important point here is that the diagonal property of the motion exactly corresponds to the environmental property conveyed by the orientation-tuned units. We will use this interesting relationship in allowing an artificial agent to achieve grounding through the use of its motor primitives.

the problem in figure 1b. Notice that the word “invariance” here is used in a different sense from that in traditional computer vision. In our work, invariance simply means that the state does not change over time. It should not be confused with “perceptual invariance,” such as translation invariance, rotation invariance, etc., as used by Almásy and Sporns (2001) for example.

3.2 Influence of Input Distribution on Receptive Field Formation

Previously, we developed a laterally connected self-organizing map model of visual cortical development and function (Choe 2001; Choe and Miikkulainen 2004; and Miikkulainen, Bednar, Choe, and Sirosh 2005 which the PI coauthored). In the model, the connections learned through an activity-dependent Hebbian learning rule. In that work, we showed that difference in input distribution results in differential organization of receptive field properties and lateral connection statistics, and in turn it leads to differentiation of functional performance (Choe 2001; Choe and Miikkulainen 2004; Miikkulainen et al. 2005). Such a model can be extended to test how particular motor primitives themselves can develop, and how they can actively influence the input distribution, giving rise to differential development of receptive field properties. The methods we developed in the work above will be utilized in this project.

3.3 Results from Prior National Science Foundation Support

The PI has been funded by the National Institutes of Health (#1R01-NS54252, PI: Yoonsuck Choe) and by the Texas Higher Education Coordinating Board (#000512-0217-2001, PI: Jyh-Charn Liu, Co-PI: Yoonsuck Choe), but not by the National Science Foundation (NSF) as a PI, a Co-PI, or a senior person. However, he participated, as a graduate student, in the NSF-funded project *Modeling Development and Perceptual Phenomena in the Visual Cortex* (#IIS-9811478, PI: Risto Miikkulainen). The book *Computational Maps in the Visual Cortex* (Miikkulainen et al. 2005), coauthored by the PI, is a direct outcome of the project (see the book web page <http://computationalmaps.org> for details). The *Topographica* neural map simulator project is also a continuation of the effort, where the PI is serving as an active developer (<http://topographica.org>). The project was also funded by NIH/NIMH Human Brain Project #1R01-MH66991 (PI: Risto Miikkulainen; PI on subcontract: Yoonsuck Choe). The *Topographica* simulator will serve as an integral part of this project.

This project contains substantially novel ideas compared to these prior work, where the emphasis on the motor aspect of cortical development and grounding is an entirely new direction. Furthermore, the proposed integration of sensory and motor maps helps bring the two projects together.

4 Research Plan

This section is organized into three subsections, each corresponding to one of the objectives listed in the introduction (section 1), in that precise order.

4.1 Action-based Grounding of Simple Stimulus Properties

Learning the stimulus properties represented by internal states from *within* the agent’s brain is a daunting task as illustrated in figure 1b, but with the ability to generate action, a solution can be found. We propose to design and test a learning algorithm based on the idea sketched in section 3.1. Preliminary results suggest that the sensory-invariance-driven action (SIDA) criterion allows an agent to learn the stimulus properties conveyed by a sensory neuron’s activity in terms of a motor primitive (Choe and Bhamidipati 2003, 2004). Below, we will present an extended algorithm, which allows for a graded filter response and a graded measure of invariance, in addition to the usage of natural images instead of synthetic ones as input.

4.1.1 Methods

Input preparation and response generation: Consider the agent described above (figure 2a). First, we will preprocess the raw input I_R by convolving it with a difference-of-Gaussian (DoG) filter (Rodieck 1965). A small area in the resulting input I_D will be sampled (the input is 640×480 and the sampling area is 31×31), producing I . (Figure 3 shows an example input.)

In order to determine the sensory state, we will use oriented Gabor filters. (Gabor filters are known to resemble the receptive fields in the primary visual cortex of mammals (Daugman 1980).) Using the Gabor filters, we calculate the filter response. The filter response is a column vector \mathbf{r} where each element r_i ($i = 1..n$, where n is the number of filters) corresponds to the sum of pixel-wise product of the input and the oriented Gabor filter: $r_i = \sum_{x,y} G_i(x,y)I(x,y)$, where (x,y) is the location in the two matrices, and G_i has the orientation tuning of $\theta_i = \lfloor (i-1)\pi/n \rfloor$. The value r_i is simply the vectorized dot-product of G_i and I . The vector \mathbf{r} is then normalized with its ℓ_2 -norm $|\mathbf{r}|$.

Finally, based on the filter response \mathbf{r} , a scalar value representing the sensory state s is calculated as $s = \arg \max_{i=1..n} r_i$, where each value of s corresponds to a unique orientation $\theta = \lfloor (i-1)\pi/n \rfloor$ for $i = 1..n$. The set of all possible s values constitutes the set of sensory states S .

For each orientation, there are two matching directions of motion. For example, for θ of 0° , the two directions are 0° and 180° . Thus, the set of actions A has $2n$ movement-direction (or action) vectors as members (for example, see figure 2a): $A = \left\{ (d \cos(\theta), d \sin(\theta)) \mid \theta = \frac{(i-1)\pi}{n}, \text{ for } i = 1..2n \right\}$, where d is

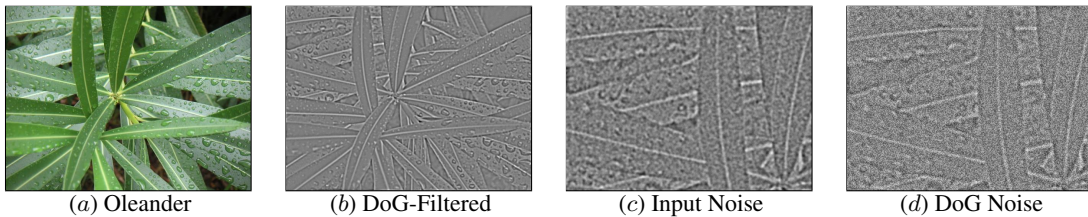


Figure 3: **Difference-of-Gaussian (DoG)-filtered Natural Image and Noise-Added Versions.** (a-b) A natural image and the filtered counterpart are shown. (c) Input noise added before DoG-filtering of the input in (b) is visualized. (d) Noise added after DoG-filtering of (b) is shown. In (c) and (d), only the upper left quadrant of (b) is plotted to show the details.

the distance of each movement, θ the direction of motion, and n the number of orientation filters.

Learning algorithm: Given a particular sensory state $s(t)$ at time t , taking an action $a(t)$ takes the agent into sensory state $s(t+1)$. The state transition depends on the particular edge feature in the visual scene, thus it is probabilistic. The reward $\rho(t+1)$ is simply the degree of sensory invariance achieved across states $s(t)$ and $s(t+1)$. One way to measure the *degree* of invariance $\rho(t+1)$ is to calculate the dot-product across the successive sensory filter responses:

$$\rho(t+1) = \mathbf{r}(t)^T \mathbf{r}(t+1), \quad (1)$$

where $\mathbf{r}(t)$ is the filter response vector at time step t , and “ \mathbf{x}^T ” represents the transpose of \mathbf{x} . With this formula, when the previous filter response is the same as the current, the reward becomes maximized ($\rho(t) = 1$) and in the opposite case minimized ($\rho(t) = -1$). The benefit of using the vector \mathbf{r} instead of directly comparing the scalar values s is that a graded measure of invariance can be obtained instead of a hard *invariant* or *not-invariant* judgment.

The task of the agent is to learn a state-to-action mapping so that it maximizes the reward $\rho(t)$ at time t . However, because of the probabilistic nature of the state transition (which heavily depends on the edge features in the input image), a deterministic state-to-action mapping is not viable. Given the current state $s(t)$, we can think of the conditional probability $P(a(t)|s(t))$ so that if we choose action $a(t)$ with this probability, the probability that the next state $s(t+1)$ being the same as $s(t)$ is maximized. Given an estimate of $P(a(t)|s(t))$, which we will call the *reward probability function* $R(s(t), a(t))$, we let the agent execute the following policy π at each time step t :

1. Given the current state $s(t) \in S$, randomly pick action $a(t) \in A$.
2. Perform action $a(t)$ with probability $R(s(t), a(t))$.
3. Repeat steps 1 to 3 until exactly one action is performed.

To reflect the fact that eye movements follow a fairly straight to slightly curved trajectories between targets (Doyle and Walker 2002), the policy above will be augmented with a momentum mechanism where, with a 30% chance, the action from the previous time step $t-1$ will be repeated, bypassing the steps above. In practice, for step 2 above, the action will be performed if a random draw from $[0..1]$ is less than $cR(s(t), a(t))$, where the parameter c controls the strictness of this check. When the location of gaze reached the image boundary in I_D , the movement will be wrapped around and continued on the opposite edge of the input.

The remaining question is how can $R(s(t), a(t))$ be learned? For that, we will use a simple update rule:

$$R^{<t+1>}(s(t), a(t)) = R^{<t>}(s(t), a(t)) + \alpha \rho(t+1), \quad (2)$$

where $R^{<t+1>}(\cdot, \cdot)$ is the reward probability function at time $t+1$, and α the learning rate parameter. Finally, $R^{<t+1>}(s(t), a)$ values are normalized by $\sum_{a' \in A} R^{<t+1>}(s(t), a')$ for all $a \in A$.

The algorithm above takes elements from reinforcement learning (Sutton and Barto 1998; Werbos 1987), especially the TD(λ) algorithm (in the extreme case where $\lambda = 1$, i.e., identical to the Widrow-Hoff delta rule) (Sutton 1988). (In fact, a test run with the delta rule $R^{<t+1>}(s(t), a(t)) = R^{<t>}(s(t), a(t)) + \alpha(\rho(t+1) - R^{<t>}(s(t), a(t)))$, without the divisive normalization, resulted in similar results.) The use of the reward probability function $R(s, a)$ (for $s \in S$ and $a \in A$) is similar to the Q -learning algorithm where the action-value function $Q(s, a)$ is estimated and used to construct a policy (Watkins 1989). (We have explored this option, and reported preliminary results in Choe and Smith (2006).) *Thus, the main novelty of the algorithm lies in the choice of the reward ρ .* In pilot simulations, the above learning rule converged under

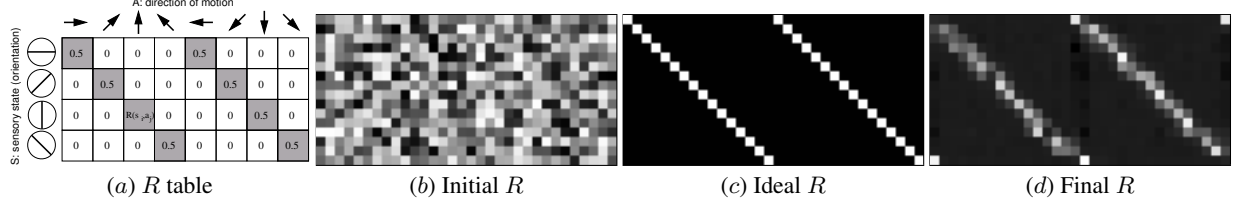


Figure 4: Initial, Ideal, and Learned $R(s, a)$ Values. (a) The reward probability function $R(s, a)$ is shown as a table. The rows represent sensory states and the columns motor primitives. In an ideal, predictable environment with straight lines only, the table should have a diagonal structure as shown: two directions of motion (e.g., 0° and 180°) per one orientation (0°), marked in gray. Natural images do exhibit a collinear structure (Geisler et al. 2001), thus the ideal case shown here can be a good approximation. (b-d) The grayscale representation of the (b) initial, (c) ideal, and the (d) learned R tables are shown. White represents the maximum value, and black the minimum value. The learned R in (d) shows a clear diagonal structure, similar to the ideal case (c). (Unpublished pilot results are shown.)

all experimental conditions. Figure 4 shows pilot results of learned $R(s, a)$ values. The learning algorithm was tolerant against input noise as well (data not shown: see figure 3c&d for example inputs). Preliminary results in figure 5 shows the gaze trajectories in the initial and the final stages of learning. Based on these preliminary results, we propose to carry out the following:

- test with an extended set of natural images to assess the effect of image statistics on learned sensori-motor mapping;
- implement the algorithm on a pan-tilt webcam;
- add lateral inhibition in r so that the response becomes more sharply tuned, leading to faster convergence;
- increase the number of filters/action primitives used (i.e., scale up); and
- extend the learning rule to include reward look-ahead.

4.1.2 Evaluation

The effectiveness of the learning algorithm will be based on two criteria:

1. K-L divergence (Kullback and Leibler 1951) between the reward probability distribution $R(s, a) = P(a|s)$ and the ideal distribution (figure 4c); and
2. windowed average of reward values over time and reward distribution.

Even though the algorithm itself is purely unsupervised, in the sense that it does not receive particular $R(s, a)$ value as a target, as shown in figure 4c, we can assume a theoretically ideal target. Note that the ideal $R(s, a)$ is not used in the training; it is only used for measuring the accuracy of the learned $R(s, a)$. In our pilot simulations, the error in $R(s, a)$ steadily decreased, reaching a steady state.

Another measure is the running average of immediate reward value ρ . A simple windowed average can be taken as reward values are generated through the iterations. Our early results showed that the windowed average steadily increases, and reaches a plateau. As for the distribution of the reward values, a simple histogram of ρ values will suffice. Preliminary results showed that initially the distribution forms two peaks, one at negative min and one at positive max reward. However, as the learning reaches the end, only the peak at the positive max remains, thus suggesting that the invariance-based learning rule is effective.

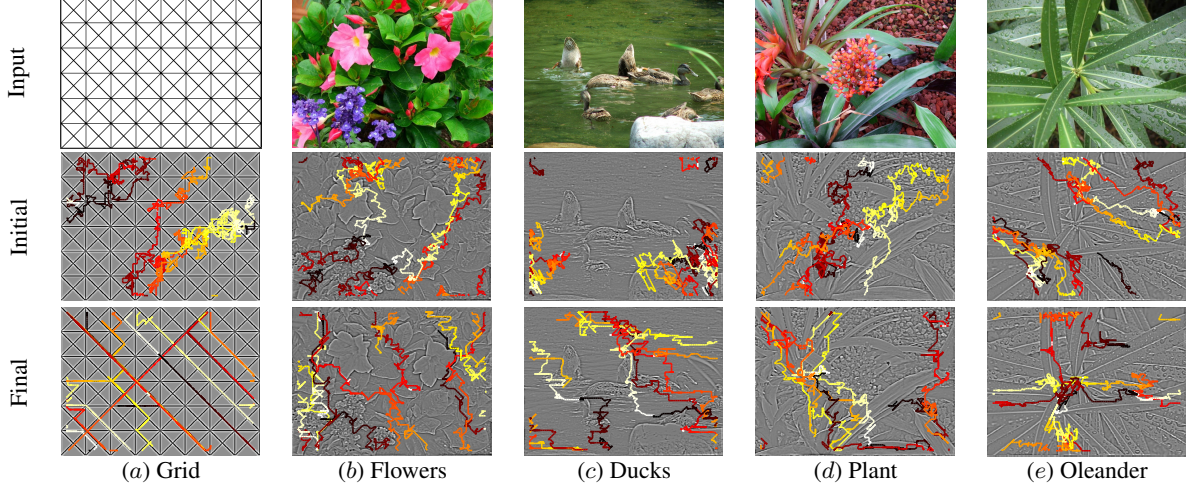


Figure 5: Gaze Trajectory at the Beginning and at the End of Learning (Pilot Result; Color Figure). Gaze trajectories near the initial and the final stages of training are shown. The color represents the flow of time, where black \rightarrow red \rightarrow yellow \rightarrow white is repeated every 768 iterations. (a) The initial trajectories are more like random walk. (b) The final trajectories show straighter motions, and those along strong edge features in the input image. Note that such motions maximally maintain invariance in the internal perceptual state of the agent, and the property of those motions (oriented motion in a particular angle θ) exactly reflects the stimulus property of the current perceptual state (i.e., the current input has orientation θ). The trajectory wraps around the borders since a toroidal boundary condition was used. (Unpublished pilot results are shown.)

Finally, how can we check if our algorithm really gives rise to true grounding? This is a rather philosophical question. For example, apply the same question to any human: It is not easy to answer for certain. The only objective measure is from the subject’s behavior (think about the Turing Test). Based on this argument, we can say that when our agent has achieved grounding when its behavioral property reflect that of the stimulus property conveyed by its internal sensory states, which might as well be the case (figure 5). However, to some, this may sound inadequate. At this point, recall that our main hypothesis was that utilization of motor-primitives form a necessary condition for grounding ($\neg MotorPrimitives \rightarrow \neg Grounding$). Without motor primitives, there will certainly be no grounding, but motor primitives alone are not sufficient for grounding. A direct test of the hypothesis will be to check if grounding is possible without motor primitives ($\neg(\neg MotorPrimitives \rightarrow \neg Grounding)$), that is, $\neg MotorPrimitives \wedge Grounding$). This can be done within the same simple visuomotor agent framework in figure 2a. Removing the action part, we only get the filters f and the internal states s . If we can, through the use of standard pattern recognition techniques, recover what s corresponds to after extended exposure to changing environmental input (the scene goes passing by) then we will have shown $\neg MotorPrimitives \wedge Grounding$, disproving our hypothesis. Thus, what kind of information and relationship among different sensory states can we extract based on only the internal states become the main issue here. We will develop a measure for this, and apply that to both our approach and the motor-primitive-less approach to objectively assess our main hypothesis.

4.2 Action-based Grounding of Complex Stimulus Properties

Building upon the work in the previous part, the agent will be extended to perform basic recognition tasks on complex visual objects using motor-primitive-based representations.

4.2.1 Methods

The task of the agent is to understand, based on the changes in its internal state over time, the properties of the input that the internal state is reflecting. The same principle of invariance can again be used in this

situation to recover meaningful action sequences that reflect the geometric properties of the stimulus object. The main idea is to extend the detection of invariance from that of a single sensory unit to that of a spatio-temporal pattern in the sensory array. The sequence of actions that maintains such an invariance at a higher level would be able to reflect a more complex stimulus property (i.e., structure) that gave rise to a particular spatio-temporal pattern.

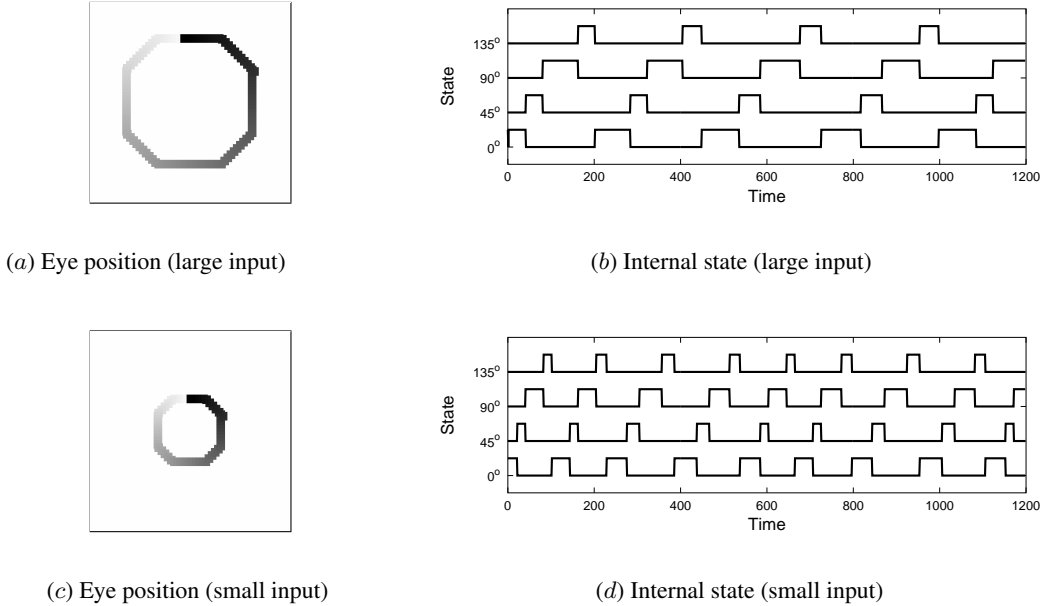


Figure 6: Inferring Stimulus Properties of a Complex Object. The agent’s position over time as it explores an octagon input and its corresponding internal state are shown. (a) The agent’s position is plotted over 250 time steps, where the grayscale indicates the time step (white is time 0, and black is time 249). (b) The activation state of the four neurons in the agent is shown over 1200 time steps. As the agent repeatedly directs its gaze around the octagon, the internal state also shows a repeating pattern, from 0° , 45° , 90° , 135° , back to 0° , for example (the pattern in the interval $[200, 449]$). Note that the entire trace in (a) corresponds to the interval $[0, 249]$ in (b). (c) and (d) show the same information as in (a) and (b), but for a smaller input. The period of the spatiotemporal activity is shorter in (d) than in (b), as the length to traverse is shorter in (c) compared to (a). The plots show actual data from a preliminary simulation using a deterministic exploration strategy.

Once the learning algorithm described in section 4.1 is extended to include graded activation of the sensory units and a graded measure of reward based on the degree of invariance, the visual agent will be able to generate an action sequence to maintain a high degree of invariance for objects that are not straight lines. For example, consider an octagon. (Note that we are using a decidedly simple form as an example here, to facilitate a straight-forward explanation.) The visual agent may be able to generate a motor sequence as shown in figure 6a, repeatedly going over the octagon in a periodic manner. As a result, in its internal state, a spatio-temporal pattern will emerge (figure 6b).

The question then is, what kind of invariance can be embedded in such a dynamic spatio-temporal pattern of activity? Also, what kind of coordinated action (e.g., a gesture) can ensure such an invariance? As we can see in figure 6b, there is a clear repetition of the pattern in the interval $[200, 450]$, from 0° , 45° , 90° , to 135° . The corresponding action sequence can be derived from the trajectory plotted in figure 6a.

Such a motor representation has a very desirable property. For example, suppose we represent the motor sequence as a sequence of direction vectors of unit length. For the example shown in figure 6a, the corresponding vector sequence would be $\leftarrow, \leftarrow, \leftarrow, \swarrow, \swarrow, \swarrow, \downarrow, \downarrow, \downarrow, \searrow, \searrow, \searrow, \rightarrow, \rightarrow, \rightarrow, \nearrow, \nearrow, \nearrow, \uparrow, \uparrow, \uparrow, \nwarrow, \nwarrow, \nwarrow$. For a similar input in figure 6c, the vector sequence is very similar, and the only difference is

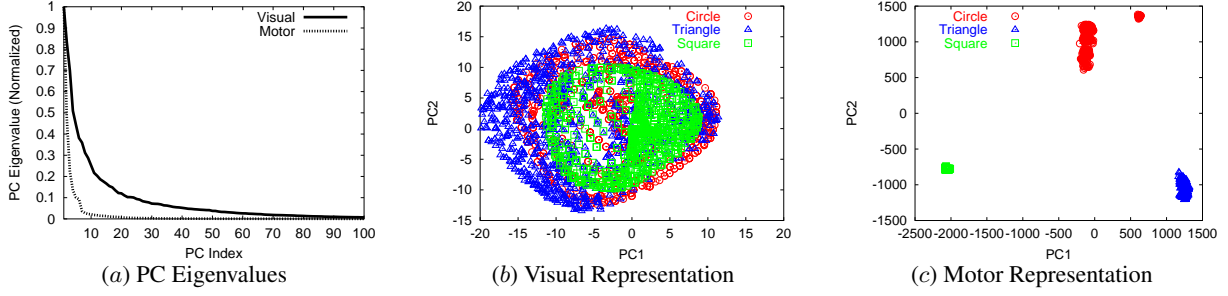


Figure 7: Comparison of Visual vs. Motor Representations. Principal components analysis results are shown for visual vs. motor representations of shapes (circle, triangle, and square). (a) The eigenvalues of the principal components (PC) of the visual (solid) and motor (dotted) representations are shown. The x -axis is the PC index, and the y -axis the associated eigenvalues. (Only the first 100 are shown, where index 1 corresponds to the first PC.) The motor representation shows a rapid drop, indicating that its intrinsic dimensionality is lower than the visual representation. (b) The projection of the visual representation data on the first and the second principal component axes are shown (PC1 and PC2, respectively). The three categories are largely overlapping. (c) The motor representation data are plotted as in (b). The three shape categories are clearly separable, suggesting that motor representations may be superior compared to visual representations for use in robust recognition tasks.

the number of vectors in the repeating pattern. A simple compression that removes redundant back-to-back vectors results in the same representation for both the large (figure 6a) and the small (figure 6c) octagons: $\leftarrow, \swarrow, \downarrow, \searrow, \rightarrow, \nearrow, \uparrow, \nwarrow$. Thus, the motor-primitive-based representation easily gives rise to scale-invariance (as well as the translation invariance which is inherently present), whereas the 2D Cartesian geometrical representation requires multiplying each point with a scaling matrix, which may be nontrivial for a simplistic agent to figure out. (Note that this concept is in line with the idea of “motor equivalence” by Lashley 1951, who argued that motor representations serve as a canonical representation for object concepts.) Our preliminary results suggest that this is indeed the case. Principal components analysis of a set of 2D bitmap-based representations of circles, triangles, and squares, and a motor-primitive-based counterpart is shown in figure 7. It is clear that the three classes in the motor-primitive-based representations are much easier to separate. We will modify the algorithm in section 4.1 so that a memory mechanism is maintained in order to detect and reward repeating spatiotemporal patterns given complex objects as inputs. We will then collect the motor sequence to use them in recognition tasks. Due to the stochastic nature of the motor policy, each run will result in a different motor sequence, so we will average over several trials to obtain a mean trajectory. We will carry out the following, as part of this section:

- develop biologically plausible algorithms for the detection of invariance in a spatiotemporal pattern (cf. dynamic time warping by Keogh and Pazzani 1999, 2001; and FFT-based approach by Tsai et al. 1994);
- develop memory mechanisms for representing and executing a combinatorial sequence of motor primitives; and
- develop methods to derive a canonical motor sequence from several stochastic runs in order to characterize a typical motor sequence to be linked to an invariant spatiotemporal pattern. (This canonical motor sequence will be used in evaluating the approach in this section.)

4.2.2 Evaluation

First, we will conduct clustering analysis on the resulting motor sequences and their bitmap counterpart, as done in figure 7. This will allow us to gain an intuitive idea about the relative merit of the motor-primitive-based approach. Next, we will use supervised neural networks to learn the mapping between

motor-primitive-based representations and their class labels, and compare the results to those from corresponding 2D bitmap-based representations. The experimental setup will be similar to our earlier work on comparing different texture representations in recognition tasks (Oh and Choe 2004). As suggested by figure 7, we expect the motor-primitive-based representations to show more robust performance, and better generalization. We will eventually test the approach on natural images. Here, we will use the algorithm to find out basic forms embedded within natural scenes.

Note that the emphasis is on understanding what is fundamentally useful about motor-primitive-based representations, and certainly not on recognition performance (since sophisticated computer vision algorithms may be able to do a much superb job). Our results will allow us to appreciate the effectiveness of motor-primitive-based grounding, as opposed to sensor-based representations.

4.3 Co-development of Sensorimotor Primitives and Grounding

Up to this point, we have largely assumed that the sensory receptive fields and motor primitives are a given. However, for developing natural agents, the receptive fields and the motor primitives themselves may adapt over time. In order to see how the perception-action coupling can positively affect each other throughout development, this part of the research effort will be devoted to this important issue, i.e., *development of grounding*.

4.3.1 Methods

Sensory invariance may again play an important role here. For example, sensory receptive fields may have to develop into a form which are amenable to invariant activation based on the natural stimulus structure; and motor primitives would also have to take shape into something that reflects the perceptual organization as well.

Consider the simple visuomotor agent discussed in figure 2a. Suppose the agent had four undetermined sensory receptive fields, and eight undetermined motor commands. What would be the configuration that would allow the agent to understand most about the environment? There are at least three approaches:

- independently develop the sensory receptive fields and the motor commands and link them up later;
- given a fixed set of motor primitives, develop the sensory receptive fields and learn $R(s, a)$; and
- simultaneously develop both, while learning the link $R(s, a)$.

In fact, independent development of sensory receptive fields and motor commands have already been studied by Pierce (1995) and Pierce and Kuipers (1997) where equivalence classes of sensors and actuators were found by random exploration and principal component analysis was used to find a small number of canonical clusters, which then formed the sensor and motor categories. This approach can be combined with our approach in section 4.1 to address the first approach above. Thus, we will focus on the two remaining approaches.

In the second case, the sensory receptive fields are adaptable and the motor primitives are fixed (the action set A in section 4.1), while the reward table R is also adaptable. The learning rule for the receptive field can be derived by first defining an energy function following Olshausen and Field (1997):

$$E(I, \mathbf{r}(t), \mathbf{r}(t-1)|\phi) = \sum_{\mathbf{x}} \left(I(\mathbf{x}) - \sum_i r_i(t) \phi_i(\mathbf{x}) \right)^2 + \lambda \sum_i V(r_i(t), r_i(t-1)) \quad (3)$$

where $E(I, \mathbf{r}(t), \mathbf{r}(t-1)|\phi)$ is the energy function associated with the retinal input I , response activation $\mathbf{r}(t)$ at learning iteration t , and connection weights ϕ in the receptive field; \mathbf{x} the spatial position within the image I ; $I(\mathbf{x})$ the pixel value at the retinal photo receptor at location \mathbf{x} ; $r_i(t)$ the activation of tuned

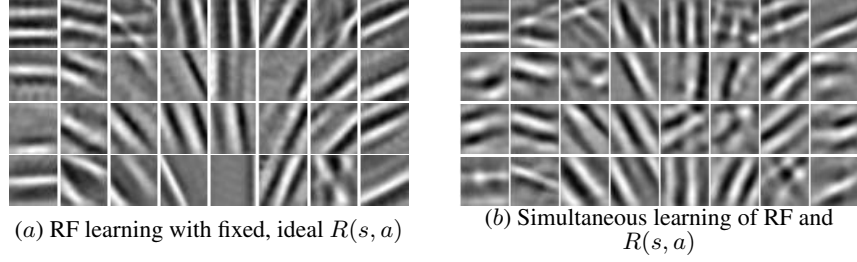


Figure 8: **Learning the Receptive Fields (RFs) and the Reward Table R .** The development of orientation preference in the receptive fields (RFs) are shown for two different learning conditions. Each row shows the learned RFs from different natural images. Each column represent one of the eight sensory receptive fields (f in figure 2). Both simulations were run on natural images. (a) The results from learning the RFs with a fixed, ideal reward table R is shown. The learned receptive fields have orientation corresponding to the motor direction. (b) The same as (a), except that noise (Gaussian, 1% amplitude) was added to $R(s, a)$ and $R(s, a)$ also adapted, following the invariance criterion. The receptive fields are not as well-defined as in (a), but the oriented features are still clearly visible. (Unpublished pilot results are shown.)

receptive field i ; $\phi_i(\mathbf{x})$ the connection weight between retinal receptor at \mathbf{x} and neuron i ; λ a regularization constant; and $V(\cdot, \cdot)$ a regularization function which has a high value when invariance is not maintained across successive values of s_i . The equation was extended to take into account the activation from the previous step $s_i(t-1)$ so that invariance can be measured. This is where action comes into the picture: Different action will result in different sequence of $s_i(t)$, thus affecting the learning process.

The learning rule to minimize the energy function can proceed in two steps. First, fix ϕ and do gradient descent on r_i :

$$\Delta s_i(t) = -\frac{\partial E}{\partial r_i} = \sum_{\mathbf{x}} \phi_i(\mathbf{x}) \delta(\mathbf{x}) - \lambda V'(r_i(t), r_i(t-1)), \quad (4)$$

where $\delta(\mathbf{x}) = I(\mathbf{x}) - \sum_i s_i(t) \phi_i(\mathbf{x})$. The function $V(x, y)$ can be defined as $\log(1 + (x - y)^2)$, so that greater difference in successive r_i values will be penalized. Next, fix $r_i(t)$, and do gradient descent on ϕ_i :

$$\Delta \phi_i(\mathbf{x}) = \eta \langle s_i(t) \delta(\mathbf{x}) \rangle, \quad (5)$$

where η is the learning rate and $\langle \cdot \rangle$ represents the expected value. The resulting learning rule is similar to Hebbian learning, as in Choe (2001); Choe and Miikkulainen (2004); Miikkulainen et al. (2005). Thus, the existing simulation infrastructure will be used to implement the functionality above. Note that since the receptive fields are directly in contact with the immediate sensory sheet (in this case the retina), raw input I is available to the learning process. However, beyond this stage, I is not available. Figure 8 shows some preliminary results indicating that a variant of the above approach can be effective. The important point to note here is not the fact that Gabor-like receptive fields have been formed, but rather that the receptive fields formed those shapes as a direct result of enforcing action-oriented grounding. (Also see Choe and Yang (2006) for some preliminary results.)

The most challenging part is the third option: To simultaneously develop both the sensory and motor primitives, while learning the reward table R to link the sensory to the motor. Matarić (2001) showed how parametric motor primitives can be used to fit motion-capture data, or novel motor primitives can be extracted from such data. However, she did not show how motor primitives can emerge in a self-organizing, unsupervised manner. We will extend the work of Kuniyoshi (2006); Kuniyoshi et al. (2004) in setting up and self-organizing the somatosensory map, from which we expect to obtain insights for the self-organization of the motor map. Our motor map self-organization will proceed with somatosensory input coupled with “body babbling,” a randomly generated sequence of motion which is hypothesized to aid in the development of internal forward models (Rao et al. 2004). Our view is that body babbling should not be random, as it may need to be guided by the requirement of grounding.

For this latter task, we will experiment with the formation of a motor map, based on our experience with self-organization in the visual cortex. As part of this effort, we will develop a motor cortex module in the *Topographica* neural map simulator. Initially we will simulate a simple two-segment stick arm (Demiris and Matarić 1998), and gradually extend the model to a more complex morphology, with actuators and proprioceptive sensors, and link it up to the self-organizing maps. The different morphologies will be implemented in the *Webots* simulation environment (<http://www.cyberbotics.com>). The motor map development is expected to closely reflect that of the somatosensory map development, since the alpha motor neuron pathways (motor) and the muscle spindle pathway (sensory) are tightly coupled (Kandel et al. 2000), thus we will first experiment with somatosensory map formation. The key research issue here is how can the motor map development include considerations for grounding, through the invariance criterion. The development of visual, somatosensory, and motor maps may have to be linked through the single need for a grounded internal state. Research issues we will investigate in this section include the following:

- investigate relative timing (i.e., developmental clock) of plasticity in the sensory receptive fields, motor primitives, and the linkage between the two;
- investigate the effect of stimulus statistics and motor apparatus on the development of grounding, by systematically varying the input statistics and altering the motor capability.

4.3.2 Evaluation

To evaluate the influence of grounding on the development of sensory and motor primitives, we will compare the results with and without sensory-invariance-driven grounding. We will conduct an extensive analysis of the resulting maps. We will categorize the resulting motor map into a discrete set of motor primitives, using standard clustering techniques. (See Matarić (2001) and Demiris and Matarić (1998) for typical motor primitives.) The same analysis will be done on the somatosensory map and the visual map, and the results compared to that of the motor map. In order to test the utility of the sensory-invariance-driven grounding, we will compare the above results with those from an experiment with a different learning rule, only based on standard Hebbian learning or other approaches such as independent components analysis (Bell and Sejnowski 1997; Hyvärinen and Hoyer 2001). For biological insights, we will reference the large body of work on “mirror neurons,” neurons that activate in response to perceived gestures and also when the same gesture is enacted (Rizzolatti et al. 1996, 2001). We will also use the evaluation framework outlined in the last paragraph in section 4.1 for a thorough analysis of the necessity of motor primitives in grounding.

5 Education and Outreach

An important aspect of the research component of this project is that the subject requires an interdisciplinary approach, ranging from computer science, cognitive science, to neuroscience. The new interdisciplinary course the PI designed and taught in spring 2003 (Intelligent Neural Systems, CPSC 689-601) and offered again in spring 2004 and spring 2005 was received very well among students. For that course, the PI was awarded the departmental graduate teaching award in spring 2004. The course contained interdisciplinary material from artificial intelligence to cognitive science and neuroscience, and in the course the close relationship among these fields and their mutual relevance were made explicit. The PI will continue developing such an interdisciplinary curriculum.

It is also interesting to note that the subject of research has direct implications on the educational portion of the project. As shown in the research plan, it is clear that grounding of new knowledge is best done on the basis of action. Applying that insight to education, we can infer that students may learn more efficiently when they use their own actions that are meaningful to them to manipulate (either physically or mentally) the subject matter. Thus, it is important to identify actions that are meaningful to individual students,

and provide interactive material designed to facilitate those interactions. We will apply this philosophy in designing new course projects and assignments, and in preparing other instructional material.

The PI is also committed to equally motivating and mentoring underrepresented groups, and acknowledge that this mission is best carried out in the undergraduate classroom. This is because stirring interest in this group of students at an early stage will help them stay in school and continue on to pursue a career in research and education. In this vein, the PI has been participating in the Undergraduate Summer Research Grant (USRG) program sponsored by the College of Engineering at Texas A&M. The program attracts excellent undergraduate students from across the country, and many of these students are from minority-serving institutions. The PI supervised two undergraduate students (one minority) under this program (2003 and 2005). The PI also mentored three students supported under the NSF Research Experience for Undergraduates program (REU; 2004, 2005, 2006), and two students (one minority, both female) under the CRA-Women Distributed Mentor Project (DMP) for undergraduate women in computing research. Three of the above students applied to and were accepted by top graduate programs in the US, and one is currently applying. The PI will continue mentoring undergraduate students under NSF REU, TAMU USRG, and CRA-Women DMP. The PI is planning to apply for REU supplements to continue providing such excellent research opportunities to undergraduate students.

Sparkling an initial light of excitement in the younger generation of scientists and engineers is quite important. In line with this commitment, the PI has been participating in departmental events where the research labs are showcased to high school students, teachers, and parents. Since 2003, our lab hosted six lab tours to high school student groups and other interested parties. The PI also gave a guest lecture at the Summer Honors Invitational Program (SHIP) at Texas A&M University in 2004, where top high school students (national merit scholars) from around the country were invited to experience the atmosphere of the university. The PI will go beyond participation and take an active role in these and other events to reach out to the general public, especially the younger generation. As part of this effort, a set of web-based interactive tutorials will be authored, which illustrate the basic principles of the proposed research (cf. <http://www.whyville.com> spearheaded by James Bower at University of Texas).

All software and data resulting from this project will be publicly released under the GNU Public License (<http://www.gnu.org>). We will set up a dedicated web page for this purpose. (See <http://topographica.org> and <http://computationalmaps.org> for similar web pages contributed by the PI.) We will also organize workshops (co-located at major research conferences such as AAAI, IJCAI, NIPS, COSYNE, IJCNN, etc.) to encourage collaboration among researchers in this highly interactive, interdisciplinary field.

6 Work Plan

The PI Yoonsuck Choe will be responsible for the overall supervision of the project (years 1 to 3), implementation of tasks in section 4.1 (year 1), tasks relating to Topographica (section 4.3, year 2), and coordination of outreach activities including the development of the web tutorial (year 3). One graduate student will focus on section 4.2 (years 1 to 3), and the other on section 4.3 (years 1 to 3).

7 Summary

In this proposal we have developed ideas for the systematic investigation of the role of motor primitives in grounding, and the influence of grounding in development. We expect our project to shed new light on important issues in autonomous intelligent systems, computational neuroscience, and cognitive science, by drawing our attention to the processes internal to the brain of an agent: the issues faced by the brain, from its own perspective. Furthermore, we will apply our insights gained from this research in building an action-oriented, grounded learning framework, which we expect to contribute to mentoring and education at multiple levels.

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